LiPAD: License Plate Advance Deblurrer, a lightweight AI Powered Philippine License Plate Deblurring and Recognition

A Thesis Paper
Presented to
The College of Computer Studies
Angeles University Foundation

In Partial Fulfillment
Of the Requirements for the Degree of
Bachelor of Science in Computer Science

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The Thesis Project entitled:

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ACKNOWLEDGEMENT

Our warmest thanks are extended to our advisor, Mcs. Mellisa M. Pantig. She not only made this possible but continually conveyed a spirit of encouragement and an excitement that sustained us. Without her compassionate heart and expert guidance, this endeavor would have certainly crushed us.

We are deeply grateful to our panel of examiners: Dr. James Alejandro Esquivel, Dr. Joey Aviles, and Mr. Arn Lagazo, for their encouragement and constructive insights that greatly strengthened this study. We also acknowledge PCpl. Gerald Dungca for the valuable input he shared, as well as for connecting us with Mr. Lagazo, who served as our indispensable domain expert.

We also extend our appreciation to the College of Computer Studies for providing an environment that fosters learning, research, and innovation. Their support helped shape this work into its present form.

Our heartfelt thanks go to our families and friends, who continuously provided patience, motivation, and emotional support throughout the development of this study.

Above all, the highest gratitude is reserved for the Lord, our God, for His unfailing provision for our needs and the strength He granted us daily. We are certain He was with us throughout this journey. To Him be the highest glory and honor.

DEDICATION

ABSTRACT

Philippine traffic enforcement faces challenges from poor-quality license plate images due to motion blur, camera constraints, and low-light conditions. LiPAD (License Plate Advanced Deblurring) is a lightweight deep-learning system designed for Philippine license plates. LiPAD first used a CNN-based classifier (96.2% accuracy) to identify distortion types, enabling a self-aware approach that reduced computational overhead. Four specialized GANs restored degraded images, with the Residual Attention U-Net generator outperforming a standard U-Net in handling complex distortions. LiPAD achieved strong results for horizontal blur (SSIM: 0.84), low-light (0.84), and low-quality (0.69), with moderate performance on vertical blur (0.63). Deblurred images are processed by a CRNN for optical character recognition, yielding a 90% word accuracy rate. Integrated into a web application on single-GPU or CPU-only machines, LiPAD complies with ISO/IEC 25010 standards. By combining robust performance with a lightweight design, LiPAD provided a reliable, scalable solution for real-world traffic enforcement.

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CHAPTER 1: INTRODUCTION

1.1 Background of the Study

The rapid increase in vehicles leads to traffic challenges in law enforcement, public safety, and congestion. Traffic congestion can prompt drivers to prioritize convenience, which may lead to risky behaviors such as making illegal turns or running red lights, increasing the likelihood of accidents and injuries (Peng et al., 2022). In the Philippines, for example, the Philippine Statistics Authority (2024) reported a total of 14 million registered vehicles in the past year, as shown in Table 1.1. Likewise, the Land Transportation Office (2024) recorded more than 100,000 reckless driving violations during 2022 and 2023, emphasizing the scale of these challenges, as summarized in Table 1.2.

Table 1.1

Number of registered vehicles and their types of fuel in the Philippines, 2023

Fuel Type	Number of Vehicles
Gas	11,227,751
Diesel	3,033,831
CNG	9
LPG	3
Electric	1,359
Hybrid	6,155
Total	14,269,108

Table 1.2

Reckless Driving Frequency Violations in the Philippines in the years 2022 and 2023

Year	Number of Reckless Driving Violators
2022	57,492
2023	46,844
Total	104,336

The issues of traffic management and law enforcement are particularly acute in the country. Recent data from the Land Transportation Office's National Capital Region (LTO-NCR) highlighted the extent of the problem. Villamente (2024) reported that the number of traffic offenders apprehended by authorities in Metro Manila reached 18,025 during the first six months of 2024. This table shows a significant 124.5% increase from the same period in 2023. The dramatic rise in traffic violators indicates that traffic enforcement has become increasingly complex while demanding more effective identification and punishment methods.

To reduce accidents and improve road safety, proper addressing of strict traffic enforcement is necessary. Traffic enforcers monitor traffic violations through manual methods such as speed radar guns, while in some areas, video cameras are used to monitor violators for running red lights and failure to use a helmet. However, these methods are labor-intensive, and frequently violators are not given sufficient penalties, which leads to overall weak enforcement (Chauhan et al., 2023). With the number of offenders, it is impossible to detect each violation physically, as apprehending each offender is time-consuming and laborious.

Vehicles are normally identified through their license plates, making it possible to detect those involved in violations. License plates remain the most reliable and cost-effective method for verifying vehicle ownership. If institutions only rely on manual observation and human resources like traffic enforcers to identify plates, as Weihong and Jiaoyang (2020) and Dalida et al. (2021) suggested, they would face challenges such as human error, inefficiency, and high operational costs. Additionally, video footage that is consistently clear and of high quality is difficult to obtain in the Philippines. Factors including motion blur from fast-moving vehicles, poor lighting conditions, reflections, environmental conditions, and the use of low-cost cameras with poor capabilities result in blurry, distorted, or low-resolution images captured by surveillance cameras. These issues significantly hinder the accuracy of plate identification, making it difficult for authorities to extract and verify license plate information (Brillantes et al., 2019).

As technology advances in deep learning and computer vision, applications for detecting license plates have been developed. These applications are Automated License Plate Recognition (ALPR) systems, which are crucial for efficient recognition of vehicle license plates, and they have grown to be a significant subject for research due to their various uses in the field, like traffic management, law enforcement, and toll collection (Reyes, Cepe, Guerrero, Sevilla, & Montesines, 2021; Gong et al., 2024). These ALPRs rely on character recognition in capturing license plates, which aim to recognize each character present on the plates. However, in capturing license plates, various factors contribute to the blurring of images or frames, which may lead to undetected vehicles passing through or inaccuracy in results.

While ALPR systems have been developed to address these challenges, they often fail in real-world applications due to environmental constraints and camera-induced distortions (AlDahoul et al., 2024). The camera limitations usually cause incorrect or failed recognition because of factors such as motion blur, reflections, poor lighting, and low image quality. These ALPR systems also lack dedicated deblurring or image restoration capabilities. This limitation is particularly evident in the Philippines, where no AI-based deblurring system has been specifically trained on local license plates. Furthermore, as Reyes et al. (2021) noted, Philippine license plates are of various formats based on vehicle type, making recognition efforts more challenging. Some methods, like LPDGAN by Gong et al. (2024), demonstrated promising results in reconstructing distorted images for Chinese license plates; however, they do not generalize to the Philippine setting because of the difference in plate designs and formats.

One approach to addressing these challenges is by developing a multi-stage AI-powered license plate deblurring and recognition model that uses specific deep learning algorithms: Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), and Convolutional Recurrent Neural Networks (CRNN). Convolutional Neural Networks (CNNs) are a deep learning technique that excels in capturing spatial patterns and relationships within images (Zhang et al., 2020). In this scenario, CNNs will be employed as classifiers to identify the type of distortion present in a license plate image by extracting and classifying its features. This initial classification is important because it allows the system to apply the appropriate deblurring and recovery model tailored to the specific type of distortion.

On the other hand, GANs are designed to generate new data samples that resemble a given dataset. In this context, GANs will be used to recover and deblur the distorted license plate images. The capability of GANs to enhance image quality is particularly important in circumstances where images are captured under challenging conditions, such as low light or high motion, which are common in traffic environments. GANs improve license plate recognition by effectively recovering the images (Wang et al., 2021). Furthermore, CRNNs combine the strengths of CNNs and Recurrent Neural Networks (RNNs) to process sequential data. In this study, CRNNs will be employed for the recognition of the license plate text. CRNNs can capture both the spatial features of the images and the sequential nature of the text, which allows accurate character recognition. The integration of CRNNs ensures that the model can effectively interpret the sequence of characters on the license plates, which is important for accurate license plate recognition (Sun et al., 2019).

The purpose of the study is to apply these deep learning techniques in practice. This approach improves the recognition rates and addresses the specific needs of the Philippine setting, where license plates come in different formats and are frequently captured in challenging conditions. The study will be tailored uniquely to Philippine license plate formats, which will overcome the limitations of conventional ALPR systems, ultimately reaching the ideal traffic law enforcement and road safety on public roads.

1.2 Statement of the Problem

In the Philippines, the effectiveness of identifying vehicle license plates is hindered by the poor quality of surveillance footage, often affected by motion blur, low resolution, poor lighting, and various environmental factors. This problem limits the ability of authorities to accurately recognize license plates during investigations and traffic enforcement.

Specifically, the study seeks to answer the following questions:

1. How can a representative and well-annotated dataset of Philippine license plate images with various distortion types be gathered and preprocessed to train deep learning models effectively?
2. How accurately can a CNN-based classifier identify and categorize distorted license plate images based on the type of degradation?
3. To what extent can GAN-based models effectively restore distorted license plate images according to their specific degradation types?

4. How accurately can a CRNN-based recognition model extract alphanumeric characters from restored license plate images across various plate formats?

5. How can the classification, restoration, and recognition models be integrated into a functional web application for practical law enforcement use?

6. What is the level of conformity of the developed web application with the ISO/IEC 25010 software quality model in terms of functionality suitability, performance efficiency, interaction capability, reliability, security, and safety?

1.3 Statement of Objectives

1.3.1 General Objective

This study aims to develop a deep learning-based solution for restoring various types of blurry license plate images using CNN, GANs, and CRNN to enhance readability and enable accurate recognition. The trained models will be integrated into a web application to support law enforcement in identifying vehicle license plates from degraded surveillance images.

1.3.2 Specific Objectives

The specific objectives are as follows:

1. To collect and curate a dataset of Philippine license plate images containing six (6) to seven (7) characters, and to perform preprocessing, augmentation, and annotation for effective use in training, validation, and testing of deep learning models.

2. To design, train, and evaluate a CNN-based distortion classifier capable of accurately identifying and labeling license plate image distortions into predefined categories, achieving at least 90% classification accuracy.

3. To develop distortion-specific GAN models to restore low-quality and blurry license plate images, targeting enhanced visual quality with SSIM $\geq$ 0.80, FID $\leq$ 40, and PSNR $\geq$ 18dB.

4. To implement and optimize a CRNN-based recognition model that can accurately extract license plate characters from restored images with a character error rate (CER) $\leq$ 5% and word accuracy rate (WAR) $\geq$ 90%.

5. To integrate the trained models into a web application using a client-server architecture that processes user-uploaded images and outputs readable license plates within $\leq$ 5 seconds per request.

6. To evaluate the web application's conformity with ISO/IEC 25010 quality standards through expert reviews and user testing, assessing functionality suitability, performance efficiency, interaction capability, reliability, security, and safety using both quantitative metrics and qualitative feedback.

1.4 Significance of Study

With the current state of rapid urbanization of cities in the Philippines and the lack of a quality transportation system, the number of traffic volumes along major roads has led to an increase in motorists violating traffic rules and regulations (Jose, J. A. C. et al. 2021). ALPRs, CCTVs, dash cams, and speed cameras are used to monitor traffic and enforce rules and regulations, however, cameras may capture images that would otherwise be considered unusable due to blurriness. Since license plates are the tools used to identify a vehicle, deblurring license plates would be enough to assist enforcement officers.

This study will be specifically significant and beneficial to the following:

To the Traffic Enforcement Officers

As stewards of public safety on roads, traffic enforcers and police rely on license plates in recognizing specific vehicles. A system that would deblur license plate images would give vital information that would help enforcers to further enforce the rules and regulations against violators. This study would help enforcers be aware of the positive role of AI tools and their contribution to society. Moreover, as the system within this study assists law enforcement, it supports SDG 16 (Peace, Justice, and Strong Institutions).

To the Philippine Land Transportation Sector

This study would serve as a basis for the potential usage of AI and deep learning within the land transportation sector of the Philippines. This could also assist in the continuous improvement of traffic management in major cities throughout the nation. By encouraging public safety and crime prevention and strengthening law enforcement in the Philippines through the assistance of vehicle identification, the study promotes industry improvement and smarter infrastructures, which aligns with SDG 9 (Industry, Innovation, and Infrastructure).

To the Society

This study would serve as an eye-opener for society to recognize real-life applications of AI and deep learning that would improve overall quality of life. Additionally, the system would promote responsible driving by improving traffic enforcement, which would also help reduce road accidents that contribute to public safety. Through AI and deep learning solutions for traffic enforcement, the study supports road safety, accident reduction, and well-managed city infrastructure, which aligns with SDG 11 (Sustainable Cities and Communities).

To Other Researchers

This study would serve as a valuable reference for exploring the use of AI and deep learning concerning traffic enforcement, especially regarding the deblurring of distorted license plate images. Future researchers may build upon this study by introducing new features that would improve the model's accuracy in extreme conditions or expand the system's capabilities in recognizing various types of license plate formats, such as temporary license plates or specialized license plates. Additionally, by emphasizing continual learning and educational progress in improving traffic enforcement using AI and deep learning, the study supports SDG 4 (Quality Education).

1.5 Scope and Limitations

1.5.1 Scope

This study proposes an AI-powered license plate deblurring tool for distorted license plate images to assist traffic enforcers in managing and monitoring traffic in the Angeles City to ensure safety and quality of traffic management. The study focuses on license plates containing six (6) to seven (7) characters.

This study will be conducted over a period of 6 months, encompassing both the development of an AI model for license plate deblurring and its deployment as a web application. The web application implementation will be evaluated using the ISO/IEC 25010 standard, focusing on the following criteria: functionality suitability, performance efficiency, interaction capability, reliability, security, and safety.

Additionally, the model is designed to address and correct various common types of image distortions encountered in real-world scenarios. These include low-quality images, low-light conditions, and both vertical and horizontal motion blur.

For model training and evaluation, the dataset will consist of six specific types of image variations derived from the original undistorted license plate images. These variations include:

1. The original cropped license plate images,
2. Super-resolution enhanced versions of the original images,
3. Vertically motion-blurred versions,
4. Horizontally motion-blurred versions,
5. Low-light versions, and
6. Low-quality (degraded) versions of the original images.

To support the training of the CRNN model for license plate recognition, normal and enhanced images are paired with a corresponding text annotation representing the ground truth license plate content. These annotations are essential for supervised sequence learning and are included as part of the dataset.

1.5.2 Limitations

Despite the potential of the AI-Powered Deblurring system, the deblurring faces multiple constraints that affect its operational effectiveness in actual use. Obstacles such as highly blurred license plate images, very poor resolution images, and images with multiple types of distortion prevent accurate AI model reconstruction. While moderately blurred images can be improved by deep learning techniques, image restoration is difficult when the said obstacles are present in the image. In such cases, the model may provide inaccurate or incomplete outputs, which may affect the system's reliability.

Additionally, It is important to note that the system accepts only image files in standard formats such as JPG, JPEG, and PNG. It does not support video input or real-time video processing due to the significant computational overhead and complexity involved in such tasks. As such, any surveillance footage must first be manually processed to extract individual image frames containing the blurred license plates.

Furthermore, the effectiveness of the model is highly dependent on the quality and diversity of the training dataset. The dataset will be collected from publicly available datasets and from accommodating motorists. However, the adherence to the Data Privacy Act of 2012 (R.A. 10173) and other regulations is also necessary due to ethical concerns, such as data privacy risks and the possible misuse of restored images.

The local data gathering ensures that the format matches the standard for Philippine license plates only and that no fake or altered plates are used.

Moreover, processing purposefully altered or physically damaged license plates may provide imprecise results or cause issues for the system, as these are difficult to restore or confirm as valid license plates from fake or tampered license plates. In addition to that physical constraint, an oblique viewing angle wherein the camera is not aligned to the license plate in a perpendicular (90-degree) manner would lead to inaccuracy of deblurring, although slightly tilted license plates that are almost perpendicularly viewed are an exception.

1.6 Definition of Terms

The following terms are operationally defined as utilized in this study for a better understanding of the study:

AI-Powered Model. It refers to a computational system that uses artificial intelligence techniques to analyze and process distorted license plate images. This model employs deep learning algorithms to improve recognition rates and adapt to the specific challenges posed by the Philippine license plate formats and different environmental conditions.

Deblurring. It refers to the process of enhancing the clarity of distorted license plate images captured under various challenging conditions. This involves the application of advanced algorithms that specifically target and rectify distortions such as low quality images, low light, and motion blur. The goal of deblurring is to transform these unclear images into recognizable formats that can be effectively used by traffic enforcement officers to identify vehicles.

LiPAD (License Plate Advanced Deblurring). In this study, this refers to the name of the license plate deblurring system.

Low Quality Image. It is a type of image distortion that refers to an image that contains a relatively small number of pixels and/or distorted due to low bitrate capturing of the image, which results in limited details and clarity.

Philippine License Plate Formats (2014 - 2022 and 2023 Onwards). The Philippine license plate formats refer to the specific designs and alphanumeric arrangements used on vehicle registration plates in the Philippines. In the context of this study, it focuses on two distinct formats: the older format used from 2014 to 2022, which is still prevalent, and the new format introduced in 2023 onwards.

Recognition. It refers to the process of accurately identifying and extracting the alphanumeric characters present on license plates after they have been deblurred. This involves using deep learning algorithms and computer vision techniques to analyze the restored images of license plates to enable the system to determine each character and convert it into a readable format.

Resource-Constrained Environments. In this study, resource-constrained environments are defined as places where law enforcement authorities face limitations in terms of technological infrastructure, computational power, and financial resources. These environments necessitate the development of efficient and accessible solutions that can operate effectively despite these constraints.

Synthetic Data. In this study, synthetic data refers to the augmented versions of the default dataset of license plate images. Pertaining to a variety of distorted images, namely, low quality, low light, horizontal motion blur, and vertical motion blur.

YOLOv5. In this study, YOLOv5 pertains to a pre-trained YOLO model that predicts license plates using CNN and provides each with a bounding box. Through this bounding box, YOLOv5 is a tool for cropping images to extract license plates.

CHAPTER 2: REVIEW OF RELATED LITERATURE

2.1 Traditional and Modern Deep Learning ALPR

Automated License Plate Recognition (ALPR) systems have evolved from traditional computer vision techniques to more robust deep learning-based solutions. Earlier ALPR models used edge detection, color analysis, texture patterns, and character segmentation to identify license plates (Padmasiri et al., 2022). These conventional methods were lightweight and computationally efficient, making them suitable for basic applications. However, as Shashirangana et al. (2020) highlighted, such systems often failed in real-world conditions with poor lighting, motion blur, or environmental noise.

To overcome these limitations, modern ALPR solutions now adopt deep learning architectures such as Convolutional Neural Networks (CNNs) and object detection models like YOLO (You Only Look Once). These methods significantly improve accuracy and robustness by learning complex features directly from data, enabling reliable recognition even in challenging scenarios. The proposed system builds upon these advancements by leveraging a lightweight deep learning model optimized for real-time plate recognition in variable outdoor environments.

2.2 Deep Neural Networks in ALPR

Modern ALPR systems have greatly benefited from the rise of deep learning, with Deep Neural Networks (DNNs) driving improvements in detection, deblurring, and recognition tasks. Among these, models like YOLO (You Only

Look Once) and Convolutional Neural Networks (CNNs) have shown strong performance even in complex environments involving motion blur, low lighting, and fast-moving vehicles (Khan et al., 2023).

Multiple studies demonstrate YOLO's practicality. Sun et al. (2019) developed an end-to-end ALPR system for Chinese plates using YOLOv2 and YOLOv3, achieving high-speed detection suitable for real-world deployment. Similarly, Nande et al. (2022) used YOLOv4 in CCTV footage of fast-moving vehicles, highlighting its efficiency through advanced data augmentation like CutMix and Mosaic. More recent works have explored even newer versions: Chopade et al. (2024) employed YOLOv8 for Indian plates, using a two-model setup to first detect vehicles and then localize plates, while Liu et al. (2024) utilized YOLOv5l to handle unconstrained environments with high precision.

Building on these findings, the proposed LiPAD system adopts YOLOv5 for the preprocessing stage, specifically for the detection and cropping of Philippine license plates. YOLOv5 offers an optimal trade-off between speed, accuracy, and resource efficiency, making it ideal for real-time performance on resource-limited hardware. Compared to other YOLO variants and models like Faster R-CNN, YOLOv5 maintains competitive precision while being lightweight enough for practical use in the Philippine setting. This includes dealing with local challenges such as reflective plates, weather-influenced lighting, and motion blur from fast-moving vehicles. Furthermore, its PyTorch-based implementation allows seamless integration with the rest of the LiPAD pipeline.

2.3 Philippine-Specific ALPR Systems

One of the major challenges in developing ALPR systems for the Philippines is the diversity of license plate formats. This includes series from 1981, 2003, and the newer 2014 design, all varying in layout, font, and color. According to Pacaldo et al. (2021) and Amon et al. (2019), such variation, when combined with real-world conditions like dirt, lighting inconsistencies, and motion blur, complicates accurate recognition.

Brillantes et al. (2019) tackled this issue using Faster R-CNN to detect and classify Philippine license plates across these formats, achieving a precision of 82.6%. While this result shows promise, Faster R-CNN remains computationally intensive, making it less ideal for lightweight, real-time deployment, a gap addressed by the LiPAD system through its use of YOLOv5 for plate detection.

In another approach, Henry et al. (2020) designed a multinational ALPR system that used a layout-based detection algorithm to distinguish single-line and double-line plates, removing the need for manual format adjustments. Although applicable to diverse formats, this method still encountered issues under motion blur and camera distortion, environmental challenges that the LiPAD system mitigates through a dedicated deblurring stage based on Generative Adversarial Networks (GANs). This ensures improved clarity before plate recognition, particularly in high-speed or low-quality footage common in Philippine roads.

2.4 GAN-Based Deblurring Method

Generative Adversarial Networks (GANs) have become popular for deblurring license plate images, addressing challenges such as motion blur, low image quality, and poor lighting, common in ALPR systems for fast-moving vehicles.

Sereethavekul and Ekpanyapong (2023) proposed the License Plate Recovery GAN (LPRGAN), a lightweight model designed for real-time processing on resource-constrained devices. LPRGAN uses a multi-stage hybrid architecture, starting with a distortion detector to select the proper recovery model, followed by image enhancement. It employs adaptive layer fusion to focus on essential features while skipping redundant computations. Its shallow encoder-decoder structure has fewer than one million parameters for 256 by 128 image recovery and uses a simplified loss function to reduce training complexity. LPRGAN outperforms traditional single-task methods like CNNs and Transformers, making it a strong inspiration for LiPAD's deblurring stage, which prioritizes efficiency for Philippine settings.

Gong et al. (2024) introduced the License Plate Deblurring GAN (LPDGAN) supported by the LPBlur dataset, containing over 10,000 blurred and sharp image pairs. LPDGAN improves deblurring by combining feature fusion, text reconstruction, and partition discriminator modules. However, it requires large datasets and higher computational power, limiting its use in resource-constrained environments. Similarly, Pan et al. (2024) developed

LPSRGAN, a GAN-based super-resolution model that reconstructs low-resolution plates into high-resolution images, achieving higher recognition accuracy but also demanding significant computational resources and large datasets.

Real-ESRGAN by Wang et al. (2021) extends ESRGAN for blind super-resolution on real-world images by simulating combined degradation effects like blur, noise, and compression. Although not specialized for license plates, it effectively removes artifacts and enhances details. However, its training required four NVIDIA V100 GPUs, indicating high computational demand, which challenges its use in low-resource contexts.

Hybrid GAN-based approaches also show promise. Kukreja et al. (2020) proposed a GAN-CNN hybrid model where GANs generate synthetic data to improve image quality and CNNs perform recognition. While aligned with LiPAD's GAN and CRNN stages, the model's computational complexity limits practical deployment. The lightweight design of LPRGAN offers a better balance of performance and efficiency for environments with limited resources like the Philippines.

A major challenge with GAN-based methods is their reliance on large datasets and high-performance GPUs. Gong et al. (2024) used LPBlur with 20,816 images and a GeForce RTX 3090 GPU, while Pan et al. (2024) trained on LicensePlateDataset10K using two RT3090 GPUs. Based on a study by Pacaldo et al. (2021) such datasets and hardware are difficult to obtain in the Philippines due to limited infrastructure and diverse plate variations. LPRGAN mitigates these issues by training on a smaller dataset that has 16,194 Thai license plate images using an RTX 2080 GPU and maintaining a lightweight architecture. LiPAD aims to follow this approach by combining synthetic and real Philippine data for effective deblurring without heavy resource demands.

2.5 CNN and Other Deblurring Methods

Besides GANs, CNN-based and hybrid deblurring methods have been explored to tackle image degradation in ALPR systems. These offer alternative or complementary solutions, especially for resource-constrained environments like the Philippines.

CNN-based deblurring has made great progress in restoring sharp images from blurred captures. For example, Nande et al. (2022) developed a method using U-Nets with ResNet encoders to restore blurred CCTV images of fast-moving vehicles. Their approach uses skip connections and residual blocks to better adapt features during restoration. Li et al. (2019) proposed a CNN model that predicts motion blur kernel sizes by framing it as a regression problem, improving deblurring without needing manual parameter tuning. Rossi et al. (2021) designed a dual CNN system where one U-Net denoises degraded license plate images and a second CNN recognizes the character sequences. Shim et al. (2024) used a Convolutional Autoencoder trained on noisy-clean image pairs to denoise images efficiently, demonstrating CNN's lightweight computational needs compared to other deblurring methods. Shruthi et al. (2023)

also highlighted that CNNs generally require less computing power, reinforcing their suitability as alternatives to GANs for projects like LiPAD.

However, CNNs mainly handle single degradation tasks and are less effective with complex image distortions. Sereethavekul and Ekpanyapong (2023) pointed out this limitation when comparing CNNs to GANs. This challenge is supported by Wang et al. (2021), who noted that CNN models trained on ideal assumptions like bicubic downsampling or simple Gaussian blur often fail on real-world images with mixed and complex distortions. Their Real-ESRGAN model overcomes this by using a higher-order degradation model and enhancing the discriminator with U-Net and spectral normalization to better restore fine details. Their results show that traditional CNNs alone are insufficient for handling diverse real-world degradations, making advanced generative models like GANs more suitable for practical image restoration.

Beyond CNNs, other innovative methods exist. AlHalawani et al. (2024) introduced DiffPlate, a diffusion model using U-Net architecture for super-resolution of license plate images from surveillance cameras. While it improves low-resolution images for traffic applications, its high computational cost limits use in low-resource settings like the Philippines. Nirmala et al. (2023) proposed a hybrid model combining GAN, CNN, and Extreme Learning Machine (ELM) for license plate recognition. Here, the GAN enhances image quality, CNN extracts features, and ELM speeds up classification, achieving a 98.9% success rate. This hybrid reduces training time compared to standalone GAN or CNN models, but its effectiveness against motion blur from fast-moving vehicles is still unclear.

These alternatives show potential for hybrid and non-GAN solutions to address ALPR deblurring challenges. However, their computational demands and limited focus on Philippine-specific conditions highlight the need for more tailored, lightweight models like LiPAD aims to develop.

2.6 CNN for Image Distortion Classification

Convolutional Neural Networks (CNNs) are widely used in computer vision tasks such as image classification due to their ability to learn hierarchical features directly from raw image data. Unlike traditional models that rely on manual feature extraction, CNNs automatically identify patterns and spatial hierarchies, making them particularly effective in distinguishing subtle image variations, a crucial capability when detecting different types of distortions (Elngar et al., 2021; Sereethavekul & Ekpanyapong, 2023).

In the context of image distortion classification, CNNs are effective because distortions often manifest as spatial anomalies or changes in texture, blurriness, or noise, which CNNs can detect at various levels through their layered architecture. CNNs utilize convolutional layers to extract local features, pooling layers to reduce spatial dimensions, and fully connected layers to perform final classification, mirroring how humans process visual information (Elngar et al., 2021; Sereethavekul & Ekpanyapong, 2023).

Among the popular CNN architectures, VGGNet and ResNet have shown strong performance in visual classification tasks. VGGNet, known for its deep layers and use of multiple 3x3 convolutions, achieves high accuracy but can be computationally heavy and prone to overfitting in deeper forms like VGG-19 (Wahyu Mulyono et al., 2024). ResNet, on the other hand, addresses these issues through its shortcut connections that allow better gradient flow and identity mappings, making it more suitable for deeper models without performance degradation (Chopade et al., 2024; Wahyu Mulyono et al., 2024).

With its proven capability to handle complex visual patterns and prevent performance degradation in deep networks, this study adopts ResNet as the primary architecture for the image distortion classification system.

2.7 CRNN for License Plate Recognition

Convolutional Recurrent Neural Networks (CRNNs) are widely used in automatic license plate recognition (ALPR) due to their ability to combine spatial feature extraction and sequence modeling in a single trainable architecture. In a CRNN, convolutional layers extract visual features from license plate images, which are then passed to recurrent layers that learn the sequential nature of characters in the plate. This approach eliminates the need for character-level segmentation, which is often difficult in real-world settings where plates may be blurred, tilted, or occluded (Sun et al., 2019; Bensouilah et al., 2021; Liu et al., 2023).

This combination makes CRNN ideal for recognizing distorted or reconstructed license plates, which is highly relevant in the proposed LiPAD system. Given that LiPAD uses GANs to reconstruct low-quality plates before recognition, a model capable of handling imperfect or slightly altered spatial features like CRNN is essential.

CRNN models have achieved high accuracy across various countries and conditions. Tee (2019) developed a lightweight CRNN model tailored for Malaysian plates, reaching 99.27% accuracy with near real-time performance. Liu et al. (2023) improved CRNN with channel attention to adapt better in unconstrained scenes, while Xu et al. (2024) applied CRNNs on ship license plates under fog and tilt conditions. These studies show the model's flexibility across noisy, inconsistent, or degraded plate visuals are similar to the ones that LiPAD aims to process after GAN reconstruction.

To optimize for both accuracy and speed in resource-constrained environments, this study will utilize PP-OCRv4, a CRNN-based text recognition model from the PaddleOCR framework. PP-OCRv4 integrates several improvements like Unified-Deep Mutual Learning (U-DML) and Enhanced CTCLoss to improve recognition on similar-looking characters, making it ideal for recognizing local license plates that may contain repetitive or closely-shaped letters and numbers (Du et al., 2021). Additionally, its lightweight backbone, PP-LCNet, ensures fast inference on limited hardware, which aligns with LiPAD's goal of achieving real-time recognition without requiring high-end GPUs.

The CRNN model from PP-OCRv4 will be fine-tuned using Philippine license plate datasets and outputs from LiPAD's GAN component. By leveraging this robust CRNN-based architecture, LiPAD ensures high recognition accuracy even on reconstructed or distorted plates, highlighting CRNN's key role in the system's overall performance.

2.8 Dataset Procurement for Deblurring and Recognition

Creating a reliable dataset is critical to the success of the LiPAD system, especially for training its deblurring GAN and CRNN-based recognition module. In related works, researchers have emphasized the need to simulate real-world conditions like motion blur, low light, and compression artifacts. For instance, Sereethavekul and Ekpanyapong (2023) developed a Thai license plate dataset categorized by degradation type to train LPRGAN, while Gong et al. (2024) introduced LPBlur, a paired dataset of sharp and blurred license plates used for training LPDGAN.

However, replicating these efforts in the Philippine setting is more challenging due to local factors such as diverse plate styles, inconsistent lighting on roads, and limited infrastructure for large-scale data collection (Pacaldo et al., 2021). To address this, the LiPAD system will adopt a hybrid dataset strategy that combines synthetic and real-world Philippine license plate images.

Similar to the approach of Sereethavekul and Ekpanyapong (2023), plate images will be sourced from publicly available datasets and online sources, then automatically cropped using YOLO. These images will be enhanced and augmented with various degradation types to simulate real-world conditions such as low-quality compression artifacts to replicate low-bitrate uploads, low-lighting effects to represent nighttime or poorly lit areas, horizontal motion blur to simulate fast vehicle movement, and vertical motion blur to mimic camera shake. These augmentations ensure that the GAN is exposed to a wide range of realistic distortions, improving its ability to reconstruct license plates in varied conditions.

Following the LPRGAN authors' insight that a generator cannot exceed the quality of its training data, this study will also include enhanced versions of the original plates to ensure that the GAN learns from the highest possible visual details. Furthermore, LPBlur (Gong et al., 2024) will serve as a design reference for simulating blur patterns, but the final dataset will focus on Philippine-specific data. This includes actual Philippine license plate photos, which will be anonymized in compliance with the Data Privacy Act of 2012, ensuring ethical data handling and proper consent from plate owners.

This local, augmented dataset is essential not just for the GAN's deblurring performance, but also for improving the downstream recognition accuracy of the CRNN in the LiPAD pipeline. By capturing the specific challenges of Philippine road conditions, this approach ensures that the system is tailored for local deployment, rather than relying solely on foreign datasets.

Recent studies in ALPR have demonstrated that deep learning models such as YOLO, CRNN, CNNs, and GANs significantly improve performance in license plate detection, recognition, and deblurring, even under challenging conditions like motion blur or low resolution. YOLO is consistently chosen for real-time detection due to its balance of speed and accuracy, while CRNNs offer high recognition performance through efficient sequence modeling. GAN-based models like LPRGAN and LPDGAN are effective in reconstructing blurred or degraded plates but often require high computational resources and large datasets. Lightweight CNNs and OCR systems like PP-OCRv4 attempt to solve this by offering more efficient alternatives without sacrificing much accuracy.

Despite these advancements, current literature reveals key gaps. Many models are trained on foreign license plates, limiting their relevance to local scenarios. There is also a trade-off between deblurring quality and computational efficiency that is not often addressed. Furthermore, while CRNNs are powerful recognizers, their accuracy heavily depends on the quality of the deblurred input.

The proposed LiPAD system addresses these gaps by combining proven methods, YOLOv5 for detection in preprocessing, Real-ESRGAN for super-resolution for enhancing the ground truth, CNNs for distortion classification, LPRGAN-inspired lightweight GANs for deblurring, and CRNN from PP-OCRv4 for recognition into a pipeline tailored for Philippine road conditions. By focusing on a locally augmented dataset and prioritizing models that are both accurate and resource-efficient, LiPAD aligns itself with real-world deployment in resource-constrained environments. Its modular design ensures each component contributes meaningfully to overcoming the limitations highlighted in previous works.

CHAPTER 3: METHODOLOGY

3.1 Data Science Research Design

This study used the Design Science Research (DSR) approach to guide the development and implementation of the LiPAD system, an AI-powered license plate deblurring and recognition model. DSR is a problem-solving research approach that focuses on the development and assessment of innovative artifacts to address real-world problems (Teperi et al., 2021). In this study, the artifact was the LiPAD system, which addressed the real-world problem of challenging traffic regulation and law enforcement caused by blurry license plate images, particularly in resource-constrained environments in the Philippines. This methodology was well-suited for this study as it provided a structured framework for developing, demonstrating, and evaluating a system that used deep learning techniques to produce functional results.

The DSR methodology followed six iterative phases: (1) Problem Identification, (2) Objective Definition, (3) Design and Development, (4) Demonstration, (5) Evaluation, and (6) Communication. In the “Problem Identification” phase, the researchers identified the issue of blurry license plate images captured by surveillance cameras, which made vehicle identification and traffic regulation and law enforcement challenging in the Philippines. In the “Objective Definition” phase, the researchers defined clear and measurable goals for the LiPAD system to restore distorted license plate images and accurately recognize their characters. Next, in the “Design and Development” phase, the researchers designed the LiPAD system as a multi-stage pipeline with key components using deep learning techniques like CNN, GAN, and CRNN, and model and web app development tools. Then, in the “Demonstration” phase, the researchers deployed the LiPAD system as a web application to enable traffic enforcers to upload distorted license plate images and receive readable text outputs. Next, in the “Evaluation” phase, the researchers measured the overall performance, effectiveness, and practical reliability of the web application and its integrated model through metrics and user feedback. Finally, in the “Communication” phase, the researchers disseminated the results to provide insights to practitioners and researchers addressing similar challenges and to contribute to the field of AI-driven traffic management.

3.1.1 Framework for the Research

3.1.1.1 Description of the Framework

The study adopted the DOMINO framework, a modern data science life cycle developed to guide the iterative and collaborative development of data-driven solutions (Data Science & Product Management, 2024). DOMINO is well-suited for this study because it fits the need to develop the LiPAD system. This framework emphasizes agility, team collaboration, and ongoing maintenance, which assures that the system is efficient and practical for traffic management and enforcement. The DOMINO framework comprises six iterative stages, each of which contributes to the systematic development and deployment of the LiPAD system: (1) Ideation, (2) Data Acquisition and Exploration, (3) Research and Development, (4) Validation, (5) Delivery, and (6) Monitoring, as illustrated in Figure 3.1.

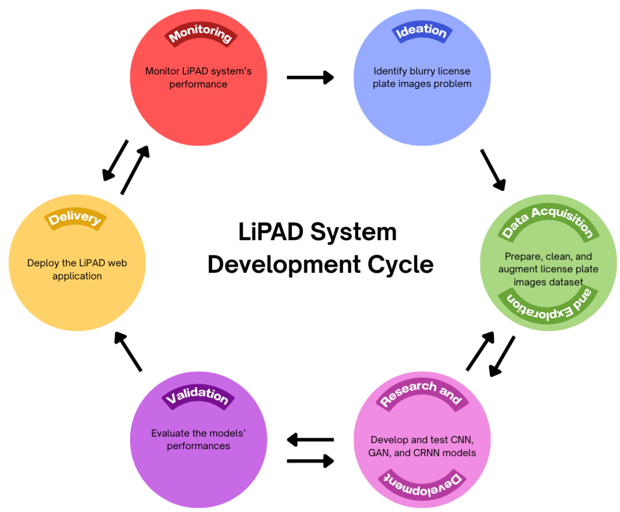

Figure 3.1. DOMINO Framework: LiPAD System Development Cycle

The "Ideation" stage focused on understanding and defining the problem before getting into data and modeling. This study involved understanding and addressing the problem of blurry license plate images that hindered effective traffic regulation and law enforcement in the Philippines. This stage aimed to conceptualize an AI-powered solution, which is the LiPAD system, that could effectively deblur and recognize Philippine license plates and enhance traffic regulation and law enforcement in Angeles City, Pampanga.

In the “Data Acquisition and Exploration” stage, the researchers focused on acquiring, exploring, and preparing data to ensure that it was appropriate for modeling. In this study, the researchers collected a comprehensive dataset of Philippine license plate images from publicly available resources and contributions from willing motorists, with compliance to the Data Privacy Act of 2012 (R.A. 10173) to address ethical considerations. The researchers also used data augmentation to simulate different distortions, particularly low-light conditions, horizontal and vertical motion blur, and low-quality captures. A pre-trained YOLO model was used to crop these images to focus on license plates instead of the whole vehicle body and isolate them to improve the quality and relevance of the dataset (Pacaldo et al., 2021).

Next, in the “Research and Development” stage, it involved developing, iterating, and evaluating the core models that powered the LiPAD system and refining them based on their performance results. This study involved training a Convolutional Neural Network (CNN) for classifying the type of distortion in license plate images, different Generative Adversarial Network (GAN) models for deblurring distorted images, and a Convolutional Recurrent Neural Network (CRNN) for recognizing characters from the deblurred outputs (Alzubaidi et al., 2021; Kupyn et al., 2020; Baek et al., 2019). Through an iterative cycle of training and testing, these models were fine-tuned to optimize their performance and ensure that the LiPAD system could effectively deblur license plate images and recognize its characters under different conditions.

The “Validation” stage ensured that the developed models met all technical and operational requirements for real-world application. In this context, the CNN, GAN, and CRNN models were evaluated using different metrics and standards adapted to their specific roles within the LiPAD system’s pipeline. The CNN’s distortion classification was assessed with metrics such as accuracy, precision, recall, F1-score, and confusion matrix to confirm its reliability in identifying license plate image distortion types. The GAN’s deblurring performance was evaluated using Structural Similarity Index (SSIM), Peak Signal-to-Noise Ratio (PSNR), Fréchet Inception Distance (FID), and render speed to verify its ability to restore and deblur different license plate image distortions. Meanwhile, the CRNN’s character recognition was measured through Character Error Rate (CER), Word Accuracy Rate (WAR), and render speed to ensure accurate text extraction.

The “Delivery” stage focused on applying and deploying the LiPAD system in a practical, real-world environment to address traffic regulation and law enforcement challenges in Angeles City, Pampanga. Here, the LiPAD system was deployed as a web application, designed with a client-server architecture to maximize its accessibility and efficiency. The frontend, designed using Vue.js, provided a responsive, intuitive, and easy-to-navigate user interface, while the backend, developed in Django, integrated the trained CNN, GAN, and CRNN models. This stage allowed users, specifically traffic enforcers, to upload distorted license plate images and receive deblurred and recognized results within seconds.

Lastly, the “Monitoring” stage involved continuously monitoring and tracking the LiPAD system’s performance after deployment to ensure its ongoing efficiency and reliability. For LiPAD, this included monitoring important metrics such as deblurring and recognition accuracy, and processing time, while also gathering user feedback from traffic enforcers and law enforcement officers to provide long-term reliability in Angeles City, Pampanga. System logs and usage analytics were employed to detect anomalies, errors, or performance degradation, enabling timely interventions and solutions.

The DOMINO framework’s components are interconnected through an iterative and collaborative process to ensure a cohesive development cycle (Data Science & Product Management, 2024). The Ideation stage sets the foundation by defining the problem to guide the Data Acquisition and Exploration stage to focus on relevant data (e.g., distorted license plate images). This prepared and cleaned data was fed into the Research and Development stage, where the CNN, GAN, and CRNN were developed, refined, and optimized iteratively, with feedback loops to revisit data preparation if needed. The trained models were then subjected to Validation to assess their technical performance and operational fit, and could be subjected to further optimization. Successful validation led to Delivery, where the LiPAD system was implemented, and continuous Monitoring ensured that the system remained effective on a long-term basis, with insights feeding back to earlier stages for updates. This cyclical relationship promoted agility and responsiveness, which are essential for dealing with the evolving issues of traffic regulation and enforcement in the Philippines.

This framework is based on modern data science principles, which use agile approaches and collaborative practices to address the challenges of real-world applications (Data Science & Product Management, 2024). Its theoretical foundation stems from the concept that data science projects require iterative testing, stakeholder alignment, and continuous maintenance to produce value, especially in areas such as traffic regulation and law enforcement, where conditions vary (Alzubaidi et al., 2021). It expands on lessons learned from earlier frameworks like CRISP-DM by integrating team-based collaboration and post-deployment monitoring, both of which are critical in resource-constrained environments where infrastructure limitations necessitate efficient and sustainable solutions (Pacaldo et al., 2021). The logical basis for selecting this framework is its alignment with the study's need to produce a helpful, user-centric system that progresses through feedback and performs efficiently over time to support goals such as improved public safety and adherence to ethical standards like the Data Privacy Act of 2012.

3.2 Data Sources and Collection

3.2.1 Ethical Considerations

3.2.1.1 Data Privacy and Security

This study prioritizes data privacy and security, especially given the sensitive nature of license plate images that may be linked to individuals or vehicles. To comply with the Data Privacy Act of 2012, all real-life license plate images collected for the dataset were anonymized by removing or obscuring any identifiable elements. Only the plate region itself was retained, and no additional information such as the vehicle's color, make, model, body type, surroundings, or any other feature that may help identify or track a specific vehicle or owner was included. Under the Data

Privacy Act, personal information refers only to data that can identify an individual, and cropped license plate images without contextual information do not fall under this category (Republic Act No. 10173, 2012).

The images were captured only in public roads, streets, and open spaces where license plates are naturally visible to anyone. According to the National Privacy Commission, publicly exposed information that is visible in public spaces carries no reasonable expectation of privacy and may be processed without consent, provided that no additional personal data is collected (National Privacy Commission, 2024). Because of this, there was no need to obtain individual consent from vehicle owners as long as the collected images did not include any identifying context beyond the plate itself.

To further maintain privacy and ethical handling of data, the researchers also implemented strict privacy-preserving measures. These included collecting images only in public spaces, cropping all photos to include only the license plate region, anonymizing all real-world images, and securely storing the dataset with access limited only to authorized researchers. In addition, the synthetic data generated to augment the dataset contained no real personal information, which further reduced privacy and security risks.

These measures ensure that the study complies with legal and ethical standards while protecting individual privacy and maintaining the integrity of the data used for developing the CNN, GAN, and CRNN models.

3.2.1.2 Bias and Fairness

To ensure fairness in the LiPAD pipeline, this study addressed potential biases in both the dataset and the deep learning models. The dataset included a combination of synthetic and real Philippine license plates, augmented with degradations like low quality, low light, and motion blur, as outlined in the "Data Transformation" section. To mitigate bias, the dataset was carefully curated to represent the diversity of Philippine license plates, including various formats, fonts, colors, and conditions, as non-standardized designs are a known challenge in the Philippine context (Pacaldo et al., 2021). This ensured that the models were not biased toward a specific plate type or condition, promoting equitable performance across different scenarios. During model training, techniques such as balanced sampling and data augmentation were employed to prevent overfitting to overrepresented classes and to improve robustness against underrepresented ones. Additionally, the evaluation metrics were analyzed across different subsets of the dataset to identify and address any disparities in performance, ensuring fairness in license plate detection, deblurring, and recognition. These steps aimed to create a system that performs consistently and fairly for all Philippine license plates, supporting unbiased traffic enforcement and investigation applications.

3.2.2 Data Sources

The dataset for this research was derived from two primary sources: publicly available datasets and manually collected data by the researchers. The training and validation sets exclusively used data obtained from RoboFlow, an online platform known for its extensive collection of computer vision datasets. These datasets featured annotated images of license plates and vehicles, contributed by users and open-source projects, and were well-suited for model training due to their diversity and quality. In contrast, the test set will be developed separately through experimental data collection. Researchers will manually capture real-world images of Philippine license plates under varying conditions to ensure that the test data remains entirely independent of the training and validation sets, allowing for a more accurate evaluation of the model's performance in practical scenarios.

3.2.3 Data Collection Methods

The researchers collected data through a combination of online sourcing and experimental image capture. The publicly available dataset from RoboFlow was accessed and downloaded directly from the platform's web interface, including the local_lpr Dataset (Philippine license plates, 2024), Plate Number Text Recognition Dataset (Capstone Project, 2025), Vehicle Plate Number Dataset (Capstone Project, 2024), CAR_DATASET (TEAM59CAR, 2024), and PH Vehicle Identification System Dataset (Tech Titans, 2024). Meanwhile, the test dataset will be gathered experimentally by manually capturing license plate images using mobile devices or digital cameras. This collection was carried out in real-world public settings, such as roads, where images of license plates were captured. Only the characters on the license plates were recorded; no additional identifying information, such as vehicle model, color, or other features, was included to maintain privacy. For low-quality license plate images, frames were extracted from open-source CCTV video footage of locations in the Philippines. The selected frames were then cropped to isolate the license plate, creating the low-quality dataset used in this study. Additionally, to enhance the training dataset and increase its diversity, data augmentation techniques were applied to the normal dataset. This synthetic data generation process supports the creation of more robust and generalizable deep learning models.

3.2.4 Data Description

3.2.4.1 Data Format and Structure

The dataset collected for this research initially consisted of images in JPG, JPEG, and PNG formats. These image files were structured as unstructured data, as they contained visual content rather than textual or tabular information. However, after preprocessing, all images in the dataset were converted into JPG format to ensure uniformity and compatibility across all stages of data handling and model training.

3.2.4.2 Key Variables and Features

The key features of the dataset are the license plate formats and their characters, specifically focusing on the formats for both motor vehicles and motorcycles. For motor vehicles, the important variables are the seven-character format such as LLL DDDD, as shown in Figure 3.2, and the six-character format such as LLL DDD, as depicted in Figure 3.3, where "L" represents a letter and "D" represents a digit. For motorcycles, the format consists of six characters such as DDDLLL, as illustrated in Figure 3.4, with the same letter-digit structure. These formats were defined by the Land Transportation Office (LTO) under the Motor Vehicle License Plate Standardization Program of 2013, including motor vehicle license plates with the six-character format from previous years which were still in circulation. These features are crucial to the research as they determine the structure and character types to be recognized, generated, and classified by the model, ensuring the system adheres to the official Philippine license plate standards.

Figure 3.2. Motor Vehicle - 7 Characters Plate, WikiMedia Commons, 2023

Figure 3.3. Motor Vehicle - 6 Characters Plate, WikiMedia Commons, 2023

Figure 3.4. Motorcycle - 6 Characters Plate, WikiMedia Commons, 2023

3.2.4.3 Data Size and Volume

The overall data consisted of 141,992 images, divided into six distinct sets. These will include:

1. An original undistorted dataset: 20,332 images.
2. An enhanced version of the original dataset: 20,332 images, and
3. Four distorted datasets:
    a. Low-light distorted dataset: 20,332 images.
    b. Low-resolution distorted dataset: 20,332 images.
    c. Vertical motion blur distorted dataset: 40,332 images, comprising two subsets of 20,000 images each.
    d. Horizontal motion blur distorted dataset: 20,332 images.

In addition to the image data, data from normal and enhanced will be annotated with corresponding license plate text to support training and evaluation of the CRNN-based license plate recognition module. These annotations are an integral part of the dataset and will be used as ground truth for sequence learning and character-level prediction tasks. The total volume of the dataset is approximately 6 GB.

3.2.5 Data Preprocessing

3.2.5.1 Cleaning

The license plate image data were manually selected from publicly available datasets on the RoboFlow platform. Only clear and readable images were included to ensure the accuracy of the training data. Raw images that were already blurred, distorted, or low in quality were excluded during the initial selection process.

Only image files in JPG, JPEG, or PNG formats were accepted. Files in other formats were excluded during the data cleaning stage to maintain compatibility and consistency throughout preprocessing and model training.

To automate the cropping process, a YOLOv5 pretrained model was used to detect and extract the license plate region from each image. Detections with a confidence score below 0.70 (70%) were automatically discarded to avoid including inaccurate or imprecise crops. Corrupted, blank, or unreadable image files were also removed. Outliers such as altered plates, images with heavy glare, or inconsistent formatting were manually reviewed and excluded to preserve data quality and relevance to real-world traffic enforcement conditions. All images, after being cropped, were saved in JPG format.

3.2.5.2 Transformation

For the transformation of the data, distortion-specific augmentations were applied using the OpenCV library to simulate realistic variations of Philippine license plate images, including low-quality, low-light, horizontal motion blur, and vertical motion blur distortions. Additionally, the original dataset was enhanced using the open-source pretrained Real-ESRGAN model to improve image quality, particularly in low-resolution cases. To further augment the training data and improve generalization, the Compose method from the PyTorch library was applied, introducing standard image transformations such as resizing, normalization, and random adjustments. The augmentation process followed a similar approach to that of Sereethavekul and Ekpanyapong (2023), but expanded upon their methodology by incorporating both low-quality and enhanced license plate images, which were not included in their study.

The preprocessing for each augmentation for the synthetic datasets was as follows:

1. **Low Quality Images Dataset**

   A combination of image downscaling and JPEG compression was applied to simulate low-quality images for training. Using OpenCV's resize function, medium- to high-resolution images were proportionally reduced in size by a factor of four while maintaining their original aspect ratio. This downscaling step reflected real-world degradations that occurred due to digital zoom, low-end capture devices, or image resizing during transmission. After resizing, JPEG compression artifacts were introduced by encoding the images with a reduced quality setting using OpenCV’s imencode function. The compression level was randomized between twenty (20) and sixty (60) compression quality to replicate the visible degradation commonly found in images saved with lossy formats or captured under constrained bandwidth or storage conditions.

2. Low Light Dataset

OpenCV and NumPy were employed to reduce the brightness of the original images to a range between 5% and 25% of their initial intensity, simulating low-light conditions. This process mimicked real-world scenarios where license plates may be captured at night or in poorly lit environments, such as under streetlights or during adverse weather. The brightness adjustment was carried out by multiplying each pixel value by a randomly selected factor within the specified range, resulting in a visibly darker version of the original image.

3. **Horizontal Motion Blur Dataset**

To simulate horizontal motion blur in license plate images, a custom 2D convolution kernel was applied. The kernel introduced a directional blur along the horizontal axis to mimic the effect of motion. Specifically, a horizontal motion blur kernel of size k × k was created, where the central row was filled with ones and normalized to maintain pixel intensity. This technique effectively simulated pixel displacement due to motion. The kernel size, which corresponded to the blur intensity or pixel shift, was randomly selected within a specified range of ten (10) to twenty (20) using OpenCV to create variation across samples. Additionally, to increase the diversity of simulated motion blur, the Kornia library was also used to apply horizontal blur with a randomly selected kernel size ranging from fifteen (15) to forty-one (41).

4. **Vertical Motion Blur Dataset**

For vertical blur, the filtering process was similar to that of horizontal motion blur but oriented along the vertical axis. A vertical motion blur kernel was constructed where the central column was filled with ones and normalized, producing a blur effect along the 90-degree Y-axis. The kernel size was randomly chosen within the range of fifteen (15) to twenty-five (25) using OpenCV. As with the horizontal case, Kornia was also employed to apply vertical motion blur. For Kornia, two sets of datasets were prepared: a low-kernel set with kernel sizes randomly chosen between seven (7) and nineteen (19), and a high-kernel set with kernel sizes between twenty-one (21) and forty-one (41).

5. **Default Dataset**

The reference dataset consisted of regular-looking, medium- to high-quality, and well-conditioned license plate images. This dataset served as the baseline for measurement and image recovery processes. The synthetic datasets relied on this set as the default for image augmentation of the different types of distortion.

6. **Enhanced Dataset**

The enhanced dataset was generated by applying the Real-ESRGAN, specifically the RealESRGANx4plus model, to the original, undistorted image set. This model performed super-resolution enhancement, upscaling each image by a factor of 4 while restoring fine details and improving overall image quality. The enhanced images serve as high-quality references for evaluating reconstruction performance and training enhancement models.

3.2.5.3 Reduction

A reduction step was applied during preprocessing and prior to data augmentation and model training to ensure the quality and usefulness of the dataset. In this step, any image with a resolution below 96 pixels in either width or height was discarded after the detection and cropping of license plates using YOLOv5. This threshold was selected because images with such low resolutions tend to lose significant visual detail, especially when further downsampled during the low-quality transformation phase.

Downsampling already reduces the clarity of the license plate characters, and starting with a low-resolution image amplifies this issue, making the license plates nearly unrecognizable even to the human eye. Including such images would likely introduce noise into the dataset, negatively affecting the model’s ability to learn relevant features. By removing these unusable samples early in the pipeline, the research ensures that the dataset maintains a minimum quality standard necessary for effective learning and robust model performance.

3.2.5.4 Splitting the Data

The data for this project was divided into two main subsets from the initial collected dataset: the Training Set and the Validation Set. The Test Set will be gathered separately later to assess the final model's performance on real-world, unseen data

1. **Training Set**

   A total of 20,000 images were allocated for training the models. This large set provided the model with a diverse range of examples, enabling it to learn the relevant features necessary for the task. By utilizing a large portion of the data, the models can identify and learn patterns and relationships that are critical for making accurate predictions.

2. **Validation Set**

The remaining 332 images from the dataset were reserved for validation during training. This subset will help monitor the model's performance on data that it hasn't seen before, allowing fine-tuning of hyperparameters and preventing overfitting. The validation set provides insight into how well the model is generalizing to new data while optimizing it for the best possible performance.

3. **Test Set**

After the model was trained and validated, a separate Test Set of 917 manually gathered images was prepared to evaluate the model's performance on real-world, unseen data. This set is crucial for assessing how the model will behave when deployed in practice, providing an unbiased measure of its real-world applicability.

3.3 Data Science Methods

3.3.1 Algorithm/Model Selection

This study used a modular deep learning pipeline to address the restoration and recognition of distorted Philippine license plates. In the preprocessing stage, YOLOv5 was used for plate detection, and Real-ESRGAN was employed to enhance the ground truth images. The core models included a CNN for distortion classification, GANs for image reconstruction, and a CRNN for license plate recognition.

Figure 3.5 illustrates the core processing pipeline of the LiPAD system, detailing the sequential steps that occur after a license plate has been isolated from a raw vehicle image. The pipeline begins with a cropped license plate image, which is first analyzed by a CNN to classify its specific distortion type. Based on the classification, the image is routed to a specialized GAN model tailored for deblurring that particular distortion type. The restored image then undergoes a second evaluation by the CNN in a qualifying stage to ensure its quality is sufficient for recognition. If the image passes the quality check, it is forwarded to the CRNN model, which performs the final character recognition to produce the alphanumeric text output. This modular and sequential flow ensures a systematic and lightweight approach to transforming a distorted license plate image into an accurate and readable string.

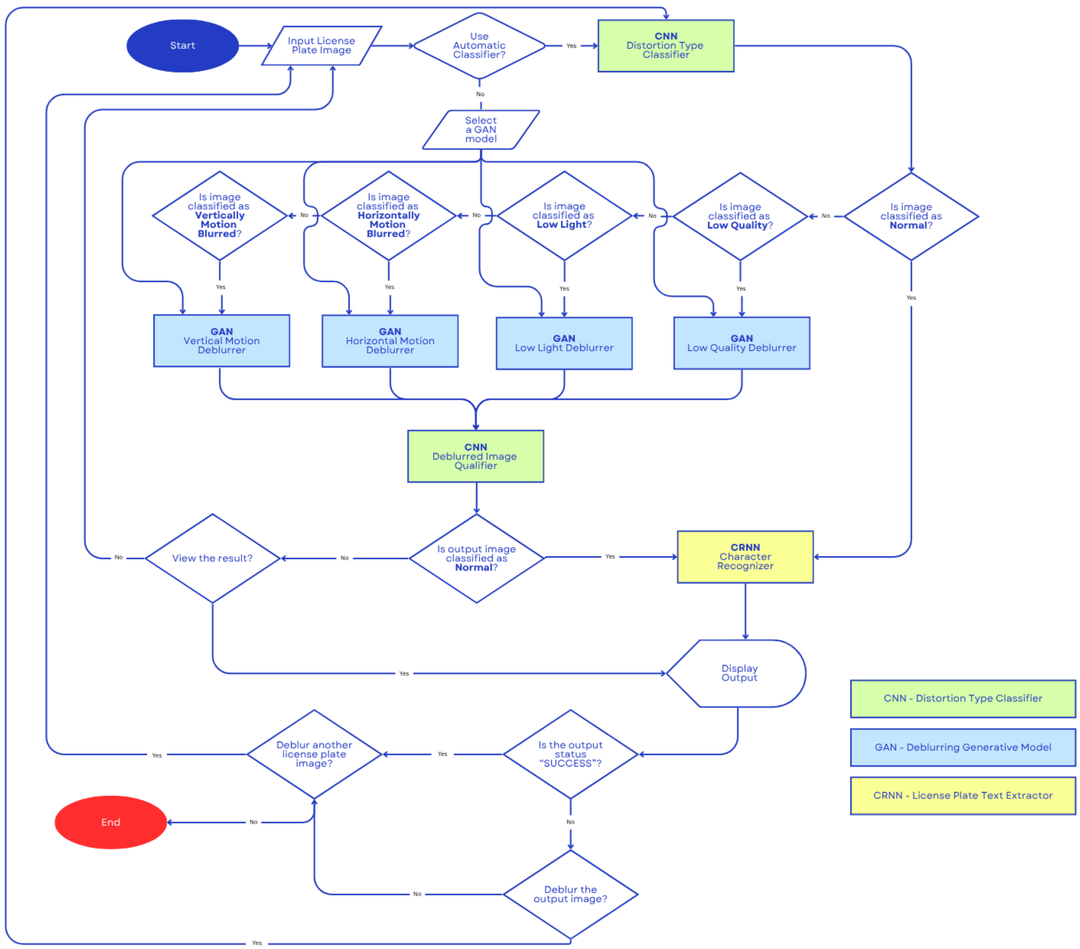

Figure 3.5. Overview of proposed system flow diagram

YOLOv5 as License Plate Detector

This study adopted the YOLOv5 object detection algorithm as a preprocessing step to accurately localize license plates in raw vehicle images. Specifically, the pre-trained YOLOv5s variant, fine-tuned for automatic number plate recognition, was utilized. This model was developed by Tejas Ramekar and is publicly available on GitHub under the repository titled "Automatic Number Plate Recognition" (Ramekar, 2022). It generates precise bounding boxes around license plates, which were subsequently used to crop plates from full images in preparation for distortion simulation and restoration model training.

YOLOv5 was selected due to its favorable balance between detection accuracy and processing speed. As a one-stage detector, it performs both object localization and classification in a single forward pass through the network, making it highly suitable for real-time applications and high-throughput preprocessing. Wei et al. (2023) demonstrated YOLOv5's strong performance in license plate detection and noted that its architecture can be further optimized for lightweight deployment, rendering it appropriate for environments with limited hardware resources.

Furthermore, Rao et al. (2023) employed YOLOv5 for license plate detection in unconstrained environments characterized by perspective distortion and oblique viewing angles. Their study highlighted YOLOv5's robustness in detecting license plates with high confidence, even when integrated with downstream correction and recognition modules. These findings correspond with the present study's use case, where cropped license plates serve as input for subsequent distortion simulation and GAN-based restoration.

Thus, the decision to integrate YOLOv5 into the data preparation pipeline was based on both practical implementation experience and support from related research literature, which validated its effectiveness in real-world license plate detection systems.

REAL-ESRGAN as Ground Truth Enhancer

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CNN as Distortion Classifier and Output Qualifier

CNNs are widely recognized for their effectiveness in tasks involving image classification, object recognition, and visual pattern analysis. In this study, CNNs were chosen as the foundational architecture for distortion classification due to their strong performance in prior research focused on image-based recognition and recovery. As highlighted in the survey by Elngar et al. (2021), CNNs have consistently outperformed traditional models across a range of classification problems, particularly in scenarios involving complex image data where handcrafted features often fall short.

The specific challenge of distortion classification required a model that could distinguish subtle variations in image quality, whether due to motion blur, low quality, or low-light conditions. Previous works successfully used CNNs to address similar problems. For instance, Sereethavekul and Ekpanyapong (2023) employed a CNN-based model to classify various types of distortion in license plate images prior to the application of their GAN-based recovery system. Their findings suggest that CNNs offer a more effective alternative to conventional techniques for categorizing degraded visual inputs.

This study adopted a ResNet architecture, based on evidence supporting its high accuracy and robustness in classification tasks. ResNets incorporate skip connections that address the vanishing gradient problem, enabling the training of deeper models without compromising performance. In a comparative evaluation of CNN architectures, Wahyu Mulyono et al. (2024) demonstrated that ResNet-50 surpasses both VGGNet and traditional CNNs in terms of classification accuracy and training efficiency.

ResNets are particularly well-suited for the present research due to their ability to retain discriminative performance across diverse and degraded image inputs. The skip connections inherent in their design help preserve low-level features while enabling more stable and deeper learning, which is an essential characteristic for distinguishing between visually similar types of distortions.

Beyond the initial distortion classification phase, the same CNN architecture was also used in another critical stage of the system, referred to as the qualifying stage. This stage served as a form of quality assurance before the final text recognition step. After the GAN-based restoration process, the output image was passed again through the CNN classifier. If the CNN identified the output as belonging to the “normal” class, the image proceeded to the CRNN model for character recognition. However, if the image was still classified as distorted, the system performed a comparison between the input and output using quality metrics. If the output was determined to be worse than the input, the system halted processing to avoid showing the user a degraded result. If the output was better, it continued to the recognition stage. This mechanism ensured that the system did not produce results that may reduce confidence or reliability from the user's perspective.

Additionally, CNNs have been effectively deployed in practical applications involving license plate recognition under real-world conditions. For example, Brillantes et al. (2019) reported high character recognition accuracy using a CNN-based Faster R-CNN system, even in traffic surveillance footage where image quality is often suboptimal. This further supports the selection of CNNs for tasks involving distortion classification in uncontrolled environments.

In summary, CNNs were selected in this study based on their demonstrated strength in visual classification, adaptability to input variability, and the architectural advantages offered by ResNets. These characteristics make ResNet-based CNN architectures an appropriate and suitable choice for addressing the requirements of distortion classification.

GAN as Deblurring and Reconstruction Model

In this study, GANs were used to restore license plate images degraded by low-quality images, vertical and horizontal motion blur, and low-light conditions. GANs have shown considerable success in image restoration tasks because of their ability to generate outputs that are not only structurally accurate but also visually coherent. Unlike conventional convolutional models that often produce overly smooth outputs due to reliance on pixel-wise reconstruction losses, GANs incorporate adversarial learning, allowing the model to recover texture and detail more convincingly. This is particularly important in license plate recognition, where the accuracy of character recognition depends heavily on the visual clarity and sharpness of small image regions (Sereethavekul and Ekpanyapong, 2023; Gong et al., 2024; Wang et al., 2021).

Although GANs are typically resource-intensive, recent studies demonstrate that lightweight and task-specific designs can retain the benefits of GAN-based restoration while remaining computationally efficient. LPRGAN by Sereethavekul and Ekpanyapong (2023), for instance, introduced a lightweight GAN model capable of addressing different distortion types using a unified architecture with under one million parameters, making it suitable for deployment on low-power machines. The model featured an encoder-decoder style generator that effectively captured degraded patterns and reconstructed cleaner images without the complexity of heavier architectures.

Other GAN-based systems, such as LPDGAN, also illustrate the strength of GANs in recovering real-world motion-blurred license plates. LPDGAN incorporates components like a partition discriminator and a text reconstruction module, designed to enhance letter-level clarity and maintain textual structure. This allows the model to specifically improve readability in severely blurred license plate images, a limitation often encountered in traditional deblurring approaches. Similarly, LPSRGAN focuses on super-resolution by introducing a degradation model that simulates complex environmental distortions. Its network is optimized with character-aware loss functions to preserve identity-critical details, which are frequently lost in standard resolution enhancement methods.

In summary, GANs were chosen for this study due to their capability to reconstruct fine details in degraded visual input, which is essential for license plate readability. Despite their known computational demands, studies such as LPRGAN confirm that GAN-based models can be optimized for lightweight yet optimal performance. Combined with the advances in architectural design and task-specific losses seen in recent works, GANs present a practical and effective solution for recovering distorted images in traffic surveillance systems.

CRNN as License Plate Recognizer

In the LiPAD pipeline, the final stage of license plate character recognition employed PaddleOCRv4's CRNN to convert deblurred images into readable text outputs. PaddleOCRv4 was selected for its lightweight design and enhanced accuracy, achieved through advanced training methods like Unified-Deep Mutual Learning and a tailored backbone for faster inference, making it well-suited for resource-constrained environments in the Philippines. CRNNs are hybrid models that combine the strengths of CNNs for feature extraction with RNNs for sequence modeling, making them particularly effective for text recognition tasks in images (Sun et al., 2019; Bensouilah et al., 2021). The CRNN processed the deblurred license plate images output by the GAN after distortion classification by the CNN and recognized the alphanumeric sequences, ensuring that the characters were accurately identified for traffic enforcement purposes in the Philippines.

The CRNN operated through a multi-step process to achieve character recognition. First, the input image, which was a deblurred license plate, was resized to a fixed height while preserving its aspect ratio, ensuring consistency in processing. The CNN component, optimized in PaddleOCRv4 with a lightweight backbone, extracted spatial features from the image, generating feature maps that captured patterns such as the shapes, edges, and textures of the characters. For instance, in a Philippine license plate like “XYZ-5678,” the CNN identified the visual characteristics of each character despite variations in fonts or minor imperfections from the GAN output. These feature maps were converted into a sequence of feature vectors, where each vector corresponded to a vertical slice of the image, representing the progression of characters from left to right.

Next, the RNN component, implemented with Gated Recurrent Units (GRUs) in this study, inspired by Bensouilah et al. (2021), modeled the sequence of feature vectors as a time series. The GRU processed each feature vector sequentially, capturing dependencies between characters by leveraging its memory of previous steps. For example, after recognizing “XYZ” as letters, the GRU could infer that the next character might be a hyphen or a number, based on the Philippine license plate format. This sequential modeling was crucial for handling the variable-length sequences of Philippine plates without requiring explicit character segmentation, which is often error-prone in degraded images (Xu et al., 2024).

The final stage used a transcription layer based on Connectionist Temporal Classification (CTC) to convert the RNN’s sequential predictions into a coherent character string. CTC processed the probability distributions generated at each time step, aligning them while removing blanks and compressing repeated predictions unless contextually appropriate—preserving valid duplicates such as those found in license plates. This step was especially important in ensuring accurate recognition despite spatial misalignments or distortions that may result from the GAN-based restoration process, which could introduce irregular character spacing in real-world Philippine conditions (Pacaldo et al., 2021).

3.3.2 Model Development/Training

Each model in the proposed pipeline was developed and trained independently to ensure optimal performance for its specific role in the system. The overall pipeline consisted of four core components: (1) a CNN-based distortion classifier, (2) GAN-based distortion recovery models, (3) a CNN-based generated image qualifier, and (4) a CRNN-based license plate text recognizer. The development and training processes for each component are described in detail below.

CNN Distortion Classifier

To classify the type of distortion present in a given license plate image, a CNN was trained in a supervised manner using a labeled dataset across five classes: normal, low-quality, low-light, vertical motion blur, and horizontal motion blur. The initial model architecture was based on ResNet18, trained from scratch without pre-training. Following this, the researchers experimented with ResNet18 pre-trained on ImageNet using transfer learning, as well as deeper variants such as ResNet34 and ResNet50.

Transfer learning involved replacing and fine-tuning the final layers of the pretrained networks to adapt them to the five-class distortion classification task. After training and evaluation, the model that yielded the highest performance across key evaluation metrics—accuracy, precision, recall, and F1-score—was selected for integration into the pipeline. This ensured that the classifier used in the final system was both robust and generalizable across various distortions.

In addition to its role in initial distortion classification, the same CNN model was also used in a later stage of the pipeline as a “qualifier.” In this stage, the model assessed the output image generated by the GAN and compared its classification result with the original input. If the output image was classified as “normal,” it was passed to the CRNN for character recognition. If not, the system compared the output with the original distorted input using image quality metrics. If the output was determined to be worse than the input, the system halted further processing and prompted the end user to decide whether they still wanted to view the result. This qualifying step acted as a quality assurance mechanism, helping to maintain the reliability and credibility of the system by preventing the display of results that were more degraded rather than improved.

To improve performance and reduce overfitting, data augmentation was applied, and learning rate scheduling techniques were used to enhance model generalization and training efficiency.

GAN-Based Distortion Recovery

For restoring distorted license plate images to a clearer state, GANs were used. Separate GANs were trained for each distortion type: horizontal blur, vertical blur, low light, and low quality. Despite targeting different distortions, all of the GANs shared the same generator and discriminator architecture to maintain consistency in design.

The generator was based on an Attention Residual U-Net architecture, which combines the strengths of U-Net's encoder–decoder structure with residual connections and attention mechanisms. The residual blocks helped stabilize training and allowed the network to learn deeper features, while attention modules enabled the generator to focus on the most relevant regions of the license plate, such as characters and edges, that are critical for readability.

The discriminator followed a PatchGAN design, where the image was divided into overlapping patches and each patch was classified as real or fake. This approach encouraged the generator to produce locally realistic details across the entire image, rather than just optimizing for overall appearance. As introduced by Isola et al. (2018) in the pix2pix framework, PatchGAN has been shown to be effective for image-to-image translation tasks by focusing on texture-level fidelity rather than global coherence. The discriminator was trained using Binary Cross Entropy with

Logits Loss, a numerically stable variant of binary cross-entropy that integrates the sigmoid activation into the loss function.

The following loss functions are combined to guide the generator's training process:

- L1 Loss was used for pixel-level reconstruction accuracy.
  Perceptual Loss based on VGG16 features was applied to capture high-level visual similarity,
- Adversarial Loss from the discriminator was employed to enforce realism.
- SSIM Loss was incorporated to encourage structural similarity and preserve fine details.
- Textual Loss derived from PaddleOCR was utilized to ensure that the restored license plates remained textually consistent and recognizable.

Training data for these GANs consisted of paired images: degraded inputs and their corresponding enhanced versions of the original dataset. The enhanced dataset was chosen over the original to ensure that the generator learned to reconstruct images to the highest possible visual quality. As referenced in the LPRGAN study, generators cannot produce outputs of better quality than their ground truth; therefore, providing enhanced versions as ground truth ensures better reconstruction potential.

CRNN PaddleOCR for License Plate Recognition

The researchers fine-tuned PaddleOCRv4 to customize the model for the specific dataset and OCR task. The process began with the preparation of the dataset, formatted according to the requirements of PaddleOCR, with each image paired with its corresponding ground truth text. The dataset was structured in a text file format, where each line contained the image path and its label. Subsequently, the researchers selected an appropriate pre-existing configuration file from PaddleOCR, based on a pretrained model suited for text recognition tasks. This configuration was modified to accommodate the custom dataset by specifying the paths for training and validation data, as well as defining critical parameters such as batch size, learning rate, and the number of epochs allocated for fine-tuning.

Pretrained weights from the selected model were utilized to leverage knowledge obtained from large-scale OCR datasets, facilitating a more efficient adaptation to the specific OCR requirements of this study. The training process involved monitoring the model's progress by saving checkpoints at predefined intervals. Upon completion of the fine-tuning, the model's performance was assessed using a validation set to evaluate its accuracy and ensure it was not overfitting to the training data. After fine-tuning, the model was evaluated against the baseline PaddleOCR model. The researchers compared the fine-tuned model to the base model and selected the better-performing one based on evaluation results.

Finally, the selected model was tested on unseen images to verify its generalization capability and practical effectiveness for license plate recognition.

3.3.3 Model Validation and Evaluation:

Evaluation Metrics

To assess model performance, a variety of evaluation metrics were used for each component of the pipeline:

CNN Classifier/Qualifier

- **Accuracy**

  Measured the overall proportion of correct predictions, indicating how often the classifier was right. High accuracy ensured that the CNN classifier reliably categorized license plates, which was essential for initial classification tasks in the LiPAD pipeline before further processing.

- **Precision**

  Reflected the correctness of positive predictions for each class, helping evaluate class-specific performance. This metric was crucial for identifying how well the classifier distinguished between different Philippine license plate types, reducing false positives in enforcement scenarios.

- **Recall**

  Indicated the model's ability to identify all instances of a given class. High recall ensured that the classifier captured all relevant license plates, minimizing missed detections that could hinder traffic enforcement in the Philippines.

- **F1-score**

  Combined precision and recall into a single metric, providing a balanced measure of classifier performance, especially useful in class-imbalanced scenarios. This was important for ensuring consistent performance across diverse Philippine plate formats, where some classes were underrepresented.

- **Confusion Matrix**

  Visualized correct and incorrect predictions across all classes, offering detailed insight into misclassifications. This helped identify specific classification errors, allowing for targeted improvements in the classifier for Philippine settings.

GAN Reconstruction

- **Fréchet Inception Distance (FID)**

  Quantified the quality and realism of generated images by comparing their feature distribution with that of real images, with lower FID indicating higher quality. This metric ensured the GAN produced realistic deblurred images, which was critical for improving the input quality for CRNN recognition in the LiPAD pipeline.

- **Structural Similarity Index (SSIM)**

  Evaluated perceived image quality based on structural and luminance similarities between original and reconstructed images. Higher SSIM ensured the GAN preserved essential structural details of license plates, enhancing readability for downstream recognition tasks in unconstrained Philippine conditions.

- **Peak Signal-to-Noise Ratio (PSNR)**

  Measured the ratio between the signal or image data and noise, with higher values indicating better reconstruction fidelity. This metric ensured the GAN minimized noise in deblurred images, improving the clarity of Philippine license plates captured under degraded conditions like motion blur or low light.

- **Render Speed**

  Indicated the time of processing per second, measured in seconds per image. A lower render speed ensured the GAN could deblur images quickly, which was vital for rapid enforcement in resource-constrained Philippine settings.

CRNN Recognition

- **Character Error Rate (CER)**

  Quantified the rate of incorrectly recognized characters by calculating the Levenshtein distance between the predicted and ground truth character sequences, normalized by the length of the ground truth. A lower CER indicated fewer character-level errors, which was important for understanding specific recognition challenges in Philippine plates with diverse fonts or formats.

- **Word Accuracy Rate (WAR)**

  Measured the percentage of license plates with at least one character recognition error. WAR was calculated as 1 minus the Word Error Rate, where a word referred to the entire license plate string. A higher WAR indicated better plate-level recognition, ensuring the system's practical utility for enforcement tasks where the entire plate needed to be correctly identified.

Cross-Validation Techniques

To evaluate the performance of each model, a simple train-validation split was employed. This approach involved dividing the dataset into two distinct subsets: one for training the model and another for validation. By keeping the validation set completely separate from the training data, the researchers ensured that the model was evaluated on unseen data, providing an unbiased estimate of its generalization capability.

While more robust evaluation methods, such as k-fold cross-validation, can offer deeper insights into model performance across different data partitions, a single train-validation split was chosen in this study for its simplicity and efficiency, particularly given the computational demands of training deep learning models like GANs and CNNs. This method still allowed for meaningful comparisons between models, provided that the same split was used consistently.

3.3.4 Implementation Details

Software and Hardware

The models used in this study were developed using the Python programming language, with Jupyter Notebook serving as the primary environment for running experiments and testing. Several Python libraries and frameworks were employed throughout the development process, including PyTorch for building and training the neural networks, OpenCV and NumPy for image processing and manipulation, and Matplotlib for visualizing results.

All training and testing were carried out on two desktop workstations with the following specifications:

- Workstation 1: AMD Ryzen 7 5700X CPU with an NVIDIA RTX 3060 GPU (12GB VRAM)
- Workstation 2: AMD Ryzen 7 5700X CPU with an NVIDIA RTX 4060 Ti GPU (16GB VRAM)

These systems provided the necessary computing power to handle large image datasets and train deep learning models efficiently, including tasks that required GPU acceleration. In addition, Google Colab was used for supplementary training, testing, and prototyping, particularly for experiments requiring cloud-based GPU acceleration and collaborative development.

The trained models were integrated into a web application to make the system accessible and usable in real-world scenarios. This application allowed users to upload images of distorted license plates and receive a clearer, deblurred output along with the recognized plate characters.

The web application was developed using Visual Studio Code as the main development environment. The backend was built using Django, a Python web framework that facilitates API creation and serving machine learning models. Django handled communication between the user interface and the trained models, managed the uploaded images, and returned the processed results to the frontend.

The frontend was designed using Vue.js, a progressive JavaScript framework that allows for the development of responsive and interactive interfaces. Through the web interface, users were able to upload image files, view the results, and interact with the system in a straightforward way without needing to understand the underlying AI models. Tailwind CSS, a utility-first CSS framework, was also used to handle user interface styling and layout.

For storing relevant data such as user submissions, results, and logs, the system used PostgreSQL as the database. This setup made it possible to track usage and manage processed images.

Libraries and Tools

Several open-source libraries and tools were used throughout the development, training, and evaluation of the models in this study. Each library played a specific role in handling different stages of the system, from data preparation to model training and deployment:

- **PyTorch** was the primary deep learning framework used for building, training, and fine-tuning all neural network architectures, including CNNs, GANs, and CRNNs.

- **YOLOv5**, a pre-trained object detection model, was used to automatically detect and localize license plates in raw images. This automated the process of predicting license plate regions and ensured consistent input for the deblurring model.

- **OpenCV** was used for most image preprocessing tasks, such as resizing, cropping, simulating low-light conditions, applying motion blur, and introducing compression artifacts. It was also used to draw bounding boxes for detected license plates during preprocessing.
- **Kornia**, a differentiable computer vision library built on top of PyTorch, was used to simulate more realistic and varied motion blur effects by applying horizontal and vertical blur with randomly selected kernel sizes. This enhanced the variability and complexity of the dataset used for training.
- **NumPy** was used for array manipulation and pixel-level transformations, particularly when adjusting image brightness, performing matrix operations, and preparing image data for model input.
- **Scikit-learn** was used for computing evaluation metrics and generating confusion matrices and classification reports. This library helped assess the performance of the distortion classifier and the overall recognition accuracy of the system.
- **Matplotlib** served as the primary visualization tool for displaying image outputs during training and testing. It was also used to compare original, degraded, and restored images side by side for visual inspection.

- **tqdm** was used to display progress bars during model training, providing real-time feedback on the training process, including iteration counts and estimated completion time, which helped monitor training efficiency and identify potential issues early.

- **Seaborn**, built on top of Matplotlib, was used to create visually appealing statistical plots. It was particularly helpful for generating heatmaps of confusion matrices, performance summaries, and distribution plots during the evaluation phase of the distortion classification model.

Parameter Settings

YOLO Detection in Preprocessing

- Confidence Threshold: 70% or 0.70.

CNN Classifier

- Training Policy: Fit One Cycle for dynamic learning rate scheduling

- Maximum Learning Rate: 0.01

- Number of Epochs: 30

- Batch Size: 64

- Kernel Size: 3

- Optimizer: Adam
- Weight Decay: 1e-4
- Gradient Clipping: 0.1

GAN Deblurring Generator (Attention Residual U-Net)

- Number of Epochs: 100
- Initial Learning Rate: 0.0002 or 2e-4
- Optimizer: Adam ($\beta 1 = 0.5$, $\beta 2 = 0.999$)
- Learning Rate Scheduler: ReduceLROnPlateau
  - Mode: min
  - Factor: 0.5
  - Patience: 10
  - Minimum LR: 1e-5
- Loss Function Weights:
  - Adversarial Loss: 0.25
  - L1 Loss: 100
  - SSIM Loss: 5
  - Perceptual Loss: 5.0

    - Textual Loss: 10

GAN Deblurring Discriminator (PatchGAN)

- Number of Epochs: 100 (same as generator)
- Initial Learning Rate: 0.0002 or 2-e4
- Optimizer: Adam (β1 = 0.5, β2 = 0.999)
- Learning Rate Scheduler: ReduceLROnPlateau
    - Mode: min
    - Factor: 0.5
    - Patience: 12
    - Minimum LR: 1e-5

CRNN Recognition

- Learning Rate: 0.0005
- Batch Size: 32
- Number of Epochs: 100

Experimental Setup

Baseline Models:

- **CNN Classifier Baseline**

- ResNet18
  - This served as the primary baseline. It provided a reference point for performance without the influence of pre-learned features. Training from scratch allowed for assessing how well the model could learn purely from the license plate distortion dataset.

- **CRNN Recognition Baseline**
  - PaddleOCRv4 pre-trained without fine-tuning
    - This served as the baseline model for the optical character recognition (OCR) component. PaddleOCRv4 is a well-established, pre-trained CRNN model designed for general text recognition tasks. Using it without fine-tuning provided a reference point for how well the model performed on license plate images generated by the GAN and from the custom dataset.

Comparative Analysis

To evaluate the effectiveness of the proposed models, each was compared against its respective baseline using consistent evaluation metrics and controlled testing conditions.

For the CNN distortion classifier, performance was compared between the ResNet18 model trained from scratch as the baseline and the proposed models that incorporated transfer learning, including pretrained ResNet18, ResNet34, and ResNet50. Evaluation metrics such as accuracy, precision, recall, and F1-score were used to quantify classification performance across the five distortion classes. This comparison highlighted the contribution of pre-learned features and deeper architectures to classification accuracy.

For the CRNN recognition, PaddleOCRv4 was used in its original form as the baseline and compared against a fine-tuned version adapted to both GAN-enhanced and real-world license plate images. Performance was measured in terms of character recognition accuracy and sequence-level accuracy. This allowed the researchers to assess whether fine-tuning improved recognition reliability, particularly under distortions introduced by image degradation and restoration.

CHAPTER 4: RESULTS AND DISCUSSIONS

4.1 Presentation of Results

The following are the preliminary results based on the study's statement of objectives. Each result corresponds to a specific objective according to the order of the statement of objectives, as shown in Figure 4.1.

Figure 4.1. Distortion types in the LiPAD dataset

Collection and Curation of the Dataset

The initial dataset consisted of 24,573 images of Philippine license plates collected from RoboFlow. To prepare these images for training, a YOLOv5-based detection and cropping pipeline was used. Images with a width or height below 88 pixels were filtered out to ensure sufficient resolution for the models. This curation process resulted in a final set of 20,332 usable images. This refined dataset was then split into 20,000 images for training and 332 for validation. Furthermore, manual annotations were created for the license plates to serve as accurate ground truth, which is essential for training the CRNN recognition model.

To ensure that the models were robust to a range of real-world distortions, the dataset was expanded to include five additional augmented variants, resulting in six distinct datasets:

- Normal/Original: The baseline, unaltered images.
- Enhanced: High-quality reference images produced using the RealESRGANv4+ super-resolution model.
- Low Quality: Simulating compression artifacts.
- Low Light: Simulating poor lighting conditions.
- Vertical Motion Blur: Simulating vertical camera or object movement.
- Horizontal Motion Blur: Simulating horizontal camera or object movement

Each variant contained 20,332 images, for a total of 121,992 images. Additionally, the vertical blur image dataset was further finetuned using another set of vertical blur images with low kernel training, adding 20,000 more images to the dataset, bringing the total to 141,992 images. This diversity in the training data aimed to improve the GAN models' ability to restore degraded plates and the CRNN's accuracy in recognition.

CNN-based Distortion Classifier

With the comprehensive dataset of distorted license plate images established, the researchers developed a convolutional neural network (CNN) classifier to identify the type of distortion present in a given image. This capability was deemed essential for determining which specialized restoration model should be applied to achieve optimal results. The classifier was designed to distinguish between five categories: horizontal blur (h_blur), vertical blur (v_blur), low light (low_light), low quality (low_qual), and normal (no distortion). For this classification task, the researchers selected a non-pretrained ResNet18 architecture, which contains 11.1M parameters. Its deeper structure compared to lighter models provided sufficient capacity to learn complex distortion features while remaining computationally efficient for the task.

The dataset used to train the model consisted of 20,332 images from the curated collection, split into 20,000 for training and 332 for validation. All images were resized to 128 by 256 pixels to ensure consistent input dimensions. To enhance the model's robustness and generalization capabilities, the researchers applied data augmentation techniques, including random perspective transforms and color jittering. Each image was also normalized based on the dataset's mean and standard deviation values. Figure 4.2 shows a sample batch from the dataset after augmentation, demonstrating how the training data was visually transformed to help the model become more resilient to variations in license plate orientation, brightness, and noise.

Figure 4.2. Sample batch of augmented images from the training dataset.

Training was conducted using the Adam optimizer with a batch size of 64. The model achieved strong performance, with 96.2% accuracy on the test set and 99.7% accuracy on the validation set, demonstrating high precision and recall across all distortion categories.

Figure 4.3 presents the detailed classification report, which quantitatively confirms the model's performance across all five distortion classes. The report shows high precision, recall, and F1-scores for each category, indicating the model's effectiveness in correctly identifying and classifying the different types of image classification. To provide qualitative perspective, Figure 4.4 showcases a selection of sample images where the classifier made correct predictions, visually demonstrating its ability to accurately discern distortion types in various real-world scenarios.

Classification Report:

	precision	recall	f1-score	support
h_blur	0.98	0.91	0.94	214
low_light	1.00	1.00	1.00	146
low_qual	0.91	0.94	0.92	207
normal	0.94	0.99	0.97	188
v_blur	0.97	0.97	0.97	157
accuracy			0.96	912
macro avg	0.96	0.96	0.96	912
weighted avg	0.96	0.96	0.96	912

Confusion Matrix:

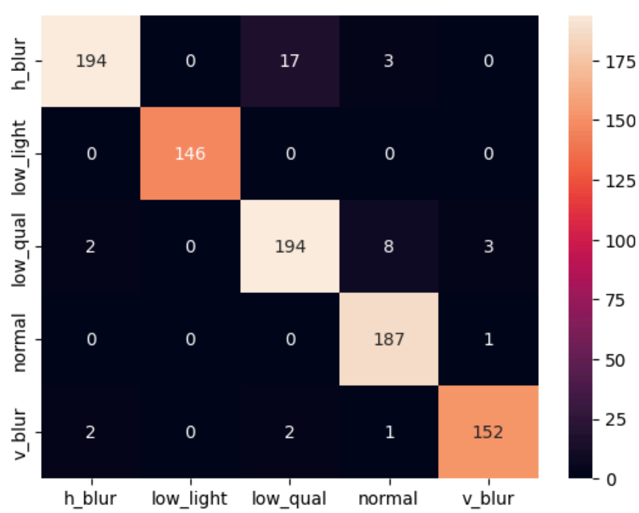

Figure 4.3. CNN-based distortion classifier classification report

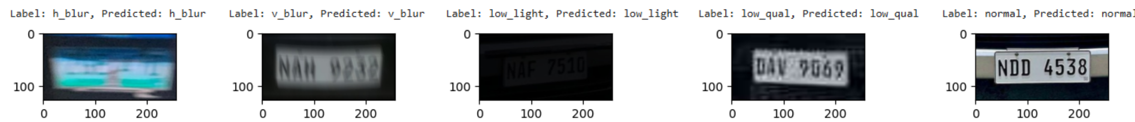

Figure 4.4. CNN-based distortion classifier sample results

However, the researchers identified certain limitations in the classifier's performance. The model occasionally misclassified high-resolution images containing subtle distortions, particularly blur, as normal. This suggested that when an image retained sufficient clarity in terms of resolution, the classifier sometimes assumed it was distortion-free even when blurring artifacts were present. Additionally, the model struggled to correctly identify distortion types when two or more distortions coexisted in the same image. The researchers attributed this challenge to the overlapping features of different distortions, making it difficult for the model to distinguish between them. Consequently, the classifier might prioritize one distortion while ignoring others, reducing overall classification accuracy in complex scenarios.

Distortion Deblurring GAN models

Following the classification of an image's distortion, the next critical step was to restore its legibility. For this purpose, the researchers trained separate GAN models tailored to four types of distortions. All models employed the Residual Attention U-Net GAN architecture, chosen for its strong capability to recover structural information and adapt effectively to different distortion types.

The generator component contained 39M parameters while the discriminator had 2.8M parameters.

Across all experiments, the researchers observed that the models generally succeeded in enhancing images where the text remained partially legible or where the overall structure of characters was still visible. However, when distortions were severe, such as multiple distortions, extremely low resolution, or smudged details, the generators struggled to reconstruct fine details. In such cases, the models either failed to recover the character altogether or produced incorrect outputs by hallucinating characters. This was especially noticeable when visually similar characters, such as "D" and "O", were involved. The model sometimes misidentified one for the other due to smudged or ambiguous edges.

Another key observation was that the models performed more consistently on license plates following the 2018 Philippine license plate format, which has clearer spacing, uniform font style, and higher contrast compared to older formats.

Low Quality Deblurring Model

The low-quality deblurring model achieved moderate success in restoring details lost due to compression and downsampling. The best model was found at epoch 55, reaching the results summarized in Table 4.1.

Table 4.1

Low Quality Metrics Table

Metric	Value
Mean PSNR	16.6732
Mean SSIM	0.6885
FID	50.87

Figure 4.6 illustrates the model's training performance over the full 75 epochs, plotting the progression of the key metrics: SSIM, PSNR, and FID. The curves demonstrate the learning trajectory, showing where the model began to converge and how the metrics stabilized. The point corresponding to epoch 55 represents the optimal balance between these metrics, justifying its selection as the final model.

The model successfully reconstructed the general outline of the plate and characters when the compression artifacts were not too strong. Figure 4.5 provides a visual example of the model's output, comparing the distorted input image (a) with the deblurred result generated by LiPAD (b). This comparison highlights the model's ability to recover legible structure from low-quality input. However, when detail loss was significant, especially around character edges, the output became overly smoothed or introduced artifacts. Hallucination errors also occurred in images where multiple characters had overlapping or broken structures.

Figure 4.5. Result on low quality deblurring model. (a) input image and (b) LiPAD output image

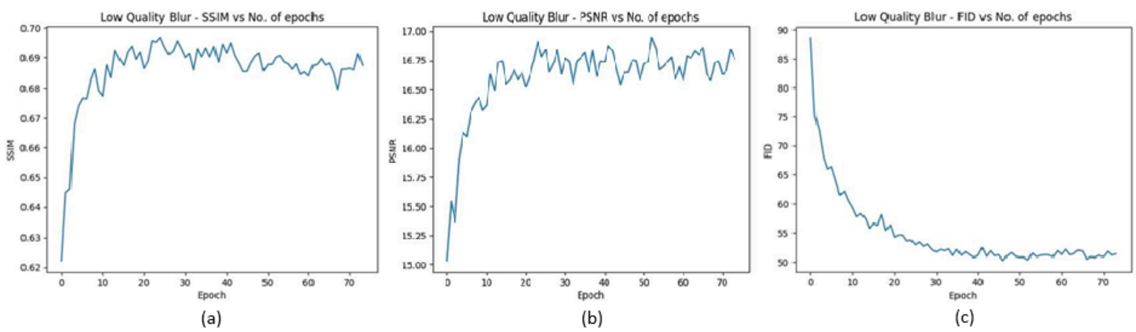

Figure 4.6. Low quality deblurring model training performance (a) SSIM, (b) PSNR and (c) FID

Low Light Deblurring Model

The low-light restoration model, which utilized the Residual Attention U-Net GAN, was primarily designed to improve brightness and reveal obscured text while preserving structural details. Unlike the models trained for motion blur or low-quality distortions, this model focused more on illumination correction than on reconstructing fine textures, although it still managed some degree of detail recovery. It achieved the metrics shown in Table 4.2 at the 80th epoch.

Table 4.2

Low Light Metrics Table

Metric	Value
Mean PSNR	19.7793
Mean SSIM	0.8401
FID	31.55

Figure 4.8 illustrates the model's training performance across the 80 epochs, tracking the progression of SSIM, PSNR, and FID. The curves show a steady improvement in image quality metrics, with the model reaching its optimal performance at epoch 80, which validates its selection as the final checkpoint for evaluation.

Compared to the other distortion-specific models, the low-light model excelled at making license plate text legible, even if some outputs remained slightly dim or color-inaccurate. Figure 4.7 provides a clear visual example of this capability, presenting a side-by-side comparison of a dark, underexposed input image (a) and the significantly brighter and more readable output produced by the LiPAD system (b). This qualitative result demonstrates the model's effectiveness in its primary task of illumination correction, successfully revealing text that was previously obscured.

Figure 4.7. Result on low light deblurring model. (a) input image and (b) LiPAD output image

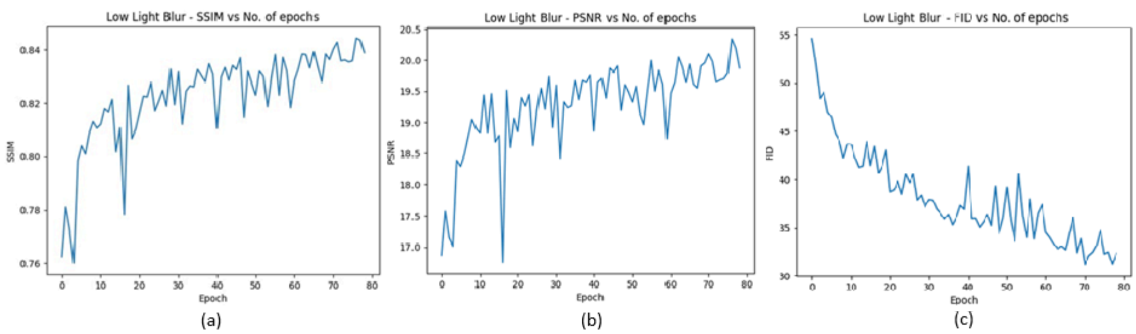

Figure 4.8. Low quality deblurring model training performance. (a) SSIM, (b) PSNR and (c) FID

Vertical Blur Deblurring Model

After two sets of initial training (80 epochs) and a subsequent fine-tuning phase focused on lower-kernel vertical blur (65 epochs), the vertical motion blur model still struggled more than expected, especially when the distortion significantly disrupted the vertical strokes of characters. The model achieved the performance metrics summarized in Table 4.3.

Table 4.3

Vertical Blur Metrics Table

Metric	Value
Mean PSNR	15.85
Mean SSIM	0.6307
FID	65.73

The model's training performance across the full 145 epochs is visualized in Figure 4.10, which clearly shows the two distinct training phases. A noticeable jump in the metrics occurs around epoch 80, marking the beginning of the fine-tuning phase. Interestingly, during this fine-tuning phase, while all the metrics declined, the qualitative quality of the outputs was observed to improve. As shown in Figure 4.9, the enhanced results demonstrate how the model produced clearer text despite the drop in numerical scores. This suggests that the fine-tuning on dataset with lower kernel motion blur prompted the model to prioritize the features of slighter vertical blur distortions, while still retaining the broader knowledge from its initial pretraining. This focus on perceptual quality over a strict pixel-to-pixel match to the ground truth resulted in more legible text, even though it led to decline in the metric scores.

Artifacts and character deformation were more pronounced in this type of distortion compared to horizontal blur. The model frequently confused characters such as "H" and "M" or "0" and "8", showing that vertical motion blur directly interferes with the vertical topology of characters. These results confirm that vertical blur is more destructive to structural information, which contributed to reduced reconstruction accuracy.

Figure 4.9. Result on vertical motion blur deblurring model. (a) input image and (b) LiPAD output image

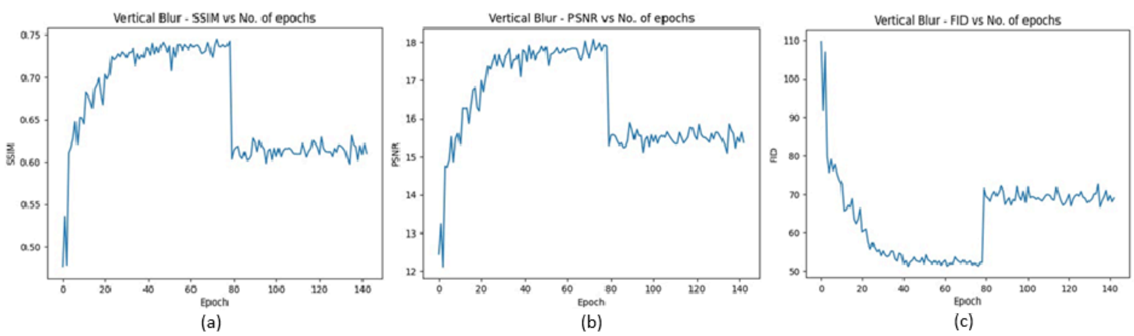

Figure 4.10. Vertical motion blur deblurring model training performance. (a) SSIM, (b) PSNR and (c) FID

Horizontal Blur Deblurring Model

The horizontal motion blur model delivered the best overall performance among the four distortion-specific models. It achieved the metrics summarized in Table 4.4.

Table 4.4

Horizontal Blur Metrics Table

Metric	Value
Mean PSNR	20.38
Mean SSIM	0.8437
FID	34.69

The training performance of the horizontal motion blur model, visualized in Figure 4.11, demonstrates a remarkably stable learning curve. Unlike other models that exhibited significant fluctuations, this model showed consistent improvement in all metrics, indicating a robust and reliable training process. The stability in training directly contributed to its superior final performance.

The visual results from this model confirms its quantitative success. As seen in Figure 4.10, which compares a blurred input (a) with the LiPAD output (b), the restorations are often visually sharp and closely resemble the ground truth. It effectively separated characters, especially on newer license plates with clearer font and spacing. However, it was consistently observed that when the image details were heavily smudged, the model failed to reconstruct the image as a whole. Despite this limitation, the high SSIM and low FID scores indicate strong structural preservation and realism compared to the other models.

Figure 4.10. Result on horizontal motion blur deblurring model. (a) input image and (b) LiPAD output image

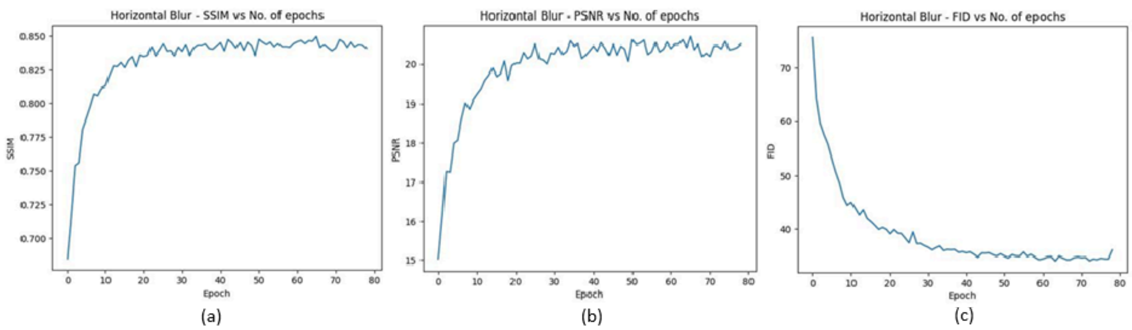

Figure 4.11. Horizontal motion blur deblurring model training performance. (a) SSIM, (b) PSNR and (c) FID

CRNN-Based Recognition Model

Once an image is restored by the appropriate GAN model, the final step in the automated pipeline is to accurately transcribe the license plate characters. The recognizer component of PaddleOCR v4 was finetuned using manually created annotations. The evaluation results are as follows:

- Finetuned recognizer (standalone):
    - CER: 0.0962

    - WAR: 0.8299
- Base PaddleOCR recognizer (standalone):
    - CER: 0.4465
    - WAR: 0.2639

This indicates that the fine-tuned recognizer demonstrated superior accuracy in standalone recognition tasks compared to the baseline model.

When evaluated in conjunction with the detection model, however, the finetuned recognizer underperformed:

- Finetuned recognizer + PaddleOCR detector:
    - CER: 0.2633
    - WAR: 0.4132
- Base PaddleOCR model (detector + recognizer):
    - CER: 0.0300
    - WAR: 0.8958

This suggests that the fine-tuned recognizer did not integrate well with the detection component of PaddleOCR.

The researchers attribute this decline in performance to the fact that only the recognizer was finetuned, while the detection model remained unchanged. Since the detection and recognition stages in PaddleOCR are optimized to complement each other, introducing a modified recognizer that differs in feature expectations from the original training distribution may have caused inconsistencies when processing the detector’s outputs. On the other hand, the base PaddleOCR model demonstrated strong performance because its detection and recognition modules were jointly trained and aligned.

Overall, while the finetuned recognizer exhibited strong results in isolation, the base PaddleOCR model outperformed it in end-to-end evaluation. For this reason, the finetuned recognizer will not be adopted for implementation, as the base model provides more consistent and reliable performance when paired with the detection component.

4.2 Presentation of the Application

Web App Model Integration

To deploy the trained distortion classifier, deblurring GANs, and CRNN recognition model into a cohesive and user-friendly system, a functional web application was developed using the Django framework for the backend and Vue.js for the frontend. The core of the system's functionality resides in the Django backend API, where all neural network models and the complete processing flow were integrated. This backend ensures smooth coordination between the various modules, handling the end-to-end pipeline that includes detection, enhancement, deblurring, and recognition.

The system demonstrated efficient processing capabilities, with performance varying based on the hardware used. The average response times for the entire pipeline were recorded as:

- With a single GPU:
    - NVIDIA RTX 3060 GPU: 1.5725 seconds per image request.
    - NVIDIA RTX 4060 Ti GPU: 1.0645 seconds per image request.
- With CPU-only: 2.4175 seconds per image.

These results indicate that the application can deliver near real-time performance when deployed with appropriate hardware support.

The system was designed with two distinct interfaces to serve different roles, one for users and another for administrators. On the user side, the web app provides a streamlined interface that allows individuals to upload and process license plate images through the recovery pipeline. In addition to the recovery functionality, the platform maintains a history log for each user, enabling easy access to past processed images. On the admin side, the application offers account management tools and access to the comprehensive system history, facilitating monitoring, oversight, and maintenance of the platform.

Overall, the developed system successfully demonstrates the technical feasibility of integrating complex deep learning models into a practical, user-oriented platform that balances performance with usability.

ISO/IEC 25010 Quality Conformity of the Web Application

Following the successful integration of the deep learning models and the completion of the web application, a formal evaluation was conducted to assess the system's conformity with the ISO/IEC 25010 software quality standards, specifically in terms of functionality suitability, performance efficiency, interaction capability, reliability, security, and safety. The evaluation was conducted through expert reviews and testing, which gathered both quantitative ratings and qualitative feedback to ensure a comprehensive assessment. The findings revealed that the LiPAD system demonstrated a high level of conformity with the ISO/EIC 25010 quality standards. Across all six dimensions, the professional evaluators consistently provided favorable ratings, with mean scores ranging from 4.5 to 5.0 on the five-point Likert scale.

Qualitatively, the system was observed to be functionally complete, accurate, and appropriate for its intended purpose, as experts confirmed it provided the necessary functions and produced correct results.In terms of performance efficiency, the system responded momentarily to user commands and utilized resources effectively, although one suggestion for improvement involved cloud deployment to further optimize speed and scalability. Interaction capability was also rated highly, as the interface was evaluated as intuitive, easy to learn, and effective in guiding users through tasks while providing feedback for error recovery.

The system also performed strongly in terms of reliability, as it operated consistently without frequent errors, remained available when needed, and recovered quickly after interruptions. Security was affirmed through the protection of sensitive data, the maintenance of data integrity, and the provision of secure authentication mechanisms. The safety of the system, such as preventing unsafe operations, providing confirmations before critical actions, and reducing the risk of data loss or misuse, was also similarly recognized. These results were further supported by the qualitative responses of the evaluators, who highlighted the usefulness of the distortion detection and restoration feature, the integration of multiple artificial intelligence models, and the overall design of the interface. Notably, no major issues or critical concerns were reported during the evaluation.

Overall, the results confirmed that the LiPAD system conformed well to the ISO/EIC 25010 quality standards. The evaluation successfully achieved its research objective, establishing a strong foundation for the system's future enhancement and deployment in real-world applications.

The Web Application Interface

1. ADMIN-SIDE

The Admin Login is the area where admins securely log in to access the LiPAD dashboard. It consists of only email and password input fields, along with convenient options such as “Forgot Password” for simple account recovery. It also manages errors such as invalid or missing credentials and prevents logged-in admins from navigating back to the login page. As shown in Figure 4.12, admins are redirected to the main dashboard once they successfully log in to begin managing the system.

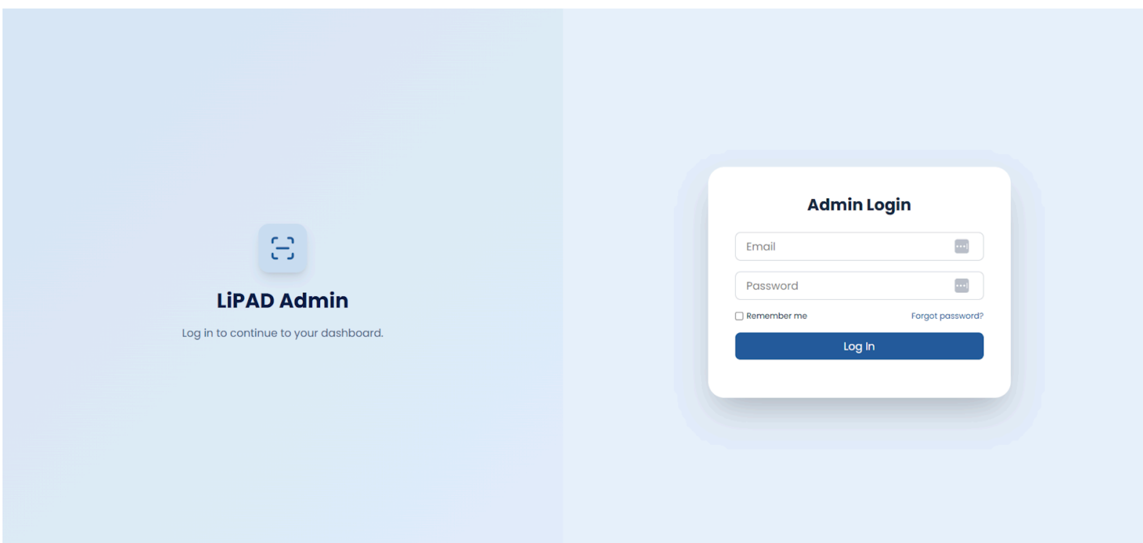

Figure 4.12. Admin Login Page.

This User Dashboard page allows admins to see, search, and manage all the user accounts in LiPAD as shown in Figure 4.13. First, at the top is a quick KPI card with the number of users and recent growth trends. Below that, admins can search for users, add new accounts using the "Add User" button as shown in

Figure 4.14, or edit and delete existing ones directly from the table. The page employs modals for adding and editing users, keeping it all tidy and user-friendly but still providing full CRUD operations for easy user management.

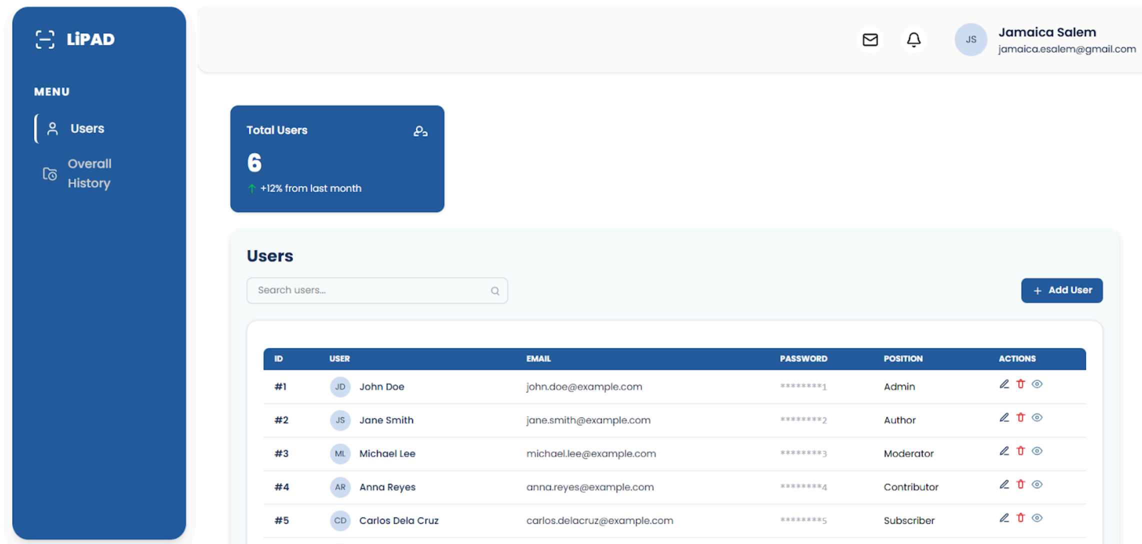

Figure 4.13. User Dashboard Page.

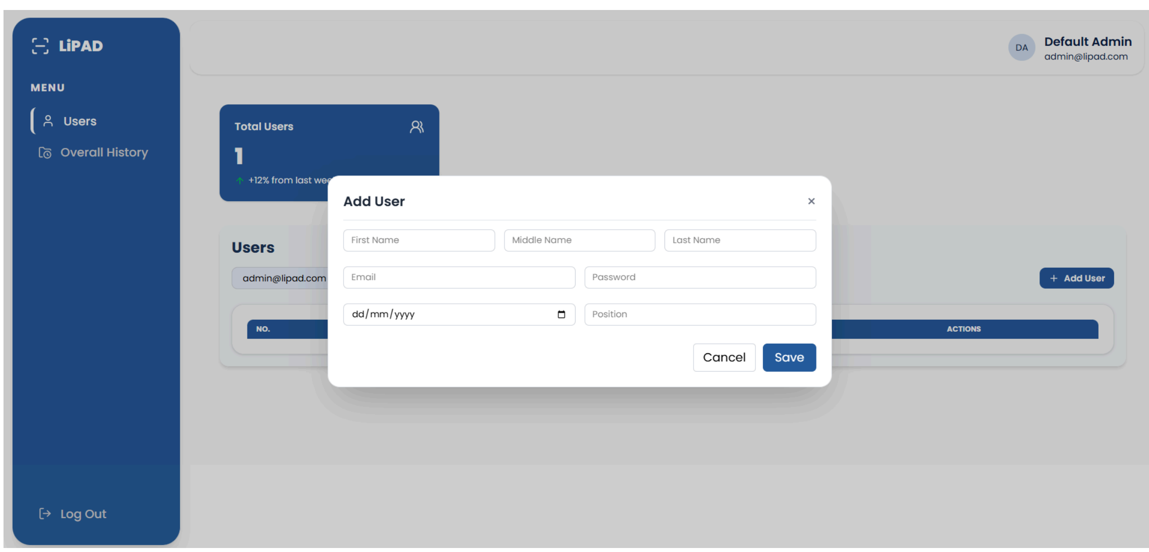

Figure 4.14. Add User Modal Form.

The Overall History page provides admins with a clear view of all deblurring activity performed by users as shown in Figure 4.15. At the top, KPI cards provide rapid stats such as the number of plates deblurred, distortion types, and success rates. Below, a complete, filterable table allows admins to filter on user, plate number, date, distortion type, or status to locate individual records rapidly. Each row includes user information, plate information, and an action panel to view or remove history items. This page is designed to be easy to monitor and manage deblurring activity, clean, and efficient.

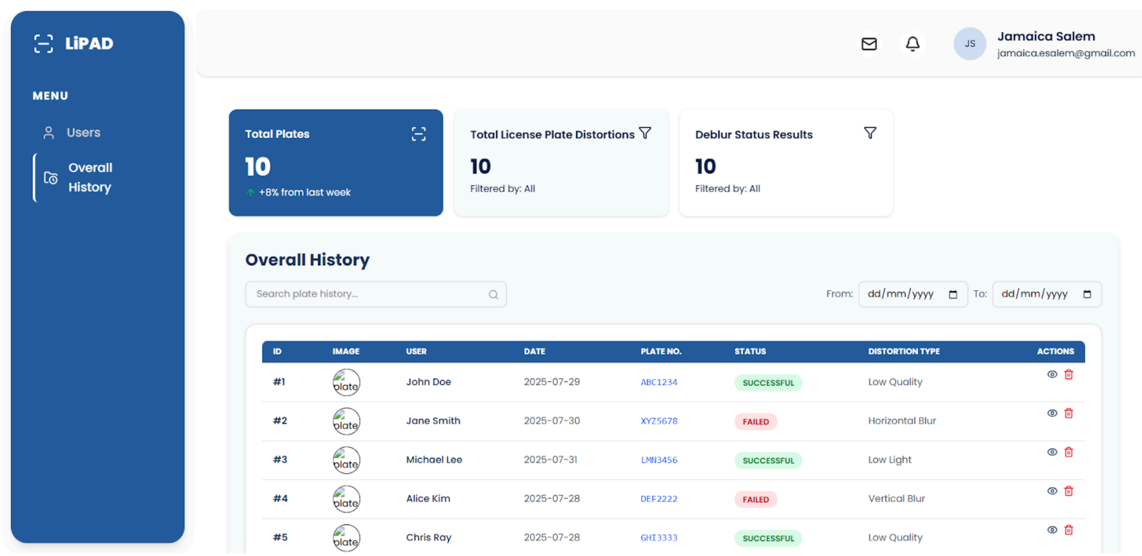

Figure 4.15. Overall History Page.

2. USER-SIDE

The User Login page is the first entry point for users to leverage LiPAD's deblurring functionality. It has a clean, responsive design with fields for email and password, and immediate error feedback for missing or incorrect entries. A loading indicator gives clear feedback during the process, and proper validation sends users to the license plate upload page. The page offers a seamless, user-focused, and secure login experience as shown in Figure 4.16.

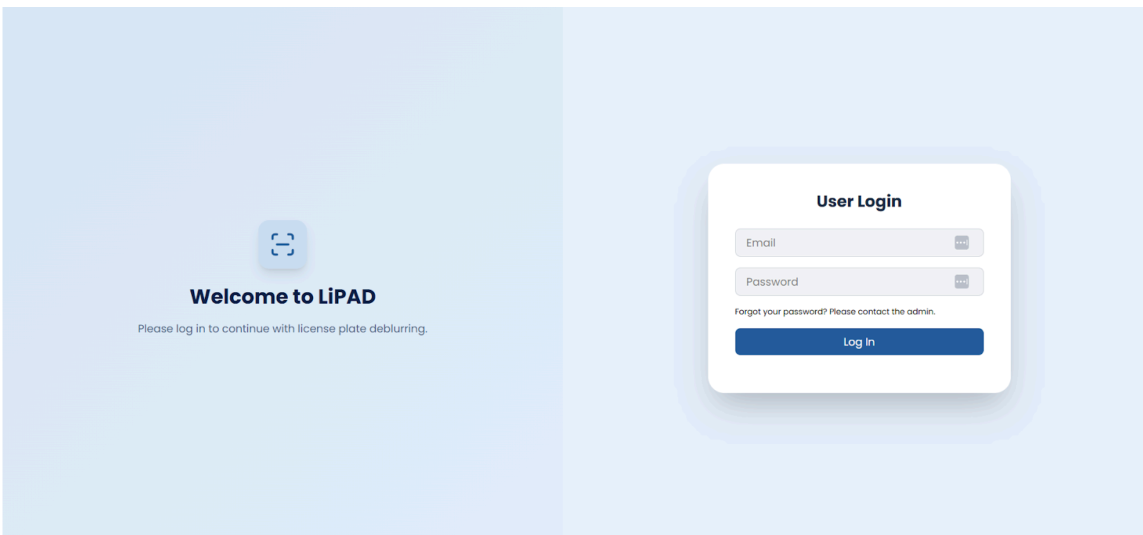

Figure 4.16. User Login Page.

The License Plate Upload page is where the user initiates the deblurring process by uploading a picture of a license plate. It provides a clean, easy-to-use interface with a drop zone or button for selecting an image. The system checks the file type and size for safety and compatibility, then securely uploads it for processing. Real-time feedback messages assist users in the event of a failed upload, while a successful upload automatically passes the image to the next page. As shown in Figure 4.17, the page maintains a simple and streamlined process, allowing users to upload images for analysis quickly and with confidence.

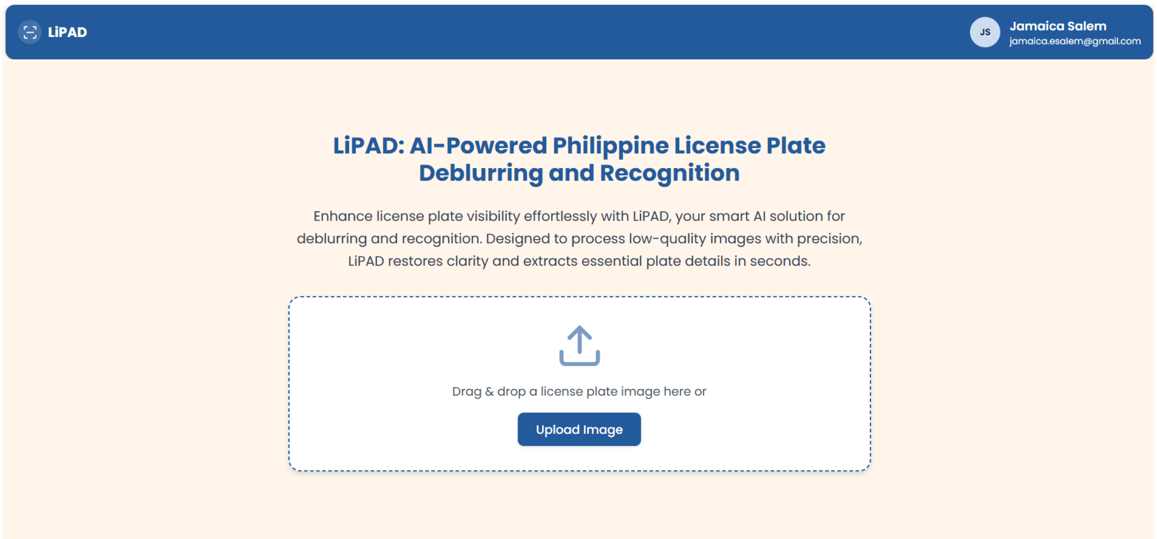

Figure 4.17. License Plate Upload Page.

The Distortion Classifier Options page helps users decide how to process their uploaded image of a license plate. It offers two options: allowing LiPAD to automatically analyze the image to determine the exact type of blur or distortion, or letting the user manually choose the distortion type if they already know it. The interface is designed to be simple, accessible, and flexible, ensuring a smooth experience. Real-time feedback mechanisms prevent repeated actions and display error messages in cases of navigation issues. As shown in Figure 4.18, the page ensures an effective and user-friendly workflow.

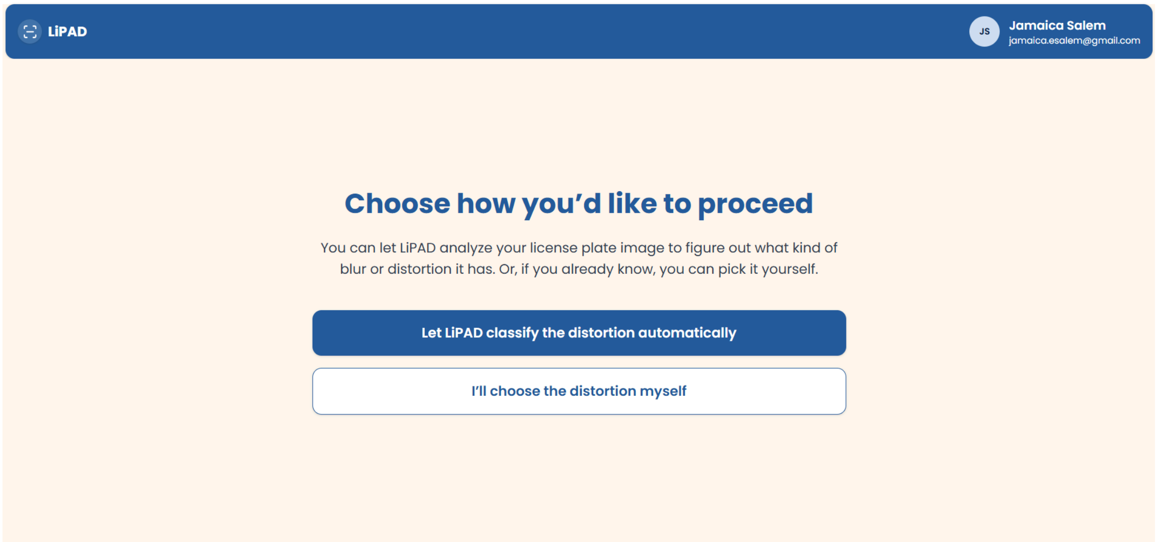

Figure 4.18. Distortion Classifier Options Page.

The Distortion Manual Classifier page allows users to manually choose the exact type of distortion in their uploaded license plate image. The interface provides four options—low quality, low light, horizontal blur, and vertical blur—each labeled with a descriptive name and a representative image to help guide the user's selection. This page is ideal for users who prefer more control over the classification process, allowing the AI to process the image under the most accurate settings for improved deblurring results, as shown in Figure 4.19.

Figure 4.19. Distortion Manual Classifier Page.

The Processing page displays a centralized, plain loading screen with pulse icon animation and dynamic AI-related messages, updated at a constant interval when deblurring images is in progress, thus offering a smooth and interactive experience to the user, as shown in Figure 4.20.

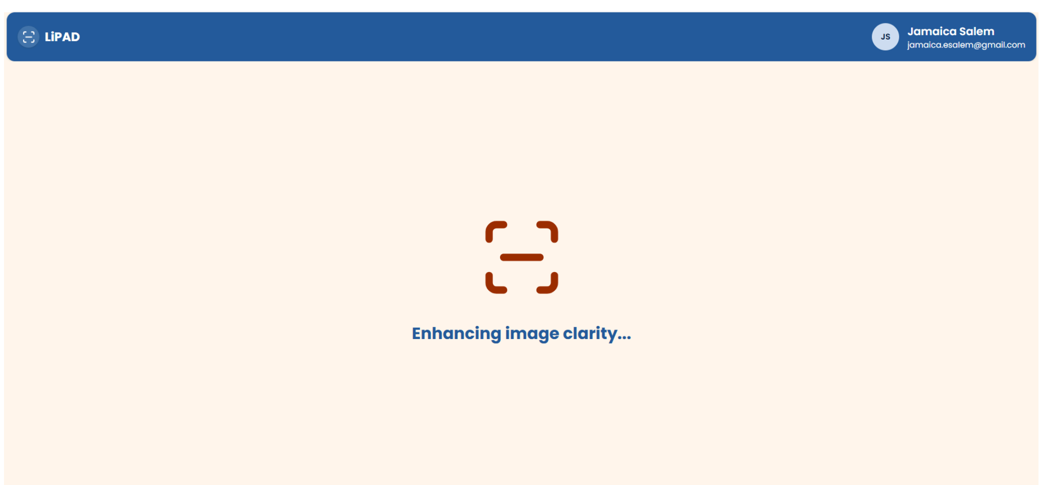

Figure 4.20. Processing Page.

The Failed Image Processing page is used to inform users when LiPAD cannot deblur or improve the uploaded image to their satisfaction, as shown in Figure 4.21. It displays a randomly chosen error message, a request asking users if they want to see the result, and two different action buttons: one to allow navigation to the result page and one to allow navigation to the upload page, thus providing an uninterrupted recovery process.

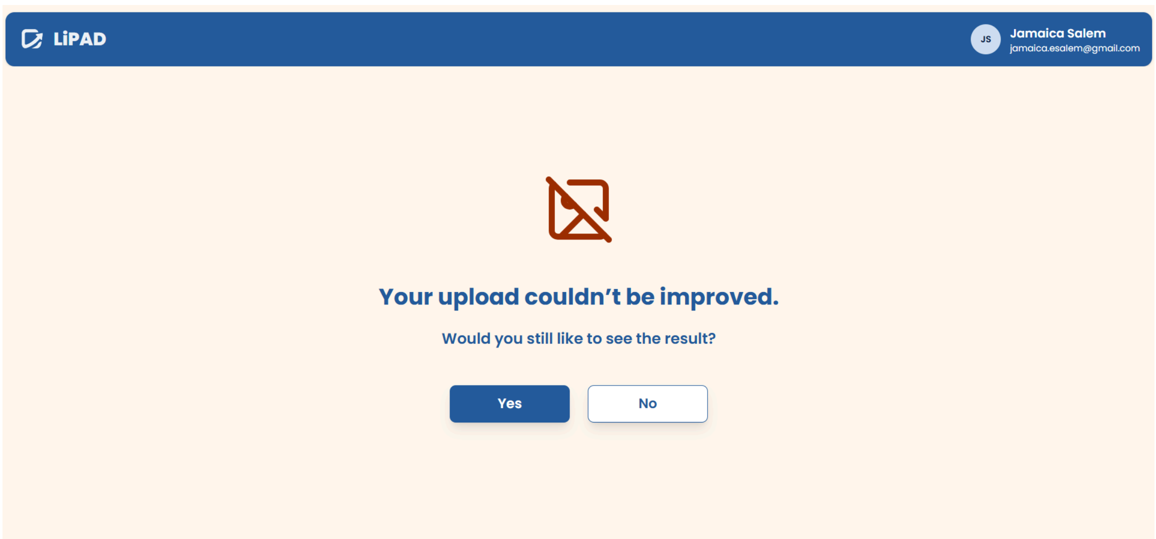

Figure 4.21. Failed Image Processing Page.

Figure 4.22 below shows the overall layout of the Results page, where the interactive slider is positioned at the center to let users compare the original and deblurred images. On the right side, the information panel displays key details such as processing time, distortion type, confidence level, and plate number detection.

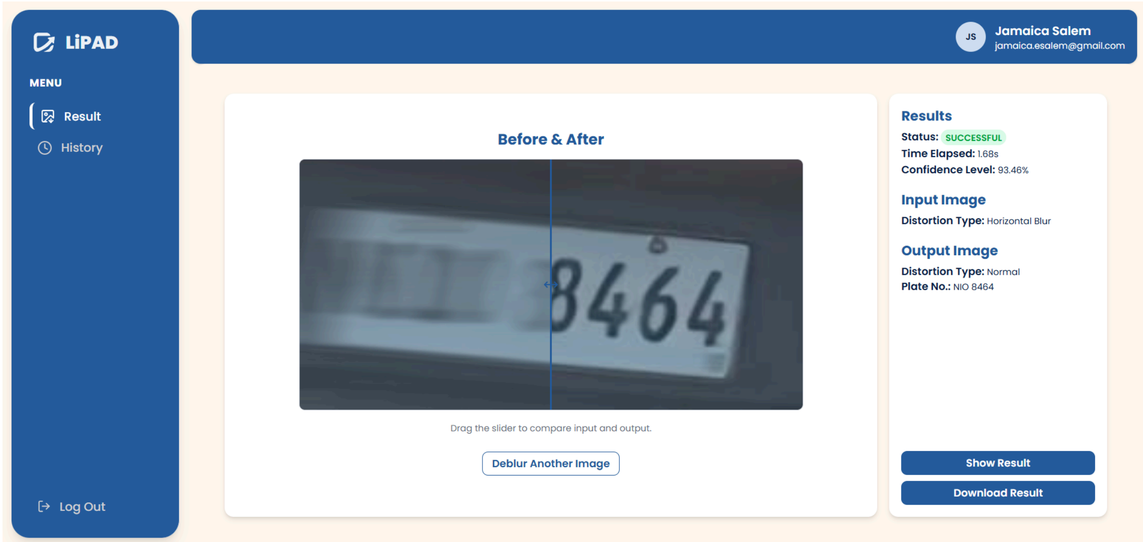

Figure 4.22. Results Page.

Figure 4.23 below presents the *Before* state of the slider, showing the original uploaded image prior to deblurring. This view allows users to clearly see the degree of distortion or blur before processing.

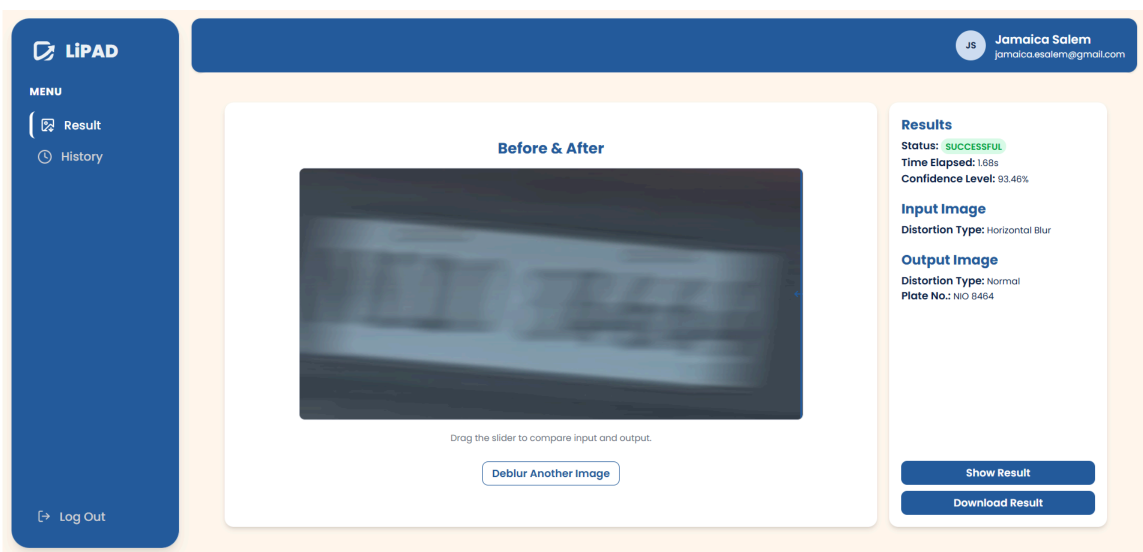

Figure 4.23. Results Page (Before).

Figure 4.24 displays the *After* state of the slider, showcasing the enhanced image after the system applies the selected deblurring model. This figure highlights the improvements made by LiPAD in restoring clarity and detail.

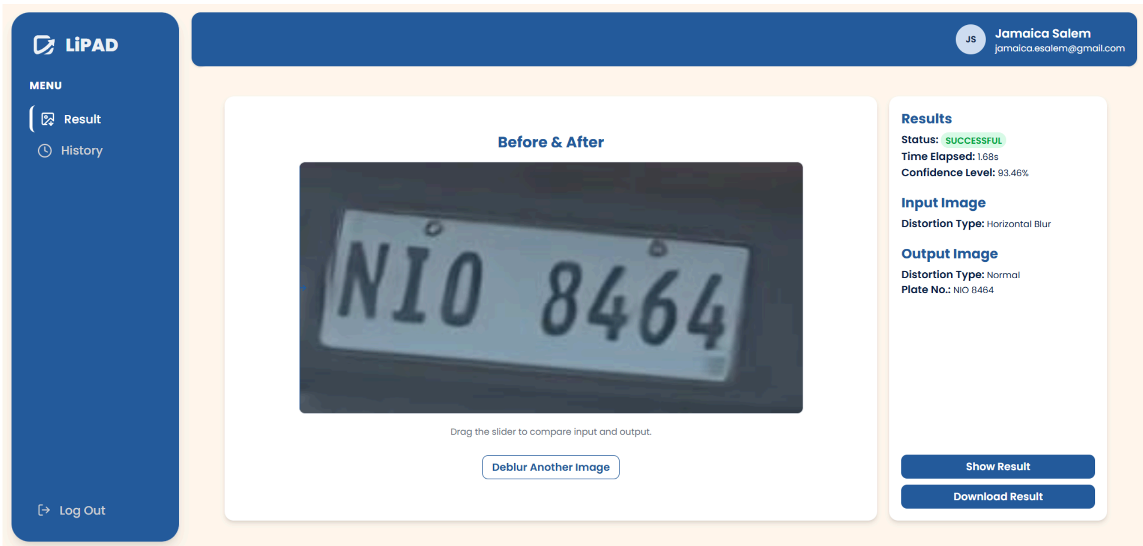

Figure 4.24. Results Page (After).

Figure 4.25 illustrates the modal window that appears when users choose to view the full-size output. This modal provides a clearer, expanded version of the deblurred image, allowing users to inspect finer details before downloading.

Figure 4.25. Result Modal View.

The History and Plate Dashboard page offers a bird's-eye view of LiPAD's performance and the logged-in user's activity. Top KPI cards display key metrics such as total plates processed, distortion type counts, and deblur success rates, accompanied by filtering options. Below, a filterable and searchable history table provides details for all processed images, including ID, date, status, distortion type, plate number, and quick action buttons for viewing or deleting records. As shown in Figure 4.26, this page enables users to monitor their activity, track performance trends, and maintain an organized record of their processing history.

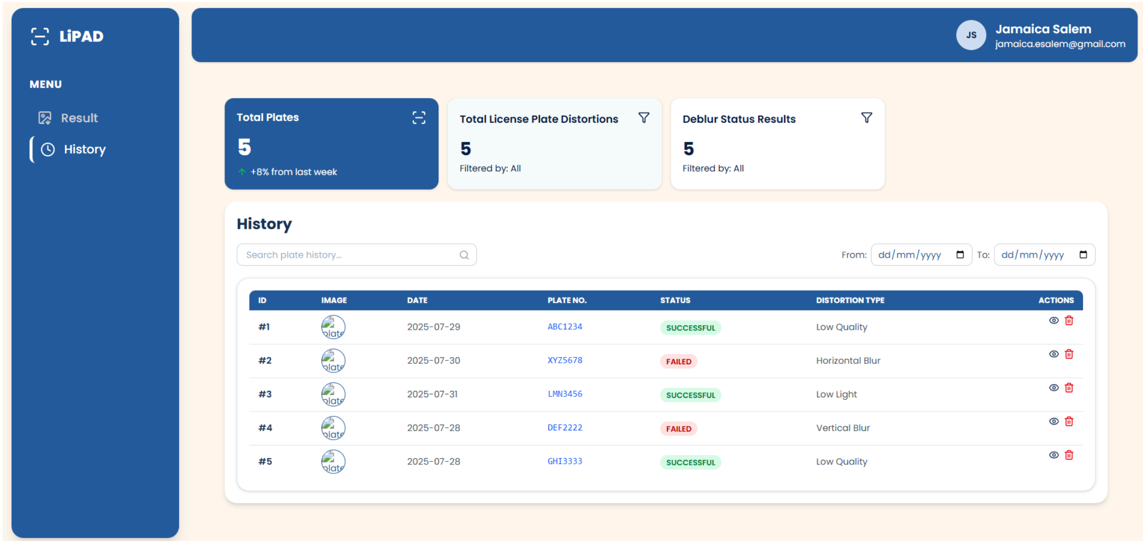

Figure 4.26. History and Plate Dashboard Page.

CHAPTER 5: SUMMARY, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Summary

This study culminated in the development of an automated system for recovering and recognizing Philippine license plate images by integrating multiple deep learning models into a functional web application. The research was founded on a curated dataset primarily composed of six- to seven-character license plates. To prepare the models for varied practical scenarios, augmentation and preprocessing techniques were applied to simulate real-world distortions, such as motion blur and low-resolution artifacts. The inclusion of these simulated distortions in the training data proved critical to achieving robust model performance, particularly under conditions likely to be encountered in real-world deployments.

A Convolutional Neural Network (CNN) based on the ResNet18 architecture was implemented to classify distortion types within cropped license plate images. This model demonstrated high reliability, achieving an accuracy of 96.2% on real-world test data and 99.7% on a validation set of synthetic yet unseen distortions. These performance metrics confirm the classifier's effectiveness in distinguishing between distortion types, a critical prerequisite for routing images to the appropriate deblurring model.

For image restoration, distortion-specific Generative Adversarial Network (GAN) models were developed, utilizing a Residual Attention U-Net generator and a PatchGAN discriminator. These models effectively enhanced blurred license plate images by reconstructing structural details and improving overall readability. Quantitative evaluations using PSNR, SSIM, and FID confirmed significant improvements in image quality compared to the degraded inputs. Although the models performed well on distortions similar to those in the training set, vertical motion blur proved particularly challenging, highlighting a potential limitation in the current approach to synthetic distortion modeling.

In the recognition stage, the evaluation revealed that the base PaddleOCR model delivered superior end-to-end performance, achieving a Word Accuracy Rate (WAR) of 89.6% and a Character Error Rate (CER) of 0.0300 when its detection and recognition modules were used together. Conversely, while fine-tuning the recognition model in isolation improved its standalone accuracy (82.9% WAR, 0.0962 CER), this approach resulted in a significant drop in integrated performance (41.3% WAR) when paired with the original detection module. This finding underscores the critical importance of co-optimizing the detection and recognition stages to ensure reliable overall OCR performance.

Finally, the complete system was integrated into a web application named LiPAD, demonstrating both practical feasibility and high software quality. The application, built with Django and Vue.js, achieved an average inference speed of

1.5725 seconds per image on a NVIDIA RTX 3060 GPU, 1.0645 seconds on a NVIDIA RTX 4060 Ti GPU, and 2.4175 seconds on a CPU. Beyond its technical performance, the system's overall quality was formally validated against the ISO/EIC 25010 model, showing strong conformity across functionality, performance efficiency, reliability, and security. These results were corroborated by expert reviews and user testing, which yielded average ratings between 4.5 and 5.0 and confirmed the system is functionally complete and user-friendly. Qualitative feedback specifically praised the effectiveness of the distortion detection and deblurring pipeline, as well as the intuitive interface. The absence of any significant shortcomings reported by evaluators affirms that the system adheres to international quality standards, confirming its strong potential for real-world deployment in applications such as traffic monitoring and law enforcement.

5.2 Conclusions

This research resulted in an integrated system for Philippine license plate image recovery and recognition, demonstrating that combining specialized deep learning models into a single framework can lead to reliable performance in real-world settings. The study validated a sequential process for image restoration, where a CNN first classifies the image distortion before specific GANs are applied to correct it. The findings from the OCR component also emphasized the need for tightly integrated detection and recognition modules, showing that a unified model achieves better end-to-end accuracy compared to using a separately fine-tuned recognition component.

The main contribution of this research is the development of a complete, deployable system that bridges the gap between model training and real-world application. All components were successfully integrated into the LiPAD web application, which was then formally validated against the ISO/EIC 25010 software quality model, confirming the system’s practical design and user-friendliness. Although the system proved effective, its performance revealed limitations, particularly in handling vertical motion blur and the need for a more diverse dataset. These challenges highlight clear directions for future work. Subsequent research should focus on improving the synthetic distortion modeling and expanding the training dataset with images from more varied sources to enhance the system's reliability and its overall usefulness for traffic monitoring and law enforcement.

5.3 Recommendations

Dataset Expansion

To enhance the reliability and generalization of the models, future research should focus on expanding the dataset to include license plate images captured from CCTV footage and other surveillance sources. Such an expansion would more accurately reflect real-world deployment conditions. Additionally, investigating alternative methods for simulating vertical blur, such as physics-based modeling or more realistic kernel generation, could improve the reconstruction quality of the vertical deblurring model.

Moreover, to enhance the system's versatility and applicability further, future work could aim to recover a broader spectrum of image distortions beyond these addressed in the study. This includes incorporating data for common real-world degradations such as Gaussian blur, out-of-focus or unfocused camera captures, and images taken under adverse weather scenarios like rain or fog. Expanding the system's capabilities to handle these diverse conditions would be helpful for creating a more robust and universally applicable license plate recognition solution.

Model Improvements

Although the ResNet18-based distortion classifier demonstrated high performance, future studies could investigate more advanced architectures, such as Vision Transformers (ViTs) or ensembles of CNNs, to improve classification accuracy in challenging scenarios. For deblurring, exploring alternative GAN architectures, diffusion-based generative models, or a unified GAN capable of handling multiple distortion types could enhance structural and textual reconstruction while reducing the need for multiple models. In the context of OCR, joint training of the detection and recognition modules is recommended to improve module alignment and end-to-end performance; incorporating additional deblurred images into the training set may further bolster recognition robustness.

System Enhancements

The web application could be extended to support batch processing for multiple images, thereby reducing overhead and improving efficiency for larger datasets. Supporting continuous video streams would also allow for the real-time recovery or detection of blurred frames across dynamic scenes. Furthermore, implementing automated vehicle detection and cropping would minimize manual pre-processing, enabling seamless handling of raw images and improving the overall user experience.

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Appendices

Appendix A: Adviser’s Endorsement

ANGELES UNIVERSITY FOUNDATION

Angeles City

COLLEGE OF COMPUTER STUDIES

2nd Semester, Academic Year 2024 - 2025

THE01 – Thesis 1

ADVISER’S ENDORSEMENT

The undersigned certifies that the thesis paper entitled

LiPAD: AI-Powered Philippine License Plate Deblurring and Recognition using Convolutional Neural Network, Convolutional with Recurrent Neural Network, and Generative Adversarial Networks Models

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has been verified, evaluated, and affirms that the same complies with the standard requirements for a thesis paper.

In view thereof, the undersigned endorses the said thesis paper for ***proposal defense***.

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April 2025

Appendix B: Certificate of Language Editing and Proofreading

Appendix C: Literature Review Matrix

Title of the Study	Author(s)	Date of Publication	Purpose/ Rationale	Technology/ Methods	Conclusion
Deep Learning Based Automatic Vehicle License Plate Recognition System for Enhanced Vehicle Identification	Mhatre, Sharma, & Maurya	2023	The study aims to develop an innovative Automatic Vehicle License Plate Recognition (AVLPR) system that uses deep learning algorithms to improve vehicle identification. With the growing demand for better security and traffic management, the system focuses on obtaining accurate and real-time license plate recognition, which is critical for applications in law enforcement and intelligent transportation systems.	Convolutional Neural Network (CNN) Lightweight Parallel CNN Image Pre-Processing Data Augmentation Character division, Optical Character Recognition (OCR), and Format Matching	The study concludes that the developed AVLPR system is a reliable and effective solution for vehicle identification tasks, achieving high accuracy in recognizing license plates. The integration of deep learning approaches ensures precise and instantaneous recognition, making the system suitable for various applications, including law enforcement and traffic management.
Unleashing the power of Convolutional Neural Networks in license plate recognition and beyond	Wang, M.	2024	The study aims to explore the application of Convolutional Neural Networks (CNN) in license plate recognition, highlighting their architecture and effectiveness in extracting features from images.	Convolutional Neural Networks (CNN) are utilized for license plate recognition, featuring three key layers: Convolutional Layers, Pooling Layers, and Fully Connected Layers. Data preprocessing techniques include resizing images, converting color images to grayscale, and	The study concludes that Convolutional Neural Networks (CNNs) have established themselves as powerful image recognition algorithms with extensive applications across various domains. Their versatility and adaptability make them essential tools in computer vision, particularly in license plate recognition.

				normalizing pixel values. Max Pooling to reduce spatial dimensions of feature maps while preserving essential features.	
Vehicle license plate recognition for fog-haze environments	Jin X., Tang R., Liu L., & Wu J.	2020	The objective of the study is to develop License Plate Recognition method for Fog-Haze environments (LPRFH), a method to recognize vehicle license plates in fog-haze conditions where traditional LPR fails due to blurred boundaries and conditions.	LPRFH uses a three-stage approach with CNNs: 1. Initial dehazing applying improved Dark Channel Prior (DCP) algorithm via k-means clustering. 2. Joint further-dehazing and detection employing Joint Further-dehazing and Region-extracting Model (JFRM) based on YOLOv3 with Darknet-53. 3. Super-resolution and recognition using six-layer convolution-enhanced SRCNN, followed by character segmentation and recognition. Dataset: 3000 real images are	The study concludes that LPRFH successfully recognizes license plates in fog-haze environments by reducing fog interference and improving image quality. The results improved higher detection and recognition accuracy over traditional methods. such as soft-matting and guided-filtering, and standard SRCNN. The simulation results on foggy traffic images validate high accuracy of 94.10% with six layer SRCNN even with tilted or stained license plates.

				used. Augmented to 1,200 images by adding noise, rotating, and other image processing. Another 300 images with motion blur were also used.	
Spatial correction and Deblurring fusion algorithm for vehicle license plate images based on deep learning	Fang D. & Daisheng Z.	2024	This study aims to address challenges in license plate detection and deblurring caused by high speed motion blurs. The researchers proposed a real-time deep learning algorithm, which they called 4xSTN(four spatial transformer networks) + DSC15(15 layers of deep separable convolutions) + DSK(dense skip connection).	Chinese City Parking Dataset(CCPD)for training. Real Time License plate deblurring using four spatial transformers (STN) and 15 Layers of Deep Learning Separable Convolutions (DSC15) and Dense Skip Connection (DSK).	The study concludes the proposed 4×STN + DSC15 + DSK network provides better image quality and high real-time performance than previous CNNL15 models. The model's deep hopping connections in the DSC created a bottleneck structure which sped up the real-time deblurring process.
Super-Resolution Towards License Plate Recognition	Nascimento, V., Laroca, R., & Menotti, D.	2024	This study aims to address the challenge of reconstructing license plates from low-resolution surveillance footage by proposing an attention-based super-resolution approach that incorporates sub-pixel convolution layers and an OCR-based loss function.	Attention-based super-resolution approach with sub-pixel convolution layers. Optical Character Recognition (OCR)-based loss function integrated in training.	The study found that the proposed attention-based super-resolution approach significantly enhances the reconstruction of low-resolution license plate images from surveillance footage. The method outperforms existing techniques in quantitative and qualitative assessments by integrating sub-pixel convolution layers and an

					OCR-based loss function.
Temperature-Resilient Polymeric Memristors for Effective Deblurring in Static and Dynamic Imaging	Lv, Ziyu, Jiang, Ming-Hao, Liu, Hui-Ying, Li, Qing-Xiu, Xie, Tao, Yang, Jingya, Wang, Yan, Zhai, Yongbiao, Ding, Guanglong, Zhu, Shirui, Li, Jia-Hua, Zhang, Miao, Zhou, Ye, Tian, Bobo, Wong, Wai-Yeung, Han, Su-Ting	2025	This study aims to enhance license plate recognition in dynamic, real-world scenarios by employing a convolutional neural network (CNN) integrated with memristor characteristics to address motion blur, a common challenge in automated license plate recognition (ALPR) systems, particularly in high-speed or variable conditions.	The method integrates a CNN with memristor-derived characteristics for license plate deblurring: 1. Convolutional Neural Network (CNN) leveraging memristor-based long-term potentiation (LTP) and long-term depression (LTD) characteristics. 2. Deconvolution techniques applied post-CNN processing. 3.. Integration of memristor array outputs to optimize CNN synaptic weights	The study concludes that the integration of a CNN with memristor-derived characteristics effectively deblurs license plate images, such as the example "5CCD082," in dynamic scenarios. By leveraging memristor LTP/LTD for precise blur kernel estimation, the approach enhances recognition accuracy by more than 30% compared to untreated blurred images, demonstrating significant potential for improving ALPR performance in challenging, real-world conditions with motion-induced distortions.
Image Deblurring using CNN and Its Application in Vehicles Licence Plate Detection.	Ahmed, S., & Jhakar, A. K.	2022	The study analyzed the effectiveness of Convolutional Neural Networks (CNN) in deblurring images, specifically for vehicle license plate	The study employed CNN-based deblurring techniques: 1.Preprocessing steps	The study concluded that CNN-based deblurring techniques significantly enhanced license plate detection accuracy. The

			detection. It aimed to improve recognition accuracy in low-quality images affected by motion blur and noise.	included noise reduction, contrast enhancement, and edge sharpening. 2.Training datasets consisted of paired blurred and sharp images for supervised learning. 3.Performance was evaluated using PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index). 4.Real-time processing was implemented for practical applications.	approach demonstrated effectiveness in restoring image clarity, improving recognition rates even in challenging conditions. However, the study suggested further optimizations to reduce computational complexity and improve real-time performance for large-scale applications.
Deep Learning Based Automated Image Deblurring	Ch.M. Shruthi, Vemullapal li Ramachan dra Anirudh, Palla Bhargava Rao, Birru Shiva Shankar, & Akhilesh	2023	This study aims to use CNN models with autoencoders to automatically remove blur and provide quality images. Additionally, to make the deblurring process user friendly, Tkinter-based GUI was used for uploading images and viewing the result real time.	Convolutional Neural Networks (CNNs) and autoencoders for deblurring. Tkinter-based GUI for user-friend interface. RealBlur dataset for training.	Image deblurring with the use of CNN and autoencoder provided an automated way for deblurring images. Additionally, with the use of Tkinter GUI, provided a user friendly approach in deblurring. Overall, the model relies on massive datasets to provide higher accuracy but with further improvement it has potential.

	Pandey				
Motion-blur kernel size estimation via learning a convolutional neural network	Li L., Sang N., Yan L., & Gao C.	2019	The objective of this study is to solve the problem of motion blur kernel size estimation, a crucial input parameter for image deblurring algorithms. The traditional methods are manual trial and error, which is inefficient and inaccurate. In order to improve the effectiveness of deblurring algorithms, the authors attempt to automate this process using a convolutional neural network (CNN) to estimate a precise kernel size.	Convolution Neural Network (CNN) Max-pooling layers, batch normalization, ReLU Evaluation Metrics: Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), Gradient Magnitude Similarity Deviation (GMSD), and Gradient Similarity (GSM) Datasets: Levin's dataset, Sun's dataset, and Lai's dataset (all referenced in the document)	The proposed CNN based method is able to accurately predict motion blur kernel sizes in an end-to-end manner without the need for manual adjustments. It improves the performance of existing deblurring algorithms on synthetic and real blurry images. This approach is a solution for different image types and noise levels, and provides a practical preprocessing step for the image restoration tasks.
Image Deblurring for CCTV Captured Images of Fast Moving Vehicles pdf	Nande, S., Ganesh S., Krishnan S., & Pampattiw ar K.	2022	This study attempts to tackle the problem of image blur in CCTV footage of fast moving vehicles, especially for license plate detection and recognition. It aims to create an automated system to deblur images, detect license plates and recognize characters, increasing accuracy and efficiency over manual or traditional methods for traffic monitoring applications.	Frame Detection: Katna library Image Deblurring: U-Net, ResNet License Plate Detection: YOLOv4 with CSPDarknet53 and PANet Character Recognition:	The proposed system is effective in deblurring CCTV images, license plate detection with high accuracy (91.06% using YOLOv4), and character recognition, better than other methods such as Wiener Filter and Lucy Richardson.

				OpenCV	
GAN-based synthetic data augmentation for increased CNN performance in Vehicle Number Plate Recognition	Kukreja V., Kumar D., Kaur A., Geetanjali., & Sakshi	2020	The study aims to improve Automatic Vehicle Number Plate Recognition (AVNPR) for an automated parking system, eliminating the need for physical slips or cards, as well as reducing human interaction in the vehicle security process. It targets the issue of poor recognition accuracy in noisy, low-quality images with the help of deep learning and presents a hybrid GAN-CNN method to improve over the traditional methods.	The method integrates GAN for data augmentation with CNN for recognition: 1. Image preprocessing applying edge detection and normalization. 2. GAN (StarGAN) 3. CNN with convolutional layers, ReLU activation, max pooling, dropout layer, and SoftMax. Implemented in Python and TensorFlow	The hybrid GAN-CNN model achieves a 99.39% recognition accuracy, better than the existing models (CNN at 98.3%, ANN at 75%). It improves CNN performance by augmenting the dataset with GAN-generated images and provides a novel, effective solution to vehicle number plate recognition which can be extended into future hybrid extensions such as SVM integration.
A Dataset and Model for Realistic License Plate Deblurring	Gong, Feng, Zhang, Hou, Liu, Siqi, Huang, & Liu	2024	The research focuses on enhancing vehicle license plate recognition in intelligent traffic systems by resolving motion blur issues caused by fast-moving vehicles that reduce identification precision particularly in real-world driving conditions such as high speed and low light conditions. The research presents both a realistic large-scale dataset and a specialized deblurring model to address the issues of	LPBlur Dataset: Dataset of 10,288 captured with two synchronized cameras with different exposure times. Post-Processing Pipeline: Refines images with noise reduction, Enhanced Correlation Coefficient Maximization for alignment, and YOLO v5/CRNN for cropping.	The LPBlur dataset serves as a reliable foundation for testing and training while LPDGAN delivers superior performance than existing motion deblurring methods by improving license plate recognition accuracy by 21.24% in real-world scenarios but requires additional development for extreme degradation conditions.

			synthetic datasets and ineffective existing algorithms that cannot perform well in real-world applications.	LPDGan Model: Designs a Generative Adversarial Network (GAN) with Swin Transformer-based encoder/decoder for deblurring. Feature Fusion Module: Integrate multi-scale latent codes using Spatial Feature Transform (SFT) to combine feature scales. Text Reconstruction Module: Enhances character clarity via convolutional layers and L1 loss against CRNN outputs. Partition Discriminator Module: Refines letter details with WGAN-GP adversarial loss. Training and Optimization: Trains on LPBlur with Adam optimizer, multi-scale reconstruction loss, and adversarial losses. Evaluation Metrics: Assesses results using	

				PSNR, SSIM, Perceptual Loss, and Text Levenshtein Distance (TLD). Feature Fusion Module, Text Reconstruction Module, Partition Discriminator Module, Swin Transformer	
Adaptive Lightweight License Plate Image Recovery Using Deep Learning Based on Generative Adversarial Network	Sereethavekul, W., & Ekpanyapong, M.	2023	The study aims to develop a lightweight deep learning-based data recovery system for license plate images using a Generative Adversarial Network (GAN) principle. The proposed system addresses multiple recovery tasks from a single network design, enhancing the speed and effectiveness of license plate image recovery while being suitable for deployment on low-power machines.	Generative Adversarial Network (GAN) for data recovery. Encoder-decoder style inspired by autoencoder.	The study concludes that the proposed License Plate Recovery GAN (LPRGAN) system effectively addresses multiple image recovery tasks from degraded license plate images using a lightweight deep learning approach. It demonstrates the ability to recover images at resolutions up to 720p at 15 frames per second on a single graphic card, while also being efficient enough to operate on low-power devices.
Number plate recognition from enhanced super-resolution using generative adversarial network	Kabiraj A., Pal D., Ganguly D., Chatterjee K., & Roy S.	2022	This study aims to improve number plate recognition from low-resolution images, where poor boundary and contrast lead to inaccurate digit detection. It attempts to upscale low-resolution images to	This method combines ESRGAN for image enhancement with an OCR pipeline: 1. Super-resolution using ESRGAN with 24	With minimal training data and post-processing, the ESRGAN-enhanced OCR model achieves an accuracy of 85% compared to the 15% accuracy for low-resolution originals. Resolution

			high-resolution using Enhanced Super Resolution Generative Adversarial Network (ESRGAN) to recover useful details for applications where high-spec cameras are unavailable.	Residual in Residual Dense Blocks (RRDBs), convolutional layers (5x7), and ReLU activation, trained with adversarial loss and perpetual loss. 2. Preprocessing converting images to grayscale and applying Gaussian blur for denoising. 3. OCR via contour detection and bounding boxes.	enhancement improves character detection and outperforms ProSR (76% accuracy) and other OCR methods.
A deep learning-based pipeline system for license plate detection and recognition using YOLOv7 in complex traffic scenes	Zhang, R., Chen, B., Zhang, Y., & Xia, T.	2023	This study aims to establish an automatic pipeline system for real-time license plate detection and recognition (LPDR) in complex traffic scenes, addressing challenges such as blurred, dark, or bright images, and varying distances. It focuses on utilizing advanced techniques like DeblurGANv2 for image deblurring, YOLOv7 for license plate detection, and LPRNet for license plate recognition, thereby improving the effectiveness of LPDR in difficult scenarios.	DeblurGANv2 for image deblurring. YOLOv7 for license plate detection. LPRNet for recognition.	The study presents that the developed automatic pipeline system for license plate detection and recognition (LPDR) effectively addresses the challenges posed by complex traffic scenarios, such as blurred or poorly lit images. By integrating DeblurGANv2 for image deblurring, YOLOv7 for license plate detection, and LPRNet for license plate recognition, the system demonstrates significant improvements in LPDR performance.
A New Image	Hamdi, A.,	2021	The aim of the study is to	Double Generative	The results of the study

Enhancement and Super Resolution technique for license plate recognition	Chan, Y. K., & Koo, V. C.		overcome the limitations of LPR systems due to low-quality images, which is normally due to fast-moving vehicles and low-resolution analogue cameras. In order to improve LPR accuracy, an image enhancement and super-resolution technique based on Double Generative Adversarial Networks (D_GAN_ESR) is developed to restore distorted images to a higher quality for better character recognition in real-world scenarios.	Adversarial Networks for Image Enhancement and Super Resolution (D_GAN_ESR) Adversarial loss, perceptual loss, identity loss, L1 loss 2 Datasets: 1) motion blurred images, 2) analogue-style noise generated via CycleGAN evaluated using PSNR-Pixel, SSIM, PSNR-F, Tesseract, and easyOCR	demonstrated that the D_GAN_BSR structure can effectively improve and upscale distorted license plate images and improve the LPR performance in comparison to baseline methods. Its designed dual-GAN architecture along with complex loss functions made it run computationally more expensive during training but resulted in cleaner and higher resolution images, particularly when it came to motion blur. The reduction in error rates and increase in correct predictions was a good improvement on the LPR accuracy, and it is a better alternative method for real-life applications with the trade-off of having a long training time.
Improving Licence Plate Detection Using Generative Adversarial Networks	Boby, A., & Brown, D.	2022	This study aims to improve license plate visibility and recognition accuracy in real-world scenarios by utilizing deep learning techniques, specifically a one-stage object detector known as YOLO and super-resolution generative adversarial networks, to address challenges such as occlusion and poor lighting in licence plate images.	YOLO (You Only Look Once) to locate license plates. Super-resolution generative adversarial networks (GANs).	The study concludes that the integration of deep learning techniques, specifically YOLO for object detection and super-resolution generative adversarial networks for image enhancement, significantly improves licence plate recognition in challenging real-world conditions. By training these systems on datasets featuring

					difficult-to-detect licence plates, the research demonstrates enhanced performance in terms of accuracy and clarity, addressing the complexities of noisy input data that often hampers traditional recognition systems.
Enhancement of License Plate Recognition Performance Using Xception with Mish Activation Function	Pattanaik, Anmol, Balabantaray, Rakesh Chandra	2023	This study aimed to enhance vehicle license plate recognition (VLPR) performance in challenging real-world conditions by addressing motion blur, low resolution, and environmental complexities such as varying weather and lighting, using a combination of advanced deep learning techniques for localization, image enhancement, and character recognition.	1. Haar Cascade classifier 2. DCTGAN (Generative Adversarial Network with Discrete Cosine Transform Discriminator) 3. Improved Bernsen Algorithm (IBA) with Connected Component Analysis (CCA) 4. Modified Xception model leveraging pre-trained ImageNet Implemented in Python using TensorFlow and Keras.	The study concluded that the proposed approach significantly improved license plate recognition under complex conditions, achieving a detection rate of 99.3%, recognition rate of 99.0%, and overall accuracy of 98.3% across five datasets (Stanford Cars, FZU Cars, HumAIn 2019, AOLP, and self-collected). Outperforming models like YOLO and Faster RCNN, it effectively handled motion blur, low resolution, and environmental challenges, though it struggled with images containing multiple vehicles.
L□-Norm-Based Sparse Regularization Model for License	Zhao, Wang, Jiao, Yin, & Li	2020	The research focuses on enhancing license plate deblurring in traffic surveillance systems by solving general	Statistical Distribution Analysis: Examine gradient histograms.	The L□-norm-based model optimized with ADMM surpasses L0 and L1 norm regularization methods,

Plate Deblurring			deblurring method limitations that ignore sparse gradients when faced with motion and defocus blurs. The study creates a unique regularization model which uses these characteristics to enhance recognition precision.	L□-Norm Regularization Model: Enforcing sparse gradients. Alternating Direction Method of Multipliers (ADMM): Solve iteratively with Fourier transforms, Generalized Soft-Thresholding (GST), and closed-form solutions which optimizes deblurring. Synthetic Blur Applications: Applies Gaussian, motion blur and noise. Performance Metrics: Uses Peak Signal-to-Noise Ratio (PRNR) and Structural Similarity Index Measure (SSIM).	achieving higher PSNR (30.41) and SSIM (0.9982) by better capturing license plate gradient sparsity. This makes the model a promising generalized approach for deblurring.
An efficient automated vehicle license plate recognition system under image processing	Islam, Mahmud, Chowdhury	2023	Create an efficient automated vehicle license plate recognition system through image processing that operates without human involvement to overcome resolution and illumination issues.	Multi-stage approach in MATLAB 2018b: Preprocessing stage: enhance image quality by converting to grayscale and applying nonlinear bilateral filtering.	The system achieves license plate character recognition with a 94.17% accuracy rate which surpasses current methods but faces challenges when identifying damaged plates or similar characters (‘0’ vs ‘O’, ‘1’ vs ‘I’).

				Localization stage: Extract the plate region using Otsu's thresholding algorithm, sobel edge detection, and morphological operations. Segmentation stage: Isolate characters with connected component analysis and bounding box filtering. Recognition stage: Identify characters via template matching.	
Deblurring via Stochastic Refinement	Jay Whang, Mauricio Delbracio, Hossein Talebi, Chitwan Saharia, Alexandros G. Dimakis, & Peyman Milanfar	2022	This study aims to propose the use of a conditional diffusion model for stochastic blind image deblurring. This stochastic approach aims to deblur images with-out sacrificing pixel level distortion which will be compared to standard diffusion models.	Specialize predict and refine conditional diffusion model Performance comparison of the conditional diffusion model against standard diffusion models. GoPro Dataset and HIDEdataset.	This study presents a new framework for deblurring stochastically blind images while focusing on retaining image quality using a conditional diffusion model. Diffusion models heavily rely on computation cost, however this new approach reduced this burden specifically on the sampling. Additionally improving the quality of the deblurred images. But this resulted in slower sampling, large network size, and continual heavy reliance on computational power. Suggesting that diffusion

					models are too expensive to be incorporated.
License Plate Recognition Methods Employing Neural Networks	Khan M., Ilyas M., Khan I. R., Alshomrani S., & Rahardja S.	2023	This study aims to evaluate and summarize state-of-the-art license plate recognition (LPR) methods that utilize deep neural networks (DNNs) and computer vision algorithms. Additionally, it aims to provide a resource for researchers by focusing on neural-network-based approaches, describing their architectures, datasets, and performance.	This paper reviews LPR methods that uses DNNs including: Convolutional Neural Networks (CNN), Faster Regional CNNs (FRCNN), You Only Look Once (YOLO), Single Shot Detectors (SSD), and Long Short-Term Memory (LSTM). It also reviews datasets: Caltech, Application Oriented License Plate (AOLP), Peking University Data (PKU), Chinese Car Parking Dataset (CCPD), and Federal University of Parana-Automatic License Plate Recognition (UFPR-ALPR)	The review finds that DNN-based LPR methods have greatly improved traditional methods in terms of accuracy and robustness, achieving over 99% accuracy in datasets like AOLP and PKU using CNNs and YOLO. While CNNs and LSTMs provide finer character recognition performance at the cost of speed, YOLO excels in speed with a processing time.
Automated license plate recognition for resource-constrain ed environments	Padmasiri, Shashiran gana, Meedeniya , Rana, & Perera	2022	The study aims to develop a hardware-efficient ALPR system for resource-constrained edge devices, ensuring accuracy, energy efficiency, and real-time performance under varying illumination conditions. It	Lite LP-Net model for license plate detection and recognition Neural Architecture Search (NAS) strategies	The study successfully demonstrated an Automated License Plate Recognition system achieving competitive accuracy compared to server-grade solutions while operating on

			addresses the limitations of traditional high-end solutions by proposing optimized neural networks for different hardware configurations.	Infrared blaster for nighttime image capture Synthetic data generation technique for nighttime license plate dataset Image-to-image translation techniques for converting RGB to TIR images Resource-constrained edge devices (e.g., Raspberry Pi 3b+) 4 Battery-powered operation for remote deployment GSM module for SMS communication	resource-constrained devices. The system proved effective in both daytime and nighttime conditions, showing robustness to angle variations and different illumination conditions 2. Additionally, the solution validated its real-world applicability through successful SMS communication testing 4 and practical deployment capabilities in remote areas without internet connectivity or direct power supply.
Research on License Plate Recognition Algorithms Based on Deep Learning in Complex Environment	Wang & Jiaoyang	2020	The study aims to comprehensively survey and improve license plate recognition (LPR) algorithms, particularly those based on deep learning, to increase their speed and accuracy in challenging environments. This is important since traditional algorithms usually fail to operate well due to environmental constraints, restricting their practical uses in	A comprehensive review of existing LPR algorithms, categorizing them based on processes. Analysis of deep learning models for improved feature extraction. Examination of three	The study concludes that deep learning algorithms offer substantial improvements over traditional LPR methods, particularly in terms of robustness and real-time processing capabilities. It highlights that these advanced algorithms can effectively handle the complexities of real-world environments, leading to higher accuracy in

			real-world scenarios, particularly in modern smart cities.	main technical challenges: license plate skew, image noise, and license plate blur. Comparison of public license plate datasets regarding quantity, resolution, and environmental complexity. Datasets: Caltech Car, Caltech Car, UFPR-ALPR, AOLP, SSIG, and CD-HARD	license plate recognition tasks.
DiffPlate: A Diffusion Model for Super-Resolution of License Plate Images	Sawsan AlHalawani , Bilel Benjdira, Adel Ammar, Anis Koubaa, & Anas M. Ali	2024	The study aims to develop a generative model that would restore an image from distorted images.The model will use a diffusion model, which rely heavily on computational power. The model was used to compare against existing SwinIR and ESRGAN models.	Diffusion Model for image resolution Training Data used low quality images and high quality images of Saudi license plates. Performance comparison of a diffusion model against SwinIR and ESRGAN model.	This study concluded that diffusion models outperforms SwinIR and ESRGAN models in license plate enhancement resolution. Although it is worth considering their performance, integration of diffusion models is expensive as these models heavily rely on computation cost. Suggesting that diffusion models will unlikely not be used in the future for license plate imagery enhancement.
Multinational License Plate Recognition Using	Henry C., Ahn S H., & Lee S.	2020	This study aims to develop a deep learning based ALPR system that works across	The ALPR system consists of three stages:	The study concludes that the proposed ALPR system is able to recognize license plates

Generalized Character Sequence Detection			different license plates from multiple countries.	1. License Plate Detection using YOLOv3 2. Unified Character Recognition using YOLOv3-SPP 3. Multinational LP Layout Detection Implemented in Darknet and Python Datasets used: KarPlate Dataset (South Korea), AOLP Dataset (Taiwan), Medialab LPR Dataset (Greece), Caltech Cars (Rear) 1999 Dataset (USA), and University of Zagreb Dataset (Croatia)	from multiple countries without country specific modifications, and it achieves higher accuracy of 98.93% average on AOLP dataset and speed of 42 millisecond per image, than previous academic works mentioned in the study and commercial software such as OpenALPR and Sighthound. The researchers also point out that C++ implementation and multi-threading will improve its potential for real-time applications.
AFA-Net: Adaptive Feature Attention Network in image deblurring and super-resolution for improving license plate recognition	Kim, D., Kim, J., & Park, E.	2024	The study aims to address the challenges faced by license plate recognition (LPR) systems, particularly in dealing with low-resolution and motion-blurred images commonly encountered in automobile driving environments. By introducing the AFA-Net framework, the study seeks to enhance image restoration and recognition performance, thereby improving	AFA-Net for image restoration and LPR. Joint-IRLPRNet for simultaneous restoration and recognition.	The study concludes that the AFA-Net framework significantly enhances license plate recognition (LPR) performance by effectively addressing low-resolution and motion-blurred images from dash cams. It achieves notable improvements in recognition accuracy, sequence similarity, and character similarity compared to traditional models.

			the reliability of LPR in unconstrained settings.		Additionally, the introduction of the Joint-IRLPRNet demonstrates even more effective results by integrating image restoration and LPR in an end-to-end trainable manner.
BANet: A Blur-aware Attention Network for Dynamic Scene Deblurring	Tsai, F.-J., Peng, Y.-T., Tsai, C.-C., Lin, Y.-Y., & Lin, C.-W	2022	The study aims to build a Blur-aware Attentions Network (BANet) that would provide an accurate and efficient way of deblurring images within a single forward pass of an image instead of multiple. It focuses on providing shorter inference time in deblurring through stacked blue-aware modules (BAM).	This study proposed the use of stacked deblurring modules: 1. Two Convultional layers 2. Use a stack of Blue-Aware Modules(BAMs) to process the image 3. BAMs is composed of Blur Aware(BA) components that detect large blur and local scale blur 4. Contextual Pattern Decomposition and Compensation(CPDC) helps in identifying the large blurs and remove them adaptively 5. Within the Blur Aware(BA) component a Multi-Kernel Strip	The study concludes that the proposed BANet provides real-time deblurring that performs better against DeblurGAN-v2, SRN, and other cutting edge techniques on the GoPro and RealBlur datasets.

				Pooling (MKSP) method is used to capture each blur, with two vertical and horizontal sensors. 6. A 1x1 convolution layer is used from the output of the MKSP to additionally identify deblurring focus. GoPro dataset for training. HIDE and RealBlur dataset for testing	
Optimizing Deep Learning for Efficient and Noise-Robust License Plate Detection and Recognition	Shim, S.-O., Imtiaz, R., Habibullah, S., & Alshdadi, A.	2024	This study aims to optimize deep learning techniques for efficient and noise-robust license plate detection and recognition (LPR) in challenging environments, addressing the significant impact of noise and visual degradation on traditional LPR methods.	Convolutional Autoencoder (CAE) trained on noisy/clean image pairs for noise reduction and detail enhancement. The InceptionResNetV2 architecture, pre-trained on ImageNet, for feature extraction. A Region Proposal Network (RPN) head is added to InceptionResNetV2 Non-maximum	The study concludes that the proposed deep learning-based license plate recognition (LPR) system significantly enhances accuracy and robustness, particularly in noisy environments. By employing advanced techniques such as noise reduction, hyperparameter tuning, and bounding box refinement, the system outperforms traditional methods.

				suppression (NMS) is applied to eliminate redundant proposals. Bidirectional LSTM/CRNN network.	
Clearview: Real-time traffic signal and license plate recognition	Jadhav, A., & Aradhya, M.	2024	This study aims to introduce an innovative Android application called ‘Clearview’ that addresses the need for real-time traffic light and license plate identification, particularly in adverse weather conditions. It focuses on utilizing advanced technologies such as Generative Adversarial Networks (GAN) for image dehazing, YOLOv4 for object detection, and Tesseract OCR for character recognition, thereby enhancing traffic management systems and improving detection rates in challenging environments.	Generative Adversarial Networks (GAN) for dehazing images. YOLOv4, a real-time object detection model. Single Shot MultiBox Detector (SSD). Tesseract OCR	The study concludes that the Clearview application significantly enhances real-time traffic signal and license plate recognition, particularly in adverse weather conditions. By utilizing advanced technologies such as Generative Adversarial Networks for dehazing, YOLOv4 for object detection, and Tesseract OCR for character recognition, Clearview achieves over 90% detection rates in real-time scenarios.
Using Generative Adversarial Network Technology for Repairing Dynamically Blurred License Plates	Cheng, Y., & Chen, P.	2023	This study aims to propose a method for restoring dynamically blurred license plates using Generative Adversarial Network (GAN) technology, addressing the challenges faced in license plate recognition due to low light and dynamic blur conditions.	Generative Adversarial Network (GAN) technology. A dataset of 16,900 original license plates is employed. The research generates a dataset of 3,000 high-fidelity license	The study concludes that the proposed method utilizing Generative Adversarial Network technology effectively restores dynamically blurred license plates, achieving a restoration rate of 95.7% on a dataset of 3,000 license plates with significant blur, effectively restoring 2,873 out of 3,000 dynamic blur license plates

				plates with dynamic blur effects added. The structure of the conditional GAN (cGAN) network in the pix2pix technology.	with a blur level of 85 or more.
Enhanced Vehicle Identification: A Machine Learning Approach to Number Plate Recognition	Yasha, B. P., & Fadhillah, N.	2024	This study aims to improve number plate recognition systems by utilizing machine learning techniques like convolutional neural networks (CNNs), specifically focusing on the adaptability and accuracy of ML models under various environmental conditions.	Convolutional Neural Networks (CNNs) for number plate recognition. Support Vector Machines (SVMs). 50,000 images used in this research were collected from many online archives.	The study concludes that machine learning techniques, particularly convolutional neural networks (CNNs), significantly enhance the accuracy and adaptability of number plate recognition systems compared to traditional image-processing algorithms. The research demonstrates that the ML-based approach achieves higher precision and recall under various environmental conditions, making it a more reliable solution for automated number plate recognition.
AI-Enhanced Camera Systems for Real-Time Identification of Expired Vehicle Pollution and Insurance via License Plate Recognition	Gómez, K., Nair, A., Abhinand, C. B., Jishnu, K. S., Rahul, K., & Binny, S.	2024	This study aims to implement an AI-enhanced camera system for the real-time identification of expired vehicle pollution and insurance certificates through license plate recognition, thereby improving efficiency and compliance in vehicle regulation.	CNN-based high-accuracy license plate detection for identifying vehicle registration numbers. Optical Character Recognition (OCR).	The study concludes that the implementation of AI-enhanced camera systems for real-time identification of expired vehicle pollution and insurance certificates through license plate recognition significantly improves the efficiency of vehicle compliance checks.

A Deep Learning Solution for Integrated Traffic Control Through Automatic License Plate Recognition	Balia, R., Barra, S., Carta, S., Fenu, G., Podda, A. S., & Sansoni, N. (2021).	2021	This study aims to present a Deep Learning solution for managing traffic control tasks in Smart Cities, focusing on the integration of a risk estimation module and a license plate recognition module to enhance traffic monitoring and safety.	Smart lampposts equipped with bullet cameras Advanced System-on-Module. Faster R-CNN trained on synthetically generated videos as a risk estimation module. YOLO and Tesseract OCR.	The study concludes that the proposed Deep Learning solution for traffic control in Smart Cities effectively integrates risk estimation and license plate recognition through advanced technologies. The use of a network of smart lampposts equipped with bullet cameras and a System-on-Module allows for efficient data processing. Preliminary experimental findings indicate that the solution can successfully monitor traffic and estimate potential anomalies, showcasing its potential for enhancing urban traffic management.
Vehicle License Plate Recognition Using Shufflenetv2 Dilated Convolution for Intelligent Transportation Applications in Urban Internet of Things	Li, X., Wen, Z., & Hua, Q.	2022	This study aims to propose an efficient license plate recognition algorithm using the shufflenetv2 dilated convolution (SDC) model to enhance traffic management efficiency and reduce management costs in intelligent transportation applications within urban Internet of Things environments.	Shufflenetv2 dilated convolution (SDC) model. Shufflenetv2 as the backbone network, integrating dilated convolution and global context blocks. CIOU loss, for the coverage area of the bounding box, center distance, and aspect ratio.	The study concludes that the proposed SDC model for vehicle license plate recognition significantly enhances both license plate location and recognition accuracy. With a precision of 98.7% in license plate location, the SDC model outperforms existing methods such as Faster-RCNN, YOLOv3, and SSD. Additionally, it achieves a recognition precision of 98.2%, surpassing LPRNet, AlexNet,

				CTC loss is used to train the network based on sequences.	and RPNet.
Research and Implementation of Fast-LPRNet Algorithm for License Plate Recognition	Wang, Z., Jiang, Y., Liu, J., Gong, S., Yao, J., & Jiang, F.	2021	This study aims to propose the Fast-LPRNet algorithm, a Convolutional Neural Network-based approach for license plate recognition, addressing the limitations of traditional algorithms such as low accuracy and slow speed, while enhancing recognition performance through deep learning and FPGA hardware implementation.	Fast-LPRNet algorithm, which is a Convolutional Neural Network (CNN)-based method for license plate recognition. Chinese City Parking Dataset (CCPD). Field-Programmable Gate Array (FPGA) hardware.	The study concludes that the Fast-LPRNet algorithm, which integrates a convolutional neural network (CNN) with FPGA hardware, significantly enhances license plate recognition by improving segmentation and optimizing performance. The algorithm achieves an average frame rate of 5.45 frames per second and a recognition accuracy of 100% for 30 license plate images. Additionally, it demonstrates over 90% accuracy on the CCPD-Base dataset.
Automatic License Plate Recognition and Real-Time Car Vignette Notifications	Andrés, C., Șipoș, E., & Ivanciu, L.	2024	This study aims to develop an automatic license plate recognition system that enhances traffic management by reducing human errors and providing real-time notifications to drivers regarding their insurance and vignette expiration dates.	Two convolutional neural network (CNN) architectures for accurate single and multiple license plate detection and recognition.	The study concludes that the developed automatic license plate recognition system significantly enhances traffic management by minimizing human errors. By utilizing two convolutional neural network architectures, the system achieves high accuracy in detecting and recognizing single and multiple license plates.

Neural Network for Denoising and Reading Degraded License Plates	Rossi, G., Fontani, M., & Milani, S.	2021	The study aims to address the significant challenge faced by law enforcement agencies in denoising and interpreting severely degraded license plates. This is crucial as traditional methods often struggle with low-resolution and corrupted images, which can hinder investigations.	Couple two convolutional neural networks (CNNs) for denoising and interpreting severely degraded license plates. The first CNN is responsible for producing a denoised version of the input image. The second CNN takes both the denoised and original images to predict each character on the license plate. An artificial dataset is created and augmented to tailor the training to specific license plate formats of different countries.	The study concludes that the proposed system, which combines two convolutional neural networks for denoising and character prediction of degraded license plates, significantly enhances the ability to interpret low-resolution and corrupted license plates. It demonstrates a perceptual improvement and achieves an average character classification accuracy of 93%, making it a valuable tool for law enforcement agencies in their investigations.
License Plate Image Resolution Enhancement Using Super-Resolution Generative Adversarial Network	Mei, Y., Moelter, M., & Haddad, R. J.	2024	The study aims to enhance the visual quality of low-resolution license plate images to facilitate accurate tag recognition. By employing a Generative Adversarial Network framework with two Convolutional Neural Networks, the research seeks to improve the performance of license plate identification.	Generative Adversarial Network (GAN) framework, consisting of two Convolutional Neural Networks (CNNs): a Generator and a Discriminator. Generator for producing high-resolution (HR)	The study concludes that the proposed method utilizing a Super-Resolution Generative Adversarial Network significantly enhances the quality of low-resolution license plate images, thereby improving Optical Character Recognition accuracy. The results demonstrate a

				license plate images from low-resolution (LR) inputs. Discriminator evaluates whether the generated images are super-resolution (SR) or HR..	substantial increase in PSNR values and OCR performance, with low-resolution images achieving notable improvements from nearly negligible recognition rates to over 66%.
LPSRGAN: Generative adversarial networks for super-resolution of license plate image	Pan, Y.-J., Tang, J., & Tjahjadi, T.	2024	The study aims to develop a super-resolution algorithm for reconstructing license plate images using generative adversarial networks (GAN) to enhance the recognition rate of low-resolution license plate images. By introducing a new image degradation model and optimizing the SRGAN model, the study seeks to improve the super-resolution capability and ultimately increase the recognition rate of license plate images.	LPSRGAN, which optimizes the SRGAN model for improved super-resolution capabilities. n-stage random combination degradation model (n-RCD) to better simulate the features of low-resolution license plate images in natural scenes. Perceptual optical character recognition (OCR) loss that connects the output of the OCR network with character label values.	The study concludes that the proposed LPSRGAN algorithm significantly enhances the recognition rate of low-resolution license plate images by 12.48%, achieving a recognition rate of 93.90% for reconstructed images. The algorithm demonstrates strong performance in natural scenes, indicating its potential for broad application in real-world scenarios.
Robust Approach of Automatic Number Plate Recognition System using Deep	Mahalakshmi, S., & Dheeba, J.	2024	The study aims to identify the most effective method for recognizing registration plates from digital images captured by cameras, with a focus on	Deep Convolutional Neural Networks (DCNN) for automatic number plate recognition (ANPR).	The study concludes that the implementation of deep Convolutional Neural Networks (DCNN) significantly enhances the accuracy and

CNN			achieving high accuracy. The advancement in deep learning methods, particularly through the use of deep Convolutional Neural Networks (DCNN), enhances the precision, recall, and processing speed while reducing error rates in the Automatic Number Plate Recognition (ANPR) process.	The dataset used for training consists of 100 images.	efficiency of Automatic Number Plate Recognition (ANPR) systems. With a training dataset of 100 images, the system achieved a remarkable 99% accuracy in plate localization and 93% accuracy in character recognition. This advancement addresses the challenges posed by varying license plate styles and conditions, demonstrating the robustness of DCNNs in real-world applications.
Fast Licence Plate Recognition of Moving Vehicles Using Deep Learning Techniques	Singh, A., Adil, A. A., Kanso, H., Mounsef, J., & Amer, M.	2024	The study aims to develop a robust Automatic Number Plate Recognition (ANPR) system that can autonomously identify vehicle license plates in real-time, particularly for moving vehicles.	DarkNet53 YOLOv8 A curated dataset of front-view and back-view UAE vehicles is developed	The study concludes that the proposed Automatic Number Plate Recognition (ANPR) system, utilizing a two-stage deep learning framework with DarkNet53 and YOLOv8, demonstrates significant advancements in accurately recognizing vehicle license plates in real-time. The system achieves a remarkable 95% accuracy rate under various environmental conditions, showcasing its reliability and adaptability for practical applications.
Real-Time Vehicle License Plate Recognition	Bappy, Md. H., &	2024	The research seeks to improve the reliability of automated traffic monitoring and support	YOLOv8 Convolutional Neural	The study concludes that the dual-component Vehicle License Plate Recognition

(VLPR) Using Deep CNN	Talukder, K. H.		applications that require high accuracy and real-time data processing across various operational settings by employing YOLOv8 for real-time detection and a custom Convolutional Neural Net.	Network (CNN) A dataset of over 33,000 images.	(VLPR) system significantly enhances the accuracy and efficiency of automated traffic monitoring systems. By utilizing YOLOv8 for real-time detection and a custom Convolutional Neural Network (CNN) for high-precision character recognition, the system achieves a detection accuracy of 97.30% and a character recognition accuracy of 98.10%.
An Efficient License Plate Recognition Model Through Deep Learning Integration with YOLO and OCR Techniques	Supriya, N., Chiranjevi, D., Khader Shariff, M. I., Sowjanya, B. R. S. S., Desanamukula, V. S., & Lakshmanarao, A.	2024	The study aims to develop an efficient Number Plate Recognition (NPR) model by integrating deep learning techniques, specifically utilizing You Only Look Once (YOLO) for object detection and EasyOCR for alphanumeric extraction.	YOLO EasyOCR applied after YOLO Dataset from Roboflow	The study concludes that the integration of YOLO for object detection and EasyOCR for character recognition presents a highly effective two-step approach for Number Plate Recognition (NPR). This methodology demonstrates significant improvements in both accuracy and efficiency, leveraging a comprehensive dataset from Roboflow.
Real-time number plate detection using AI and ML	Patakamudi, S., Dara, S. T., Khan, M. A.,	2024	The study aims to develop a comprehensive and efficient real-time number plate detection system by leveraging state-of-the-art artificial intelligence (AI) and machine	Region-based Convolutional Neural Networks (RCNN) and Advanced RCNN algorithms.	The study concludes that the development of an advanced real-time license plate detection system has led to significant advancements in intelligent transportation

	Miriyala, S., Rachapudi, V., & Anguraj, D. K.		learning (ML) techniques, specifically through the integration of Region-based Convolutional Neural Networks (RCNN) and Advanced RCNN algorithms.	Advanced RCNN replaces the selective search algorithm with a Region Proposal Network (RPN) that generates region proposals directly from convolutional feature maps.	systems. By integrating region-based convolutional neural networks (RCNNs) and advanced RCNN algorithms, the research achieved unprecedented accuracy and efficiency in license plate detection.
Intelligent System for Vehicles License Plate Recognition Using a Hybrid Model of GAN, CNN and ELM	Nirmala, B., Nithya, S., Vidhiya, R., Sunalini, K. K., Kumar, B. H., & Varadharajan, B.	2023	The study aims to develop a fully automated vehicle license plate recognition system that addresses the challenges posed by the increasing number of vehicles and the limitations of current methods. It focuses on improving the accuracy of license plate recognition, which is often affected by environmental factors such as complex backgrounds, angle views, and illumination shifts.	A hybrid model combining Generative Adversarial Networks (GAN), Convolutional Neural Networks (CNN), and Extreme Learning Machine (ELM).	The study concludes that the proposed GANCNN-ELM-based technique for vehicle license plate recognition significantly enhances the accuracy of license plate detection and identification, achieving an impressive accuracy rate of approximately 98.94%. This method demonstrates superior performance compared to existing models such as GAN-ELM, GAN-SVM, and GAN-CNN, addressing the challenges posed by environmental factors in license plate recognition systems.
A Computer Vision-Based Vehicle Detection System Leveraging Deep Learning	Khan, S., Vohra, S., Siddique, S. A., Abro, A.	2024	The study aims to enhance the effectiveness and precision of traffic surveillance and administration systems through a combined approach utilizing advanced computer vision and	Advanced computer vision (CV) and deep learning (DL) techniques. Convolutional neural	The study concludes that the proposed computer vision-based vehicle detection system, which integrates deep learning techniques for vehicle detection and number plate

	A., & Ebrahim, M.		deep learning techniques for vehicle detection and number plate recognition.	networks (CNN) and object detection models. Optical character recognition (OCR) techniques.	recognition, demonstrates significant improvements in traffic surveillance and management. The system effectively utilizes CNN and object detection models to ensure reliable performance across various environmental conditions, achieving high efficiency and accuracy in real-world scenarios.
An Efficient System for Detecting Multiple Traffic Violations and Recognizing License Plates Using Video Processing and Deep Learning	Ali, Q. A.	2024	The study aims to develop a cost-effective, efficient, and robust automated system for detecting and recording traffic violations, thereby improving traffic regulation enforcement and reducing the need for human intervention.	Background subtraction technology. You Only Look Once (YOLO) algorithm. Convolutional Recurrent Neural Networks (CRNN). Optical Character Recognition (OCR) technology.	The study concludes that the proposed automated system for detecting traffic violations and recognizing license plates is both efficient and effective, achieving a real-time detection rate of 98.06% for multiple violations and an impressive license plate recognition accuracy of 98.22%. The use of advanced technologies such as background subtraction, YOLO, and CRNN algorithms demonstrates significant improvements over previous methods.
Automatic License Plate Recognition with CNN Method in Machine Learning	Jain, L., & Vashisht, G.	2024	The study aims to address the challenges of tracking individual vehicles in an increasingly technologically advanced environment by proposing an automatic license plate recognition (ALPR) system.	Convolutional Neural Network (CNN). Simple Optical Character Recognition (OCR).	The study concludes that the implementation of a Convolutional Neural Network (CNN) for Automatic License Plate Recognition (ALPR) significantly enhances the efficiency of vehicle tracking

					through improved object identification and character recognition.
Automated License Plate Recognition: A Survey on Methods and Techniques	Shashirangana, Padmasiri, Meedeniya, & Perera	2020	Analyze recent advancements in Automated License Plate Recognition systems, and the need for solutions in complex environments like lighting and weather conditions. It aims to identify open challenges and provide future research directions to optimize ALPR performance.	Multi-stage methods: License plate detection (edge-based, color-based, texture-based, character-based, statistical classifiers, and deep learning), Character segmentation (pixel connectivity, projection profiles, prior knowledge, and CNNs), Recognition (template matching, feature extractors, and deep learning) Single-stage methods: Modified VGG-16, Simplified CNN Preprocessing: Binarization, Noise removal	The study concludes that single-step deep learning ALPR systems offer higher performance and efficiency compared to multi-stage approaches, though multi-stage methods remain prevalent. It emphasizes the need for optimized solutions to handle real-world constraints like weather conditions and resource demands.
Philippine License Plate Detection and Classification using Faster R-CNN and Feature Pyramid	Brillantes, A. K., Billones Jr., C. D., Amon, M.	2019	The study aimed to develop an effective Automatic License Plate Recognition (ALPR) system that used deep learning algorithms to improve vehicle	Faster R-CNN, Feature Pyramid Network (FPN), ResNet-101, Region Proposal Network (RPN), RoI Align,	The study concluded that the developed ALPR system was a reliable and effective solution for Philippine license plate detection and classification

Network	C., Cero, C., Jose, J. A. C., Billones, R. K. C., Dadios, E.		identification in the Philippines. With the growing demand for better security and traffic management, the system focused on obtaining accurate and real-time license plate recognition, which is critical for applications in law enforcement and intelligent transportation systems.	MMDetection Toolbox, Data Preprocessing, Image Annotation, Video Frame Extraction	tasks, achieving high accuracy in recognizing different plate formats (1981, 2003, 2014, and others). The integration of deep learning approaches ensured precise and instantaneous recognition, making the system suitable for various applications, including law enforcement and traffic management.
Utilizing Synthetically-Generated License Plate Automatic Detection and Recognition of Motor Vehicle Plates in Philippines	Pacaldo, J. M., Tan, C. W., Lee, W. P., Ancog, D. G., Macalisang, H. A. R. C.	2021	The study aimed to explore the potential of synthetic data in developing an Automatic License Plate Recognition (ALPR) system to improve vehicle identification in the Philippines. With the increasing need for efficient law enforcement and traffic regulation, the system focused on addressing challenges in detecting fast-moving vehicles and handling variability in Philippine license plate designs, which is crucial for applications in border control, toll payments, and crime detection.	Synthetic Data Generation, Local Binary Pattern (LBP), 36 Cascade Classifiers, OpenCV, Hierarchical Clustering, K-means Clustering, Perlin Noise, White Noise, Image Preprocessing	The study concluded that while the use of synthetic data showed promising results for training classifiers, the approach of detecting and clustering individual characters was not effective for Philippine license plate recognition. The hierarchical clustering algorithm outperformed K-means, but inaccuracies due to false detections in classifiers limited overall performance, suggesting the need for better classifiers and clustering methods for practical applications in law enforcement and traffic regulation.
Philippine License Plate Character Recognition using Faster R-CNN with	Amon, M. C. E., Brillantes, A. K. M.,	2019	The study aimed to develop an advanced Automatic License Plate Recognition (ALPR) system using deep learning to	Faster R-CNN, InceptionV2, Region Proposal Network (RPN), TensorFlow,	The developed ALPR system effectively recognized Philippine license plate characters using Faster

InceptionV2	Billones Jr., C. D., Jose, J. A., Sybingco, E., Dadios, E., Fillone, A., Lim, L. G., Bandala, A.		improve character recognition of Philippine license plates. With the increasing need for effective traffic management and security, the system focused on addressing challenges posed by variations in Philippine license plate designs (1981, 2003, 2014, and others) and environmental factors, which is essential for applications in toll collection, traffic management, and law enforcement.	Transfer Learning, Stochastic Gradient Descent (SGD), Data Annotation, Image Preprocessing, Bilinear Interpolation	R-CNN with InceptionV2, achieving 90.011% detection rate, 93.21% recognition rate, and 83.895% overall accuracy. It's suitable for traffic and security applications, with suggestions for parameter optimization and larger datasets.
Deep Inference Localization Approach of License Plate Recognition: A 2014 Series Philippine Vehicle License Plate	Reyes, R. C., Cepe, E. M., Guerrero, N. D., Sevilla, R. V., Montesines, D. L.	2021	The study aimed to develop a license plate detection system for the 2014 series Philippine vehicle license plates using a deep learning approach, addressing the challenges posed by multiple plate versions in the Philippines. With the growing need for efficient traffic management, toll collection, and law enforcement, the system focused on achieving accurate detection using a simple yet effective algorithm, suitable for various applications such as parking systems and road violator capture.	YOLOv3, Google Collaboratory, Data Annotation, LabelImg, Pascal VOC Format, Custom Dataset Training, Object Detection, Model Evaluation, Video Testing	The proposed system effectively detected 2014 series Philippine license plates using YOLOv3, achieving 100% detection accuracy but with 40%–69% precision. The best model had a 96.21% mAP, though limited dataset size suggests more data could improve precision for traffic and law enforcement applications.
Data Modeling and Integration for a Parking	Coching, J. K., Valenzuela	2024	The study proposed a YOLOR-based License Plate Recognition (LPR) module with	YOLOR, Firebase Realtime Database (FRD), NoSQL,	The YOLOR-based LPR system with FRD effectively detected Philippine plates,

Management System with License Plate Recognition	, I. J. C., Fillone, A. M., Yeung, S. G., Concepcion II, R. S., Billones, R. K. C., Dadios, E. P		a Firebase Realtime Database for a Parking Management System (PMS) in the Philippines, addressing unique plate variations for vehicle profiling and smart parking applications like operational efficiency and ticketing.	EasyOCR, License Plate Detection (LPD), Optical Character Recognition (OCR), Data Modeling	achieving 76.41% mAP@0.5 and 57.18% precision. It supports smart parking and vehicle profiling, with potential for improved accuracy through extended training.
Philippine License Plate Localization Using Genetic Algorithm and Feature Extraction	Chan, P. M. J., Jose, J. A., Bedruz, R. A., Dadios, E. P.	2020	The study focused on license plate localization for Philippine plates (2014 series) using a genetic algorithm, aiming to support automated traffic apprehension, parking management, and toll systems by isolating plates for further OCR processing.	Genetic Algorithm (GA), Histogram of Oriented Gradients (HOG), Feature Extraction, MATLAB, Fitness Function (L2Norm), Selection, Crossover, Mutation	The GA-based system successfully localized 2014 series Philippine license plates and roughly detected other series, despite being limited to single-plate detection. It’s applicable for traffic and parking systems, with potential for multi-plate improvements.
Incorporating Deblurring Techniques in Multiple Recognition of License Plates from Video Sequences	Sagum, R. A., Gilo, A. J. G., Narag, M. A. D.	2021	The study developed a system for multiple license plate recognition from video sequences in the Philippines, incorporating image deblurring to address motion blur and camera angle issues for improved traffic monitoring.	Background Subtraction, Connected Component Analysis (CCA), Image Deblurring, Normalization, LBP Cascade Classifier, Character Recognition	Deblurring improved recognition accuracy to 66.26% for Philippine plates, aiding traffic monitoring. Limited training data suggests deep learning methods could enhance performance for real-time video-based applications in the Philippine
Utilizing Automatic Number Plate Recognition for an Intelligent Campus Gate Security	Limon, J. C., Bernoza, R., Botangen,	2024	The study developed an ANPR-based system for campus gate security at CLSU, Philippines, to automate vehicle	OpenCV-Python (preprocessing), Python, PHP, MySQL, CCTV Camera, Web Application, Database	The ANPR system enhanced campus security with a 92.21% success rate for vehicle monitoring in the Philippines. Specifying

System	K. A., Malaca, M. J., Vidania, N.		monitoring, enhance safety, and streamline entry/exit logging.	Management	detection methods and adopting deep learning could improve its effectiveness for broader applications.
Artificial Intelligence Software Application for Contactless Traffic Violation Apprehension in the Philippines	Jose, J. A. C., Billones Jr., C. D., Brillantes, A. K. M., Billones, R. K. C., Sybingco, E., Dadios, E. P., Fillone, A. M., Lim, L. A. G.	2021	The study developed a contactless traffic violation apprehension system for Metro Manila, focusing on number coding violations to automate law enforcement processes and improve traffic management.	Faster R-CNN, Inception V2, OCR, Number Coding Detection, Ruby on Rails, MVC, NoSQL, RESTful API	The system automated traffic violation apprehension in Metro Manila, improving law enforcement efficiency. Adding performance metrics and advanced models like YOLO could enhance its accuracy for Philippine traffic management applications.
OCULAR: Object Detecting CCTV using a Low-Cost Artificial Intelligence System with Real-Time Analysis	Sajol, H. C., Santos, J. C., Agustin, L. M., Zafra, J. J., Teogangco , M.	2022	The study developed a low-cost ALPR system to enhance security at a Philippine university by automating license plate detection and recording, addressing manual inefficiencies and fraudulent plates.	YOLO, Darknet Framework, Optical Character Recognition (OCR), Raspberry Pi 3 B+, Raspberry Pi Camera V2, Real-Time Video Streaming, Alert System	The low-cost ALPR system achieved 95.33% accuracy for Philippine plates, enhancing university security. Including motorcycle plates and using a higher-resolution camera could improve its applicability for broader Philippine security scenarios.
License Plate Recognition System for Improved Logistics Delivery in a	Coching, J. K., Pe, A. J. L., Yeung, S. G. D., Ang,	2023	The study developed an LPR system to support traffic management and optimize supply chain delivery in Manila	YOLOR, EasyOCR, MATLAB Simulink, SimEvents, Digital Twin Modeling, Roboflow, Image Augmentation	The LPR system increased delivery efficiency by 3.17% in Manila, benefiting SCM. A Philippine-specific dataset and real-world testing could

Supply Chain with Solution Validation through Digital Twin Modeling	C. M. L., Concepcion II, R. S., Billones, R. K. C.		by reducing delays, validated through digital twin modeling.		enhance its accuracy and applicability for local traffic management.
Advanced Technique for Detection and Recognition of the Blurred License Plate Image from Fast Moving Vehicles Using Morphological Process	Chitravalli, V., Poovendran, R.	2020	The study developed a technique to detect and recognize blurred license plates from fast-moving vehicles, addressing motion blur challenges for traffic monitoring and law enforcement.	Morphological Image Processing (dilation, erosion, opening, closing), Image Preprocessing, License Plate Detection, Character Recognition	The morphological approach improved detection of blurred plates from fast-moving vehicles, aiding traffic monitoring. Testing on Philippine plates and integrating deep learning could enhance accuracy for local applications.
License plate recognition system in unconstrained scenes via a new image correction scheme and improved CRNN	Rao, Z., Yang, D., Chen, N., & Liu, J.	2023	This study aims to create an accurate license plate recognition system for unconstrained scenes, tackling challenges like large-angle deflections and blur, to enhance real-time traffic surveillance applications.	YOLOv5l for detection, AFF-Net for segmentation and angle correction, perspective transformation, SC-CRNN with channel attention for recognition, transfer learning on CCPD dataset, CTPSD dataset of 5,500 images.	The study concludes that the proposed system achieves high accuracy in unconstrained scenes, with 98.35% detection precision and 99.16% recognition accuracy using transfer learning, offering a robust solution for traffic surveillance despite limited data.

A CRNN-based method for Chinese ship license plate recognition	Xu, F., Chen, C., Shang, Z., Peng, Y., Li, X	2024	This study aims to develop a CRNN-based method for accurate Chinese ship license plate (SLP) recognition, addressing challenges like fog, tilt, and low resolution in marine environments.	Improved Dark Channel Prior (DCP) for defogging, Hough Transform (HT) for tilt correction, data augmentation, Adaptive Histogram Equalization (AHE), Image Edge Padding (IEP), CRNN for text recognition, Edit-Distance (ED) for correction, dataset of 4759 SLP images.	The study concludes that the proposed CRNN-based method, with DCP, HT, data augmentation, AHE, IEP, and ED, achieves a high SLP recognition accuracy of 92.93%, outperforming other methods like CnOCR (73.74%), paddleOCR (74.53%), and DenseNet (79.80%).
License Plate Detection and Recognition Based on the YOLO Detector and CRNN-12	Sun, H., Fu, M., Abdussalam, A., Huang, Z., Sun, S., Wang, W.	2019	This study aims to develop an end-to-end system for Chinese car license plate detection and recognition in complex environments, addressing challenges like uneven lighting and tilt.	YOLOv2 and YOLOv3 for detection, CRNN-12 (12-layer CNN + 2-layer bidirectional GRU + CTC loss) for recognition, dataset of 7,386 images for detection and 71,790 for recognition.	The study concludes that the proposed system achieves high performance: YOLOv3 with 0.8406 IOU for detection, CRNN-12 with 98.86% recognition accuracy, and real-time speeds (0.021s for detection, 0.052s for recognition), suitable for practical applications.

License Plate Recognition Using Convolutional-Recurrent Neural Network	Tee, K. F.	2019	This study aims to develop a lightweight, segmentation-free ALPR system for Malaysian license plates, addressing limitations of Soo's (2017) CRNN model by making it end-to-end trainable, smaller, and capable of recognizing two-row plates.	EAST for text detection, custom CRNN (7-layer CNN + 2 bidirectional LSTMs + CTC loss) for recognition, trained on 25,720 images, tested on LPR44 (409 samples), LPR45 (553 samples), and Open Environment Dataset (2,533 samples).	The proposed CRNN model outperforms Soo's (2017) model with 99.27% accuracy on LPR44, 93.49% on LPR45, 78.80% on Open Environment Dataset, a prediction time of <1 second, and a smaller architecture (5.5M parameters vs. 1.9B). It handles two-row plates but struggles with lowercase letters and shadows.
An ALPR System-based Deep Networks for the Detection and Recognition	Bensouilah, M., Zennir, M. N., & Taffar, M.	2021	This study aims to develop an end-to-end ALPR system for Algerian license plates, addressing challenges like non-standardized plate designs by avoiding segmentation and using deep learning for detection and recognition.	YOLOv3 (Darknet-53 and MobileNet backbones) for detection, CRNN (VGG-12 CNN + 2-layer bidirectional GRU + CTC loss) for recognition, LPA Dataset (3,408 images for detection, 2,179 plates for recognition).	The system achieved high performance: YOLOv3 with 99% precision and 97% recall (0.050s/image), MobileNet-YOLOv3 faster at 0.032s/image, and CRNN with BGRU at 92% recognition accuracy (CER: 0.99%, WAR: 7.94%), outperforming baseline models on Algerian plates.

Appendix D: Transcript of Interview

Interview Transcript

Interviewee: PCpl. Gerald Dungca
Interviewers:
Cruz, Jansen C. - Interviewer 1
Alfonso, Aljunalei M. - Interviewer 2
Laylo, Wrenz Ivan M. - Interviewer 3
Location: Angeles City Traffic Management and Enforcement Unit Bldg., New City Hall Compound, Brgy. Pulung Maragul, Angeles City 2009
Recording Method: Audio
Date: April 15, 2025

Transcript Style: Verbatim Transcription
Transcriber: Alfonso, Aljunalei M.

[00:00]
Interviewer 1: Sir, good morning po.

[00:03]
Interviewee: Good morning.

[00:04]
Interviewer 1: Paano ko yung current process ko or practices, technology ko sa pag-identify ng mga vehicle sa mga incidents ko or accidents?

[00:12]
Interviewee: Usually, yung ginagawa namin lalo na pag-hit and run, kung yung naheat and run na sasakyan kung may dashcam yan, isa yun sa pinaka-nakakatulong samin. Ngayon, kung wala siyang dashcam, pupunta tayo dito sa LGU namin kasi dito may Command Center kaming tinatawag. Every major roads natin ay may mga CCTV tayong nakainstall dyan.

[00:49]
Interviewer 1: Number 2 po, what are the most frequent reasons you're unable to identify license plates from surveillance cameras or other sources? Is identifying license plates a problem?

[01:02]
Interviewee: Pag daylight, pag umaga, hindi gaano ang problema kasi maliwanag. Yung mga nagiging reasons lang para hindi natin ma-identify lalo na pag gabi. Unang-unang nag-ri-replek lahat yung mga ilaw ng mga sasakyan. Madilim. Tapos kapag zino-zoom na ng mga operator natin sa Command Center, nagb-blurred na siya dahil sa sobrang pixelated at layo na ng mga sasakyan na hinahabol. Tapos, isa pa, masyado silang mabilis. nab-blurred po yung ano. Yun lang naman yung mga nagiging problema namin. Sobrang bilis lang nila kasi, magawa ka na nga ng kasalanan, di ba? Bakit magba-bagal ka pa. Sigurado yun, magi-ging mabilis sila. Yun lang.

[01:53]
Interviewer 1: What types of cameras or devices do you typically use to capture license plates, if any? And what are their limitations?

[02:02]
Interviewee: Dito sa atin, sa sinasabi ko nga ang command center, hindi tayo pwedeng mag-capture ng license. O videos ng footage ng accidente o kung ano man. Ginagawa lang namin is for viewing lang. Ngayon kung gusto namin ng copy or photograph, magpapaalam muna kami kay Mayor. Ngayon, kung civilian naman yung may camera, gagawa pa kami ng request para makita lang yung footage nila. Lalo na kung naka-install lang yan sa bahay. Kung yung incidente nangyari sa daan, tapat ng bahay nila. Kung may nakita kami yung naka-install ng camera, gagawa pa kami ng request letter. Kapag establishment naman, gagawa rin kami ng letter. Nasa kanila naman. Kung pagbibigan nila kami mag view o magbigay kasi ano yan eh? Data privacy. Data privacy tapos personal nila yun. Kung ayaw nila wala kami magagawa. Hanap kami ng ibang option para makakita.

[03:15]
Interviewer 1: Pano naman kapag yung footage po na nakuha, is blurry or distorted? Ano po yung mga manual methods or tools po na ginagamit niyo para maging clear po yung license plates and ma-identify po? And paano po sila ka-effective? And gano' ko pala ka-katagal po sila ginagawa?

[03:33]
Interviewee: Yung last namin na ginawa, hit and run namin, sobrang blurred. Pumunta pa kami sa cybercrime natin, sa division ng cybercrime ng PNP, para ipa-enhance yung license plate number. Kaso, sobrang labo talaga. So far yung

lang yung pinaka-best method namin, kaso wala talaga dahil sobrang hirap.Lalo na kapag mabiles, malayo, sobrang pixelated yung nakapture natin na plaka.

[04:20]
Interviewer 2: Yung po bang ginamit nila na pang-enhance, specific lang po siya sa mga license plates o kahit anong image pwede yung i-enhance?
Interviewee: Alam ko kahit anong image pwede kahit picture ng tao pwede.

[04:30]
Interviewer 1: Parang photoshop?

[04:32]
Interviewee:
Oo, parang ganoon. Kaya naman. Kaso, blurred pa rin.

[04:35]
Interviewer 2: Hindi po talaga siya specific para sa mga license plates lang, ano? Manual method of enhancing siya.

[04:39]
Interviewee: Manual method.

[04:42]
Interviewer 1: How often do blurry or unclear license plates images prevent you from enforcing traffic rules or apprehending violators? May time po ba na sumuko na lang po sa kaso dahil hindi na po ma-identify ang license plate?

[04:59]
Interviewee: Hindi naman sa Sumuko, tinatry pa rin naman yung pinaka-best namin. Once na kami, diyan sa Command Center, may mga supervisor naman diyan na familiar sila sa mga lettering ng license, ng mga number. Kapag natry namin yung ganito, ganitong sabihin natin WW111. Papa verify namin sa LTO kapag mali siya sa description ng sasakyan, magkatry ulit kami ng other license plate na malapit dun sa WW or 112 ganun.

[05:46]
Interviewer 2: So guessing lang po siya para tas ipakonfirm ang model ng sasakyan.

[05:52]

Interviewee: Ang model lang ng sasakyan kasi familiar naman kami sa mga model ng sasakyan. Yun lang yung ano namin doon.[05:59]
Interviewer 1: Sa next question po, na ka-try na po ba kayo? O narinig nyo na po yung mga automated system for license plate recognition? Kung oo po, ano po yung mga experience nyo or concern mo sa mga ganong systems?

[06:13]
Interviewee: Automated system for license. Paano yun? Anong klaseng ano yun?

[06:16]
Interviewer 1: Yung parang embedded po sila sa mga cameras na kungwari po dadaan po yung sasakyan. Tapos mad-detect po nya yung license plate po.

[06:25]
Interviewee: Ah okay okay yan. Meron na tayong… Meron na tayong ganyan dito sa Angeles, alam nyo yung sa Clark yung akala nila nasisilaw sila pero kumikislap lang.

[06:41]
Interviewer 2: Oo Opo.

[06:42]
Interviewee: Dito meron na rin tayo. Naka-experience na rin ako. Kahit anong bilis mong sasakyan or motor. Basta sigurado ka lang sa bibigay mong letters at numbers, makuhuha niya, kung ano yung... kung ano talaga yung plaka kung ano yung… model ng sasakyan o motor, makikita rin niya.

[07:10]
Interviewer 2: Ah doon po sa gate po ng Clark na?

[07:12]
Interviewee: Unang-unang kong na experience yan sa may gate ng Clark. Ngayon meron na rin tayo dito sa Angeles. Sa boundary ng Angeles-Porac, Angeles-Magalang Road, saka sa Angeles-San Fernando boundary. Tatlo yung ganyan natin ngayon kaya hindi na kami ganoon nahihirapan. Basta dadaan lang sila dun sa routa na yun. Yun lang yung na experiece ko, tsaka… ano tawag dito. 100 % makukuha ang plaka kahit kung familiar ba kayo sa mga MV files, sa mga motor, diba? Pakahaba naman. Nakukuha rin yun. Malinaw na malinaw kahit gabi. Yun lang.

[07:50]
Interviewer 2: Pero pag sobrang bilis po ng mga sakyan…

[07:51]
Interviewee: makukuha pa rin. Yung last na hit and run naman na nag-report dito, yung tin-rack na muna namin, nai-hit and run siya sa May Marisol stoplight. Yung bilis ng motor, every seconds lang nakakalipad na siya ng lugar. Anggang napadaan namin siya sa may Angeles-Magalang Road, sa may boundary natin. Sabihin mo ng estimated na takbo niya sa 70 to 90. Nakuwa pa rin, kasi nasabi sa amin ng driver ng hit and run, yung tatlong letter, yung sinasabi niyo ng automated system. T-nype lang ng operator natin dito at lumitaw. Tamang-tama kasi alam din naman nung tao yung description ng motor eh. NMAX. Lumitaw nga. NMAX. Pareho din nung... tapos dito, kapareho nung number. So, problema nalang nga at sana letter na lang. Nakuha nadin doon yung letter. Ginawa namin doon, at the next day, pin-verify namin sa LPO at lumitaw kung kanino-registered.

[08:57]
Interviewer 2: Pero...Kaya niya po bang macapture ng... kuwari po, tumatakbo ng 120 ganon?

[09:03]
Interviewee: Hindi pa namin natry eh pero... siguro. Siguro naman. Kasi high tech naman, diba.

[09:08]
Interviewer 2: Pero, hindi po ba possible na mablur yung pag-capture niya naman pag sobrang bilis na talaga?

[09:13]
Interviewee: Siguro pwede. May chances na mag-blur yun. Tsaka... sobrang ano na yun, distorted non.

[09:22]
Interviewer 2: Parang gumagalaw na yung mga license speed sa image po, no?.

[09:27]
Interviewee: Siguro pwede yun.

[09:26]
Interviewer 3: Paano naman po yung budget concern po dun sa high tech po na mahal po ba?

[09:34]
Interviewee: Ah yun, hindi ko masasakot yan kasi LGU yan eh. Nakikisuyo lang kami kapag ganyan eh. Palagay ko mahal din kasi matagal bago nila naipundar. Saka sigurado naman nakaplano naman lahat yan bago nila nilagay.
[09:52]
Interviewer 2: Ok po.

[09:54]
Interviewer 1: Yung mga ganung system po, pwede rin po ba siya makatulong sa mga investigations like traffic enforcement na nabangit niyo po kanina? And paano po siya naging... ay nasagot na po? Nasa-sagot na po. Next!

[10:09]
Interviewer 1: May mga legal or ethical concerns po ba like privacy issues sa tingin niyo na pwede niyong consider kapag gagamit po ng mga ganung system sa Pilipinas po?

[10:19]
Interviewee: Syempre, mayroon tayong mga concerns diyan yung data privacy. Like for example, may naging kaso din kami ganyan. Napicturan niya yung plaka. Yung na hit-and-run, napicturan niya yung plaka noong naka hit-and-run sakanya. Pin-host niya sa Facebook, yun naman si naka hit-and-run pumanta sa office namin para i-report yung ganung complain. Yun nga, pwede siyang tamaan sa data privacy. Ngayon kung...Grabe naman yung nangyaring accidente or hit and run. Sabihin na nating may namatay. Pwede nating ipose pero… For further investigation lang para makatulong lang sa ating kapulisan. Malay mo, may kapitbahay pala yun nakakilala ng police, ni-report, diba? Mas mapabilis. Ngayon pinaka option talaga namin pagdating pinaka-option talaga namin may counterpart tayo dyan, yung LTO. Ipapaverify lang namin sa LTO tapos ibigay ng LTO samin kung sino yung registered owner at kung taga saan siya. Kami nun pupunta kami sa bahay, bahay nila para ipa follow-up yung nasabing sasakyan. Yun nga, sa kabilaan, huwag na huwag kayong magpupost lalo na kung paan-sarili lang. Mas maganda, ano pa rin kayo sa mga kapulisan natin o other law enforcement natin.

[12:05]
Interviewer 1: Sir, add ko lang pong question. Yung mga system po na kagaya po ng amin na makakapag enhance po ng mga nakapture ng license plates. Makakatulong po ba siya sa inyo sa pag-investiga?

[12:18]
Interviewee: Syempre naman malaking tulong sa amin yan. Lalo nga yung sinasabi namin na kapag-blurred, kayo niyong i-enhance. Diba? Mapapadali yung trabaho natin. Yung namin. Kasama niyo. Ngayong hingi kaming ng tulong. Oh. Urgent. Kaya nung... Kaya, urgent yung na hit and run, kailangan na masolve. Lalo na kung critical o malaki ang incidente yan. Ano tawag dito… Mapapadali yung pag-solve natin ng kaso dahil nga may clear na tayo ng pictures or photographs ng tao, license o kung anuman mas mapapadali dahil nga high tech na tapos ma-enhance yun ng maganda.

[13:12]
Interviewer 1: Pwede po kayong maging domain expert po namin sa thesis panel? Sa final defense pa po naman. Mga ilang months pa po yun. Mga December po, ata.

[13:22]
Interviewee: Tignan na lang natin kung hindi ganong busy. Alam mo naman sa traffic. Lalo na dito sa traffic natin, enforcement unit. Every... wag naman natin sabihing every hour may accidente eh. Busy lang talaga.

[13:39]
Interviewer 1: Pinaka last po sir. Ganun po daw, ay ganun po kadalas yung mga violators na sinasadya po nilang itago yung mga license plates nila?

[13:50]
Interviewee: Sinasadya..? Hindi naman siguro sinasadya kasi kami laging namin sinasabing “alleged”. Hindi sya sinasadya. Siguro sabi niyo naka-hit-and-run ka ngayon. Mga... kapag natrace mo, dun pa lang nila aminin na... na involved sila sa accidente eh, o kung anuman. Yun lang. Yun lang. Yun lang yung...

[14:22]
Interviewer 2: Then additional question po, kasama ay… di po po ba ano, sa title po kasi namin, linagay po namin isa ano, the deblurring license plate recognition for effective traffic regulation and law enforcement. Kasama po ba kayo sa traffic regulation din or sa law enforcement lang?

[14:48]
Interviewee: Oo syempre. Kami rin ninyo nagpapatupad ng traffic regulation kasi nga kami ang Angeles City Traffic Enforcement Unit, kami yung nagpapatupad ng batas trafico at lalo na sa mga accidente kami rin yung unang mag-re-responde diyan dahil yun yung pinaka-expertise ng ating unit.

[15:10]
Interviewer 2: Bali masasabi din po natin na apart po kayo ng traffic management?

[15:16]
Interviewee: Oo, traffic management. Part din kami ng traffic management. traffic enforcement, ano paba, yun nga yung sinabi mo, law enforcement. Yan.

[15:30]
Interviewer 2: Hindi na siguro part ito pero... Dati daw pangalan niyo, TMEU?

[15:37]
Interviewee: Angeles City Traffic Management Enforcement Unit. Ngayon, nabago ng Angeles City Traffic Enforcement Unit. Yung tatlo pa rin po, na? For traffic management, traffic regulation, and law enforcement.

[15:46]
Interviewer 2: Parang lang pumas ano, noh…

[15:48]
Interviewee: Kahit binago naman yung pangalan, pareho pa rin yung function namin. Ganun pa rin, magpapatupat pa rin namin ng mga…

[15:55]
Interviewer 2: Yung tatlo padin po noh?

[15:58]
Interviewee: Traffic management, traffic regulation, and law enforcement. Pero pinakaano namin dyan yung traffic investigation.

[16:08]
Interviewer 1: Pinaka-pinakalast na po. Kapag po, if ever po, matapos po namin yung system, pwede po ba namin, pwede nyo po bang mat-try na implement mo sa mga...

[16:23]
Interviewer 2: Sa system niyo po, sa automatic license plate uhmm, tsaka ano po, pang manually check niyo po sa mgaginagawa niyo po.

[16:32]
Interviewee: Oo naman, siyempre. Kami nga, sinusubukan namin ni-enhance kaso wala kaming alam sa ganyang AI technology. Kaya nga mas maganda, kung magawa niyo, diba? Andyan kayo, lalapit kami sa inyo para matulungan nyo kami. Para makita natin ng clear o kahit sabihin mong hindi clear, basta ma-enhance lang na maganda. Malaking bagay sa amin niyo.

[16:58]
Interviewer 2: Bali yung balak po, yung po sinasabi niya, pwedeng daw po namin ibigay sa inyo yung mismong system pag natapos na.

[17:04]
Interviewee: Kaso nasa inyo yan. Kung ibigay niyo, di ba? Para matulungan niyo rin kami.

[17:11]
Interviewer 2: Kasi yung po system namin, parang kayo na po.. Parang ipapasok nyo lang po yung na-crop na license plate. Tapos siya na po yung bahala ng mag deblur. Hindi na po kayo yung mag deblur.

[17:23]
Interviewee: Okay, okay. Mas maganda, diba? Para mas mabilis yung trabaho. Para maka-identify natin agad.

[17:27]
Interviewer 1: May lima pong… ay may apat pong ano yung system po namin. Pang low light po sa mga kuhari po. Low light kunwari kapag gabi.

[17:35]
Interviewee: Low light? Yung sinasabi ko kanina yung pag nagre-reflect yung mga ilaw. Yung ba yon?

[17:41]
Interviewer 2: More on sobrang dilim lang po.

[17:44]
Interviewee: Ah sobrang dilim, okay.

[17:48]
Interviewer 1: Tapos sa motion blur po, both direction po kapag mabilis, pagganyan po. Tsaka yung low bitrate po. Yun naman po sa mga... po sa mga CCTV na kahit malapit po pero low po yung bitrate. Yung bitrate po yun yung parang quality nung camera...Pero iba pa po siya sa resolution. Pero if... Ano po? Pwede po rin po namin i-consider yung resolution.

[18:18]
Interviewee: Kailangan talagang... malaking baga yun lalo na yung madilim. Tapos gagawa ka ng... i-input mo yung... na-capture niyong, ano tawag dito, license. Tapos i-enhance niya or makikita mo. Maganda yun, ah. Kailangan na kailangan namin yun, lalo na dito sa traffic. Kasi marami tayong mga... lawless na mga riders.

[18:44]
Interviewer 2: May mga incidents na po bang...naihirapan kayo kasi blurred po yung images.

18:50]
Interviewee: Yun nga sabi ko nga, may mga instance talaga na hindi nakakayanan ng mga CCTV natin kasi nga sobrang bilis, sobrang liwanag nang... lalo na kapag gabi, nagre-reflect yung mga ilaw. Pag ganung bagay na, gagawa kami ng ibang option.Para makuhanan yung license plate. Yun nga yung sinabi ko kanina, kung san siya dumaan, hahanap kami lahat ng CCTV. Lalo na kapag nag-slow down siya sa daan. Yung pinakamalapit, dun namin kukunin. It takes siguro kapag ganong instances na accidente, mga one month ta-trabahuhin namin yun. Pero sabi nyo nga kung andiyan na yung sistem nyo, mas mapapabilis, diba?

[19:45]
Interviewer 2: Opo.

[19:47]
Interviewee: Kung sabihin natin 1 month dati, kung kaya naman ng 1 to 3 days, mas maganda. Mas mapabilis ang pag-solve natin ng kaso.

[19:59]
Interviewee: Ano pa?
[20:02]
Interviewer 2: Pero yung naisip ko po kasi, since kailangan po talaga ng double verification. Pag nakuha niyo na po yung license plate sa system po namin, i-verify nyo pa naman pa din naman sa LTO pa naman magita po yung model ng sakyan at yung may-ari.

[20:18]
Interviewee: Oo kasi hindi naman maglalabas yung kasa, or yung kasa ng sasakyan, or anong tawag dito kasa ng mga motor. Na hindi dadaan sa LTO, diba?
[20:30]
Interviewer 2: Opo…

[20:32]
Interviewee: Lahat naka-verified sa LTO. Lahat naka may mga documents or details sa LTO. Kahit hindi mo pa nga ipare-registru yan eh. Andun pa rin. Basta may plaka. Mahihira pa lang tayo dyan pag walang plaka. Wala kang mapapaverified. Wala kang? iy-e-enhance, diba. Kase nga walang plaka.

[20:54]
Interviewer 2: Satingin ko po ok na, ano nga po kasi pangalan ninyo?

[20:58]
Interviewee: Corporal Dungca dito sa Traffic Enforcement Unit Operations.

[21:02]
Interviewer 2: Pwede po ba namin makuha contact..

[21:06]
Interviewee: Contact number? Sige, bibigay ko.

[End of interview]

Appendix E: Survey / Feedback Form

LiPAD System Evaluation Survey (Mapped to ISO/EIC 25010)

Objective:
This survey aims to determine the level of conformity of the LiPAD system with the ISO/IEC 25010 software quality model in terms of functionality suitability, performance efficiency, interaction capability, reliability, security, and safety.

Instructions:
Please rate each statement based on your experience with the LiPAD system by checking the box that corresponds to your opinion.

5 – Strongly Agree 4 – Agree 3 – Neutral 2 – Disagree 1 – Strongly Disagree

---

Section A: Functionality Suitability (Functional completeness, Correctness, Appropriateness)

Statement	5	4	3	2	1
1. The LiPAD system provides all the necessary functions to accomplish my tasks.	✓				
2. The system produces correct and accurate results for the functions provided.		✓			
3. The system functions are appropriate and help users achieve their goals effectively.	✓				

Section B: Performance Efficiency (Time behavior, Resource utilization, Capacity)

Statement	5	4	3	2	1
4. The system responds quickly to user inputs and commands.	✓				
5. The system performs well even when multiple users are accessing it simultaneously.	✓				
6. The system uses resources (e.g., memory, processing power) efficiently.	✓				

Section C: Interaction Capability (Appropriateness recognizability, Learnability, Operability, User error protection, Accessibility, Co-existence)

Statement	5	4	3	2	1
7. The system interface is intuitive and easy to recognize for its intended purpose.	✓				
8. The system is easy to learn and navigate, even for first-time users.	✓				
9. The system provides clear feedback, error messages, and instructions to help users recover from mistakes.	✓				
10. The system is accessible and works properly across different devices or browsers.	✓				

Section D: Reliability (Maturity, Availability, Fault tolerance, Recoverability)

Statement	5	4	3	2	1
11. The system performs consistently without frequent errors or failures.	✓				
12. The system is available whenever I need to use it.	✓				
13. The system continues functioning properly even if errors occur.		✓			
14. The system can recover quickly after unexpected shutdowns or interruptions.		✓			

Section E: Security (Confidentiality, Integrity, Non-repudiation, Accountability, Authenticity)

Statement	5	4	3	2	1
15. The system protects sensitive data from unauthorized access.	✓				
16. The system maintains the integrity of stored and transmitted data.	✓				
17. The system has secure authentication and login mechanisms.	✓				

Section F: Safety (Risk prevention and harm avoidance)

Statement	5	4	3	2	1
18. The system prevents harmful or unsafe operations that could affect users.	✓				
19. The system provides warnings or confirmations before performing critical actions.	✓				
20. The system reduces risks of data loss or misuse that may cause harm.		✓			

Section G: Overall Assessment

Statement	5	4	3	2	1
21. Overall, the LiPAD system conforms well to the ISO/IEC 25010 software quality model.		✓			
22. I am satisfied with the overall quality and reliability of the LiPAD system.		✓			

Section H: Open-Ended Questions

23. What features of the LiPAD system do you find most useful?

THE IMPLEMENTATION OF MULTIPLE A.I. MODELS IS A GOOD IDEA, THE CORE PART (IMAGE DEBLURRING) SERVE IT'S PURPOSE. USER INTERFACE IS CLEAN AND COMMENDABLE

24. What improvements would you suggest for the system?

FOR NOW, THE PROCESS IS SINGULAR - LINEAR. I SUGGEST FOR SEMI-AUTOMATIC MULTIPLE PROCESS FLOW IN CASE OF RETRIES

25. Are there any issues or concerns you experienced while using the system?

NOTHING THAT'S A SHOW STOPPER

Section I: Declaration of Integrity

I hereby declare that the responses I have provided in this survey are honest, accurate, and based solely on my personal evaluation of the LiPAD system.

Evaluator Name: JAY RENZ A. MORGADO

Position / Role: SOFTWARE ENGINEER

Date: SEPT 7, 2025

Signature:

LiPAD System Evaluation Survey (Mapped to ISO/EIC 25010)

Objective:
This survey aims to determine the level of conformity of the LiPAD system with the ISO/IEC 25010 software quality model in terms of functionality suitability, performance efficiency, interaction capability, reliability, security, and safety.

Instructions:
Please rate each statement based on your experience with the LiPAD system by checking the box that corresponds to your opinion.

5 – Strongly Agree 4 – Agree 3 – Neutral 2 – Disagree 1 – Strongly Disagree

---

Section A: Functionality Suitability (Functional completeness, Correctness, Appropriateness)

Statement	**5**	**4**	**3**	**2**	**1**
1. The LiPAD system provides all the necessary functions to accomplish my tasks.	✓				
2. The system produces correct and accurate results for the functions provided.	✓				
3. The system functions are appropriate and help users achieve their goals effectively.	✓				

Section B: Performance Efficiency (Time behavior, Resource utilization, Capacity)

Statement	**5**	**4**	**3**	**2**	**1**
4. The system responds quickly to user inputs and commands.	✓				
5. The system performs well even when multiple users are accessing it simultaneously.	✓				
6. The system uses resources (e.g., memory, processing power) efficiently.	✓				

Section C: Interaction Capability (Appropriateness recognizability, Learnability, Operability, User error protection, Accessibility, Co-existence)

Statement	5	4	3	2	1
7. The system interface is intuitive and easy to recognize for its intended purpose.	✓				
8. The system is easy to learn and navigate, even for first-time users.	✓				
9. The system provides clear feedback, error messages, and instructions to help users recover from mistakes.	✓				
10. The system is accessible and works properly across different devices or browsers.		✓			

Section D: Reliability (Maturity, Availability, Fault tolerance, Recoverability)

Statement	5	4	3	2	1
11. The system performs consistently without frequent errors or failures.	✓				
12. The system is available whenever I need to use it.	✓				
13. The system continues functioning properly even if errors occur.	✓				
14. The system can recover quickly after unexpected shutdowns or interruptions.		✓			

Section E: Security (Confidentiality, Integrity, Non-repudiation, Accountability, Authenticity)

Statement	5	4	3	2	1
15. The system protects sensitive data from unauthorized access.	✓				
16. The system maintains the integrity of stored and transmitted data.	✓				
17. The system has secure authentication and login mechanisms.	✓				

Section F: Safety (Risk prevention and harm avoidance)

Statement	5	4	3	2	1
18. The system prevents harmful or unsafe operations that could affect users.	✓				
19. The system provides warnings or confirmations before performing critical actions.	✓				
20. The system reduces risks of data loss or misuse that may cause harm.	✓				

Section G: Overall Assessment

Statement	5	4	3	2	1
21. Overall, the LiPAD system conforms well to the ISO/IEC 25010 software quality model.	✓				
22. I am satisfied with the overall quality and reliability of the LiPAD system.	✓				

Section H: Open-Ended Questions

23. What features of the LiPAD system do you find most useful?

The distortion detection in images

24. What improvements would you suggest for the system?

Cloud deployment for faster performance

25. Are there any issues or concerns you experienced while using the system?

None

Section I: Declaration of Integrity

I hereby declare that the responses I have provided in this survey are honest, accurate, and based solely on my personal evaluation of the LiPAD system.

Evaluator Name: GOSHEN JIMENEZ

Position / Role: SR. SOFTWARE DEVELOPER, TEAMIFIED

Date: 06 SEPT. 2025

Signature:

Appendix F: Data Samples

The dataset used in this study is composed of a total of 60,000 Philippine license plate images, organized into six equally sized subsets containing 10,000 images each. These subsets represent different visual conditions and data qualities to simulate real-world scenarios where license plate recognition systems are deployed. The construction of these datasets follows a rigorous preprocessing pipeline, ensuring consistency, realism, and suitability for model training and evaluation.

Prior to augmentation and model training, a dataset reduction step is applied to eliminate images that do not meet the minimum resolution requirement. Specifically, any image with a width or height less than 128 pixels is discarded. This resolution threshold is based on the observation that extremely low-resolution images lose critical visual information, particularly in the context of license plate recognition. When such images are further downscaled or compressed during augmentation, the characters often become indistinguishable, which may lead to poor model learning outcomes and increased noise in training. By enforcing this reduction step, the dataset maintains a baseline level of visual quality, which is essential for the learning of meaningful features by the models used in the system.

After the reduction step, the remaining images are organized into the following six datasets:

1. **Original/Normal (Undistorted) Dataset**

    This subset consists of 10,000 images captured or sourced under normal conditions, containing license plates with adequate resolution, clear visibility, and minimal distortion. These images serve as the foundational dataset for both augmentation processes and evaluation benchmarks. They represent real-world vehicle images with ideal characteristics, including centered license plates, balanced lighting, and minimal motion artifacts.

2. **Enhanced Dataset**

    The enhanced dataset is derived from the original set using the Real-Enhanced Super-Resolution Generative Adversarial Network (Real-ESRGAN), specifically the RealESRGANx4plus model. Each image in this subset is upscaled by a factor of four, with the model restoring fine-grained details and enhancing overall clarity. This dataset is intended to represent high-resolution ground truth data and is used for both training and evaluating image reconstruction modules. It provides a clear visual reference for comparing degraded and restored images.

3. **Low-Light Dataset**

    To simulate conditions commonly encountered in nighttime driving or under poorly lit environments, 10,000 images are synthetically darkened using OpenCV and NumPy libraries. The brightness of each image is reduced by randomly selecting a scaling factor between 5% and

25% of the original intensity. This is achieved by multiplying the pixel values by a random float within the specified range. The resulting images exhibit varying degrees of darkness, effectively replicating real-world visibility challenges caused by insufficient lighting.

4. **Low-Quality Dataset**

    This subset simulates image degradation from digital zoom, compression, and low-end capture devices. It is constructed by downscaling the original images using OpenCV's resize function by a factor of four while preserving the aspect ratio. Following downscaling, JPEG compression is applied using OpenCV's imencode function with a randomized quality setting between 20 and 60. This dual-step process introduces blur, pixelation, and visible compression artifacts, closely resembling license plate images from budget surveillance cameras or bandwidth-limited environments.

5. **Horizontal Motion Blur Dataset**

    This dataset contains images affected by simulated horizontal motion blur, designed to replicate the effects of vehicle movement or lateral camera shake. A custom 2D convolution kernel is applied, consisting of a matrix where only the central row contains non-zero values (all ones), and the matrix is normalized to preserve brightness. The kernel size, determining the severity of the blur, is randomly selected between 10 and 20 pixels. This technique mimics the horizontal stretching and ghosting effects commonly observed in fast-moving scenes.

6. **Vertical Motion Blur Dataset**

Similarly, vertical motion blur is introduced to another set of 10,000 images using a vertical kernel applied along the Y-axis. The kernel structure mirrors that of the horizontal blur, but the non-zero values are placed along the central column of the matrix. The kernel size varies randomly from 15 to 25 pixels, creating vertically elongated motion artifacts. This simulates scenarios such as camera vibrations on vertical axes or movement during frame capture in upward/downward directions.

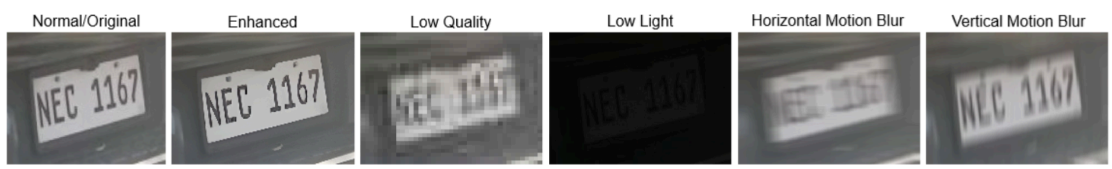


Figure 33. LiPAD Sample Images from Each Dataset Type

A visual example of each dataset type including original, enhanced, low-light, low-resolution, horizontal motion blur, and vertical motion blur is presented in Figure 6, which illustrates the visual differences introduced by each distortion technique.

In addition to the visual data, the original and enhanced datasets are annotated with the corresponding license plate text. Each image-label pair is stored in a structured format compliant with the requirements of PaddleOCRv4, where each entry includes the file path and the corresponding string label. These annotations form the ground truth for the CRNN-based OCR module and are essential for sequence learning and character-level recognition. The same labeling structure will be adopted for evaluating the OCR model on distorted and reconstructed images, allowing consistent benchmarking across all dataset types.

Appendix G: Code Listings

CNN Distortion Classifier

```
# Data transforms (normalization & data augmentation)
stats = ((0.42720765, 0.43359186, 0.44090385), (0.24280364, 0.24590165, 0.23916515))
train_tfms = T.Compose([T.Resize([128, 256]),
                        T.RandomPerspective(distortion_scale=0.2, p=0.2),
                        T.ColorJitter(hue=.2),
                        T.ToTensor(),
                        T.Normalize(*stats, inplace=True)])
valid_tfms = T.Compose([T.Resize([128, 256]), T.ToTensor(), T.Normalize(*stats)])
```

Figure 34. CNN data augmentation pipeline

The data augmentation code prepares image transformations for both training and validation/test datasets. The stats variable contains mean and standard deviation values calculated from the normal image dataset and is used for normalization. The training transformations include several augmentation techniques such as resizing images to 128x256, applying random perspective, adjusting color hue, normalizing images, and converting images to tensors. These augmentations help the model generalize better by exposing it to various transformations of the training data. On the other hand, validation and testing transformations are simpler, requiring only normalization and conversion to tensors.

```
from torchvision import models
from torchvision.models import resnet18

class DistortionClassifier18(ImageClassificationBase):
    def __init__(self, num_classes):
        super().__init__()
        self.network = models.resnet18()
        self.network.fc = nn.Linear(self.network.fc.in_features, num_classes)

    def forward(self, xb):
        return self.network(xb)
```

Figure 35. Distortion classifier architecture

The DistortionClassifier18 implements the ResNet18 architecture. The main modification is replacing the final fully connected layer with a new linear layer that maintains the same input size but outputs five classes, corresponding to the distortion types.

```
def fit_one_cycle(epochs, max_lr, model, train_loader, val_loader, weight_decay=0, grad_clip=None, opt_func=torch.optim.SGD):
    torch.cuda.empty_cache()
    history = []

    # Set up custom optimizer with weight decay
    optimizer = opt_func(model.parameters(), max_lr, weight_decay=weight_decay)
    # Set up one-cycle learning rate scheduling
    sched = torch.optim.lr_scheduler.OneCycleLR(optimizer, max_lr, epochs=epochs,
                                                steps_per_epoch=len(train_loader))

    for epoch in range(epochs):
        # Training phase
        model.train()
        train_losses = []
        lrs = []
        for batch in tqdm(train_loader):
            loss = model.training_step(batch)
            train_losses.append(loss)
            loss.backward()

            # Gradient clipping
            if grad_clip:
                nn.utils.clip_grad_value_(model.parameters(), grad_clip)

            optimizer.step()
            optimizer.zero_grad()

            # Record and update learning rate
            lrs.append(get_lr(optimizer))
            sched.step()

        # Validation phase
        result = evaluate(model, val_loader)
        result['train_loss'] = torch.stack(train_losses).mean().item()
        result['lrs'] = lrs
        model.epoch_end(epoch, result)
        history.append(result)
    return history
```

Figure 36. One-cycle training function

The fit_one_cycle function implements the training loop using the one-cycle learning rate policy. The function begins by clearing CUDA memory and setting up an optimizer with weight decay regularization. For each epoch, the model processes training batches in training mode, calculating loss, performing backpropagation, applying gradient clipping, and updating model weights. After training, the model is evaluated on the validation set. The function logs both training and validation metrics and maintains a history of all metrics.

GAN Deblurrer

```python
def train_generator(generator, discriminator, inputs, targets, g_opt, adv_lambda=1.0,
                    l1_lambda=100.0, ssim_lambda=2.5, perceptual_lambda=5.0, text_lambda=7.5):
    generator.train()

    fake_images = generator(inputs)
    pred_fake = discriminator(fake_images)

    real_labels = torch.ones_like(pred_fake)

    adv_loss = comparison_loss(pred_fake, real_labels)
    l1_loss = L1_loss_fn(fake_images, targets)
    perceptual_loss = lpips_loss(fake_images.clamp(-1, 1), targets.clamp(-1, 1)).mean()
    ssim_loss = ssim(fake_images, targets)

    # Text Loss
    fake_np = tensor_to_bgr_numpy(fake_images)
    real_np = tensor_to_bgr_numpy(targets)

    with torch.no_grad():
        fake_text = ocr_model.ocr(fake_np, cls=False, det=False)[0]
        real_text = ocr_model.ocr(real_np, cls=False, det=False)[0]

    fake_str = fake_text[0][0] if fake_text else ''
    real_str = real_text[0][0] if real_text else ''

    fake_str = fake_str.strip().replace(' ', '')
    real_str = real_str.strip().replace(' ', '')

    # Use normalized edit distance as loss
    edit_dist = levenshtein_distance(fake_str, real_str)
    norm_edit_dist = edit_dist / max(len(real_str), 1)
    text_loss = torch.tensor(norm_edit_dist, device=device)

    g_loss = (
        adv_loss * adv_lambda +
        l1_loss * l1_lambda +
        ssim_loss * ssim_lambda +
        perceptual_loss * perceptual_lambda +
        text_loss * text_lambda
    )

    g_opt.zero_grad()
    g_loss.backward()
    g_opt.step()

    return g_loss.item(), fake_images, {
        "total_loss": g_loss.item(),
        "adv": adv_loss.item(),
        "l1": l1_loss.item(),
        "ssim": ssim_loss.item(),
        "perceptual": perceptual_loss.item(),
        "text": text_loss.item()}
```

Figure 37. Train generator function

The train_generator function implements the generator training step of the GAN, combining multiple loss components to optimize image quality. It uses the generator to turn input images into fake outputs, and then it calculates adversarial loss by comparing the patch discriminator's predictions to real labels. The function uses pixel-level L1 loss, structural similarity (SSIM) loss, perceptual loss, and a text preservation loss derived from OCR-based Levenshtein distance between generated and target text. These losses are weighted by hyperparameters and combined into a total loss. After backpropagation and optimizer updates, it returns the loss value, generated images, and individual loss values for logging and monitoring.

```python
def fit(generator, discriminator, epochs, lr, adv_lambda=1.0, l1_lambda=100.0, ssim_lambda=2.5,
        perceptual_lambda=5.0, text_lambda=7.5, g_opt=None, d_opt=None, checkpoint=None):

    torch.cuda.empty_cache()

    losses_g = []
    losses_d = []
    real_scores = []
    fake_scores = []
    psnrs = []
    ssims = []
    fids = []
    g_losses_trace = []
    g_lrs = []
    d_lrs = []

     # Create optimizers
    if d_opt is None:
        d_opt = optim.Adam(discriminator.parameters(), lr=lr, betas=(beta1, beta2))
    if g_opt is None:
        g_opt = optim.Adam(generator.parameters(), lr=lr, betas=(beta1, beta2))

    # Load checkpoint state if resuming
    if checkpoint is not None:
        print("Resuming training from checkpoint...")
        d_opt.load_state_dict(checkpoint['opt_d'])
        g_opt.load_state_dict(checkpoint['opt_g'])

    g_scheduler = ReduceLROnPlateau(g_opt, mode='min', factor=0.5, patience=5, verbose=True, min_lr=1e-6)
    d_scheduler = ReduceLROnPlateau(d_opt, mode='min', factor=0.5, patience=5, verbose=True, min_lr=1e-6)

    # Train
    for epoch in range(epochs):
        torch.cuda.empty_cache()
        generator.train()
        discriminator.train()
        for inputs, targets in tqdm(train_dl):
            inputs = inputs.to(device)
            targets = targets.to(device)

            # Train discriminator
            d_loss, real_score, fake_score = train_discriminator(discriminator, generator, inputs, targets, d_opt)

            # Train generator
            g_loss, fake_images, g_loss_trace = train_generator(generator, discriminator, inputs, targets, g_opt, adv_lambda,
                                                                l1_lambda, ssim_lambda, perceptual_lambda, text_lambda)

        print('Training Data')
        print_images(inputs, 5)
        print_images(fake_images, 5)
        print_images(targets, 5)

        if (epoch + 1) % 5 == 0:
            torch.save(generator.state_dict(), f'[RAU-NET OCRDET LR]generator-Datasetv2-{epoch + 1} epoch.pt')
            torch.save(discriminator.state_dict(), f'[RAU-NET OCRDET LR]discriminator-Datasetv2-{epoch + 1} epoch.pt')
            torch.save({
                'generator': generator.state_dict(),
                'discriminator': discriminator.state_dict(),
                'opt_g': g_opt.state_dict(),
                'opt_d': d_opt.state_dict(),
                'losses_g': losses_g,
                'losses_d': losses_d,
                'real_score': real_scores,
                'fake_score': fake_scores,
                'psnrs': psnrs,
                'ssims': ssims,
                'fids': fids,
                'g_lrs': g_lrs,
                'd_lrs': d_lrs,
                'epoch': epoch + 1
            }, f'[RAU-NET OCRDET LR]Checkpoint-Logs-Datasetv2-{epoch + 1} epoch.pt')

        # Print progress
        try:
            curr_glr = get_lr(g_opt)
            curr_dlr = get_lr(d_opt)

            print('Epoch [{}/{}], loss_g: {:.4f}, loss_d: {:.4f}, real_score: {:.4f}, fake_score: {:.4f}'.format(
                  epoch+1, epochs, g_loss, d_loss, real_score, fake_score))
            print(f"Current LRs — Generator: {curr_glr:.6f}, Discriminator: {curr_dlr:.6f}")
        except Exception as err:
            print('Error:', str(err))

        mean_psnr, mean_ssim, fid = evaluate_generator(generator, valid_dl, epoch)

        g_scheduler.step(g_loss)
        d_scheduler.step(d_loss)

        # Record losses and scores
        losses_g.append(g_loss)
        losses_d.append(d_loss)
        real_scores.append(real_score)
        fake_scores.append(fake_score)
        psnrs.append(mean_psnr)
        ssims.append(mean_ssim)
        fids.append(fid)
        g_losses_trace.append(g_loss_trace)
        g_lrs.append(curr_glr)
        d_lrs.append(curr_dlr)

        save_samples(generator, test_dl, epoch + 1, sample_dir='./visualization-ocr-det-lr')

    return losses_g, losses_d, real_scores, fake_scores, psnrs, ssims, fids, g_losses_trace
```

Figure 38. GAN training loop function

The fit function orchestrates end-to-end GAN training with both evaluation and checkpointing. It initializes optimizers for both the generator and the discriminator, optionally resuming from a checkpoint. The function periodically saves model weights and training checkpoints containing states, losses, and metrics. After each epoch, it evaluates the generator on validation data using PSNR, SSIM, and FID metrics and saves generated test samples. The training process is tracked through losses, discriminator scores, and evaluation metrics, with visualizations of generated images. The function returns a complete training history for analysis.

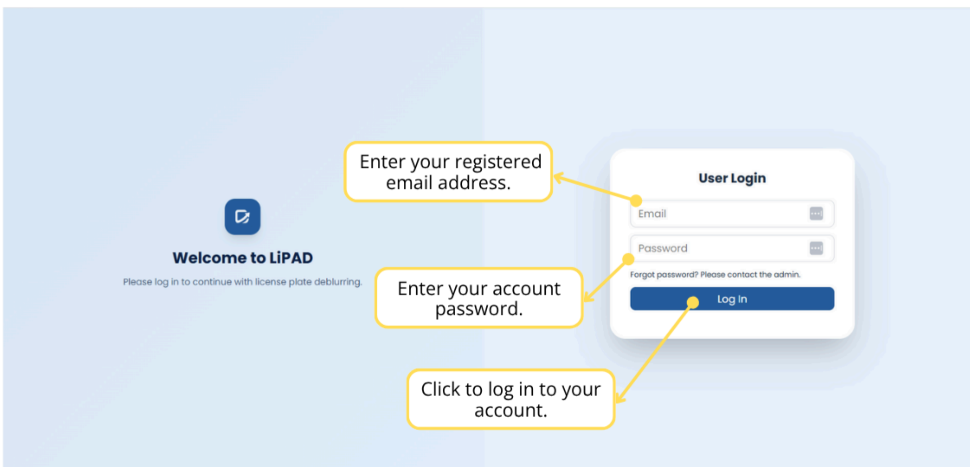
Appendix H: User's Manual

LiPAD

USER'S MANUAL

User Login Page

Purpose:
This page allows users to securely log in to access the LiPAD system for license plate deblurring.

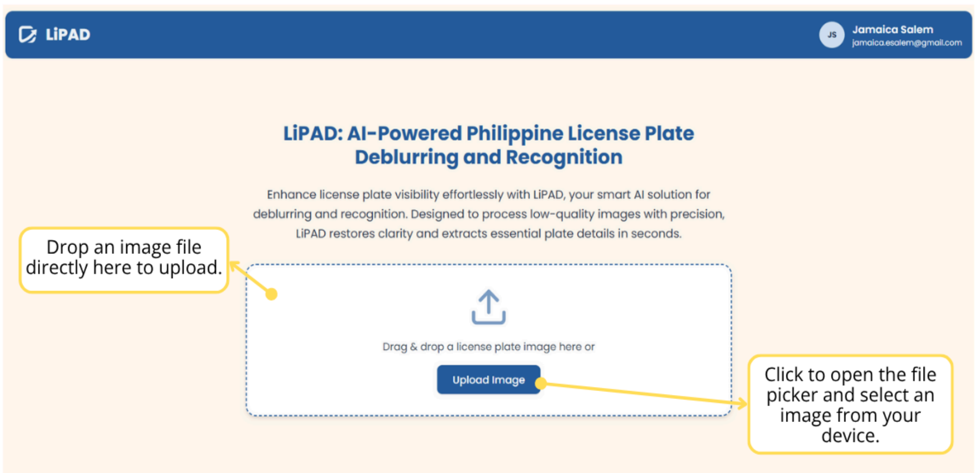


Error Message (Red Text):
Appears when login fails or when required fields are empty.

System Behavior:
If login is successful → user is redirected to the License Plate Upload page.
If login fails → an error message appears (e.g., “Email is required.” or “Login failed. Please try again.”).

Image Upload Page

Purpose:
This page allows users to upload a license plate image for the system to process.

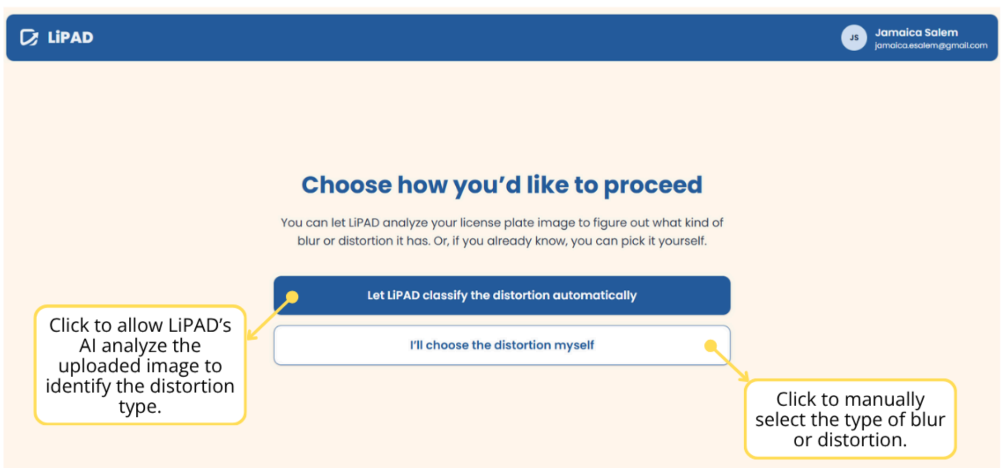


Error Message (Red Text):
Appears if no file is selected, upload fails, or there's a connection/server issue.

System Behavior:
After selecting an image, the system uploads it automatically.
Once uploaded successfully, you are redirected to the Classifier Options page. If the upload fails, an error message is shown.

Classifier Options Page

Purpose:
This page allows users to upload a license plate image for the system to process.This page lets users decide how to classify the type of blur or distortion in their uploaded license plate image.



Error Message (Red Text):
Appears when there's an issue processing or navigating (e.g., missing image ID, server error).

Manual Classifier Page

Purpose:

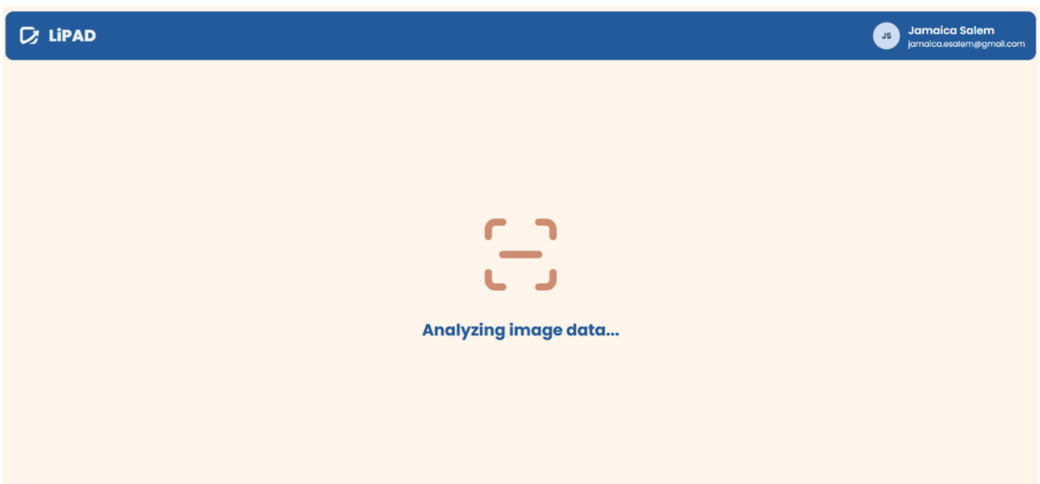
This page allows users to manually select the type of distortion affecting their uploaded license plate image.

System Behavior:

After a distortion type is selected, LiPAD processes the image and redirects the user to the Loading Page for deblurring.

Loading Page

Purpose:
This page appears while LiPAD processes the uploaded image for deblurring and license plate recognition.

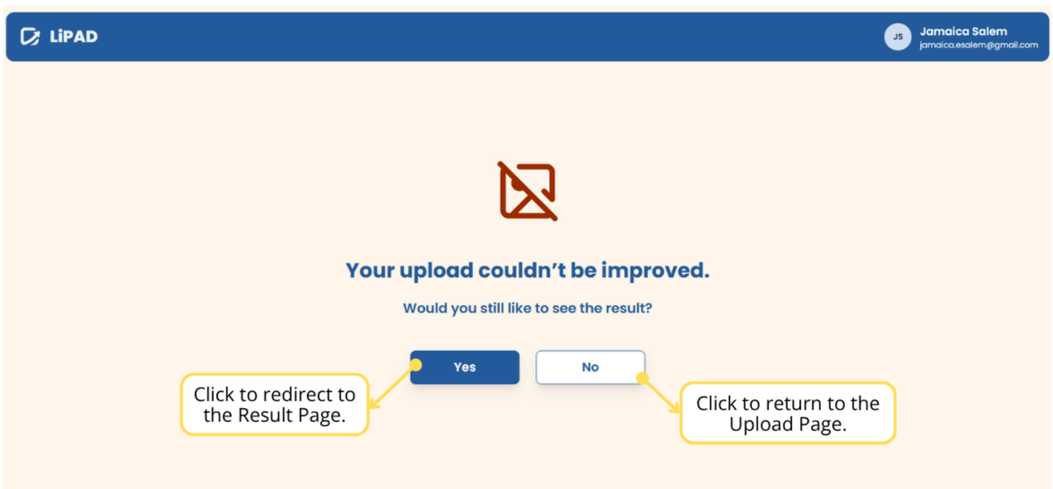


System Behavior:
LiPAD continuously checks the processing status in the background.
Once processing is complete:

- If the deblurring and recognition succeed → user is redirected to the Result Page.
- If processing fails or no plate number is detected → user is redirected to the Failure Page.

Processing Failed Page

Purpose:
This page appears when the system fails to process or enhance the uploaded image.

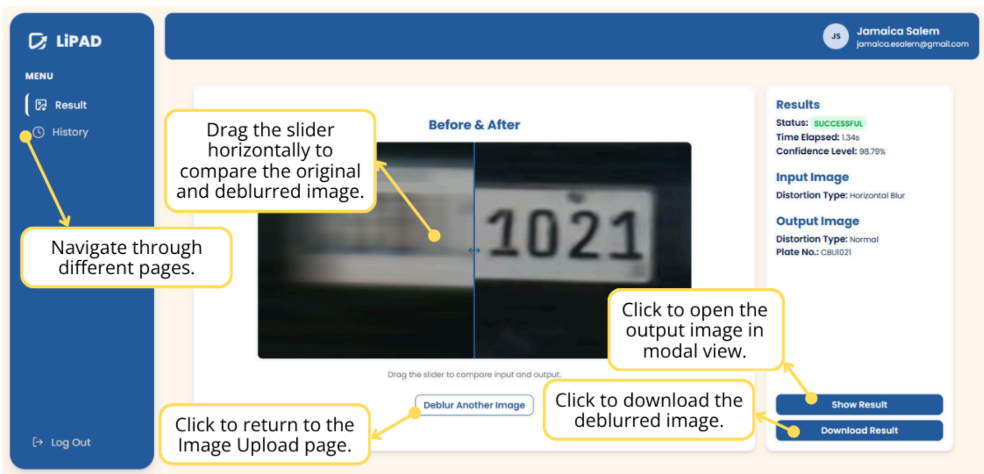


System Behavior
When the image enhancement fails, the system randomly displays an error message.

- If the user clicks "Yes", the system redirects them to the Result Page (/result) and attempts to display any available processed output using the same imageId.
- If the user clicks "No", the system redirects them back to the License Plate Upload Page (/upload) to reattempt the process.

Results Page (Success)

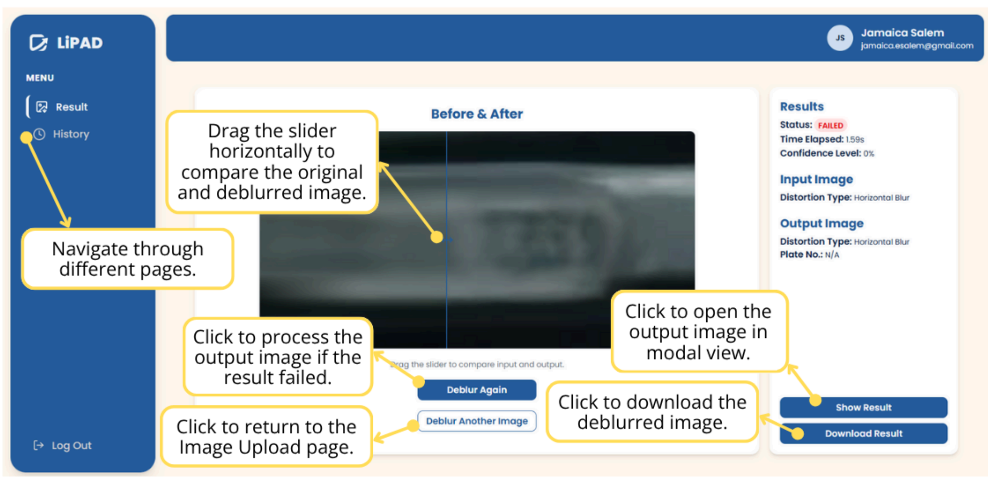
Purpose:
This page displays the comparison between the original (blurred) and processed (deblurred) images, along with processing details and actions.



System Behavior
Automatically fetches image data and result details using the imageId from the database.

Results Page (Failed)

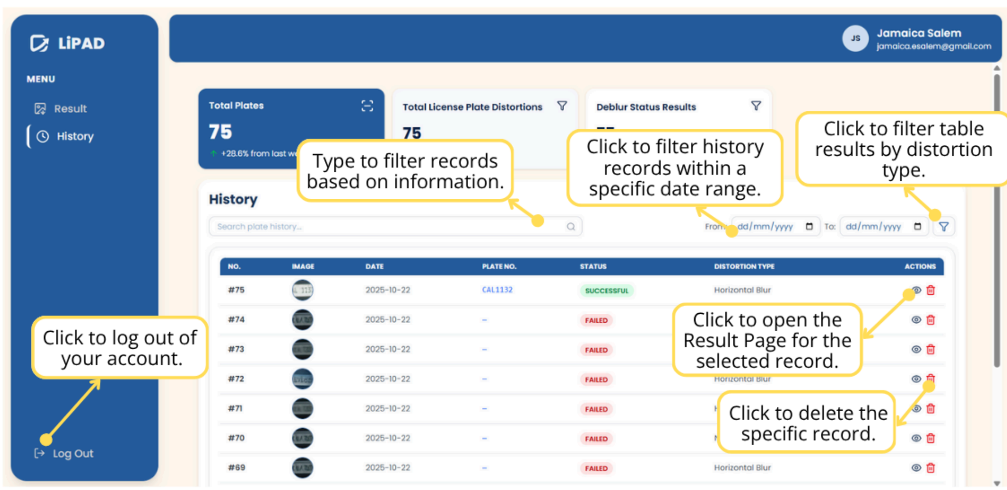
Purpose:
This page displays the comparison between the original (blurred) and processed (deblurred) images, along with processing details and actions.



System Behavior
Automatically fetches image data and result details using the imageId from the database.

History Page

Purpose:
Displays key performance indicators (KPIs) and a searchable history of uploaded and processed license plate images.



System Behavior
Automatically fetches image data and result details using the imageId from the database.

Appendix I: Additional Visualizations

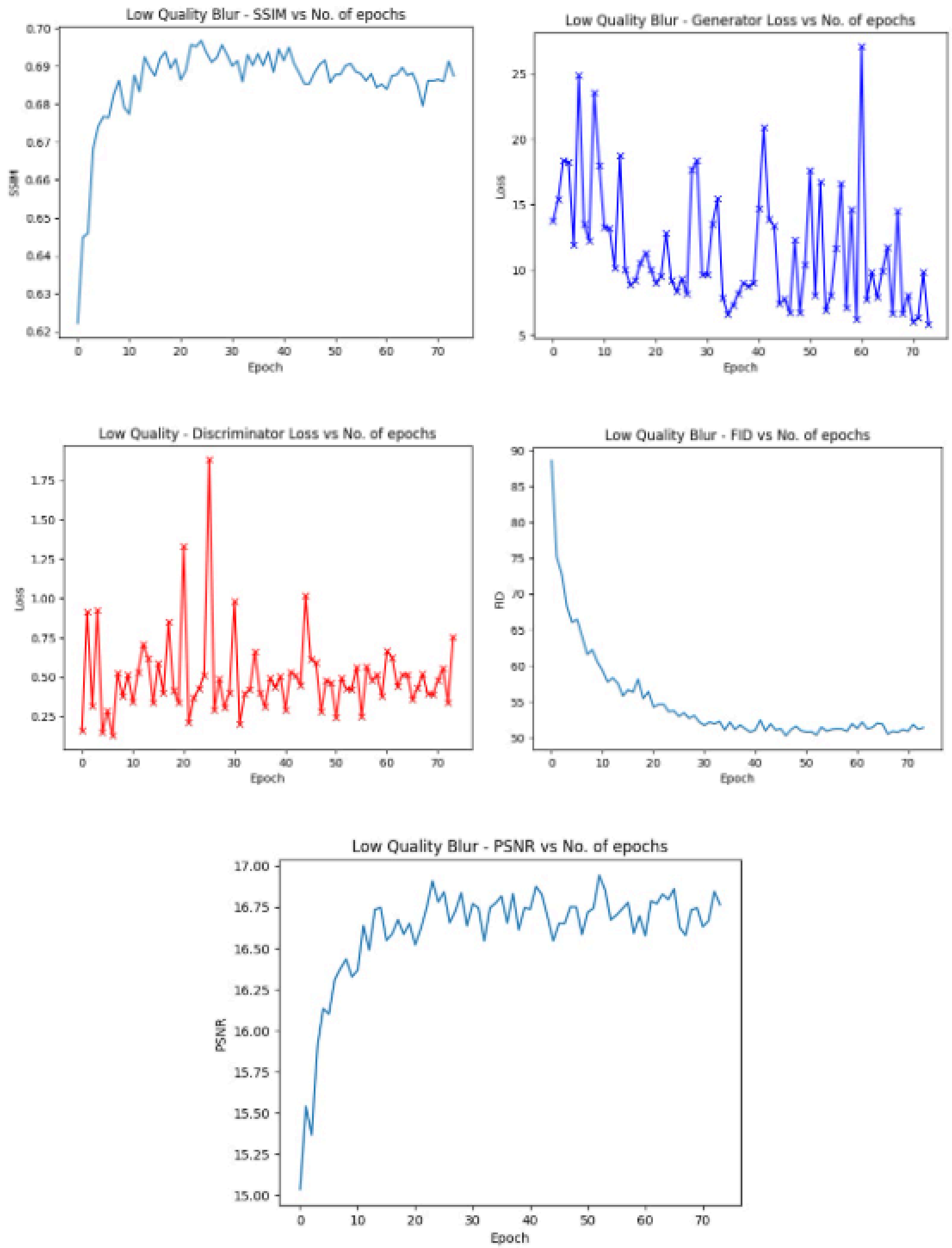


Figure 39. Low Quality Blur Visualizations

The figure illustrates the training performance of the low-quality deblurring model across 75 epochs. SSIM and PSNR steadily increased before stabilizing around 0.69 and 16.67, indicating moderate structural and fidelity recovery. Generator and discriminator losses fluctuated due to adversarial dynamics but gradually improved, while FID consistently decreased from around 85 to 50, reflecting enhanced perceptual quality. The best results at epoch 55 show that the model effectively restored general image details, though strong compression often caused smoothing, artifacts, and occasional hallucinated features.

Figure 40. Low Quality Blur Test Set. (a) Raw Test Set (b) Generated Test Set

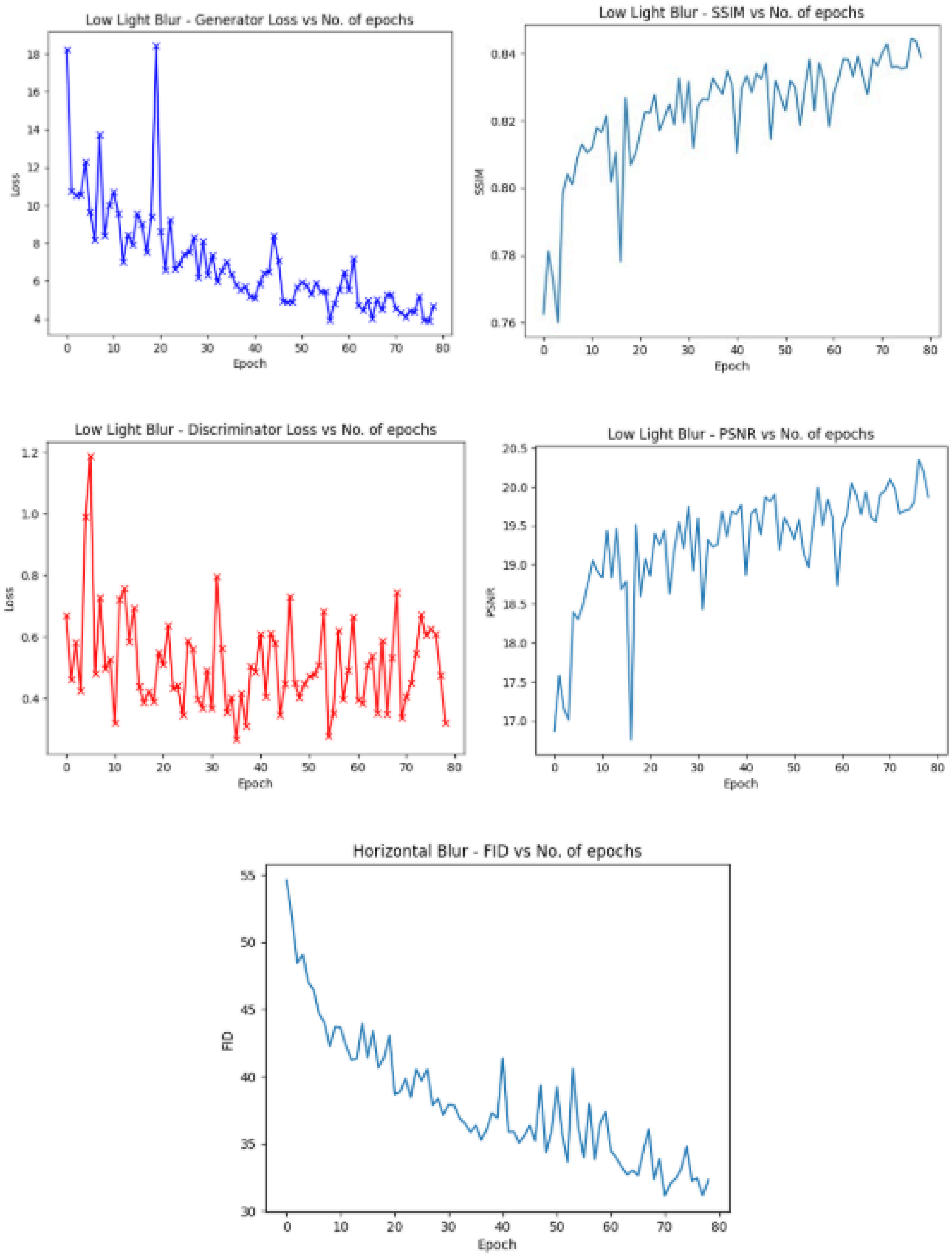


Figure 41. Low Light Visualizations

The low-light restoration model, based on the Residual Attention U-Net GAN architecture, was designed to enhance illumination and recover text visibility in poorly lit license plate images while maintaining structural consistency. Unlike models targeting motion blur or compression artifacts, its primary objective was brightness correction rather than intricate texture reconstruction, though it still managed limited detail enhancement. At the 80th epoch, the model achieved a mean PSNR of 19.7793, mean SSIM of 0.8401, and an FID of 31.55, demonstrating strong perceptual quality and effective visibility recovery. Overall, it produced clear and readable license plates, with only minor imperfections such as dimness or slight color deviations in certain outputs.

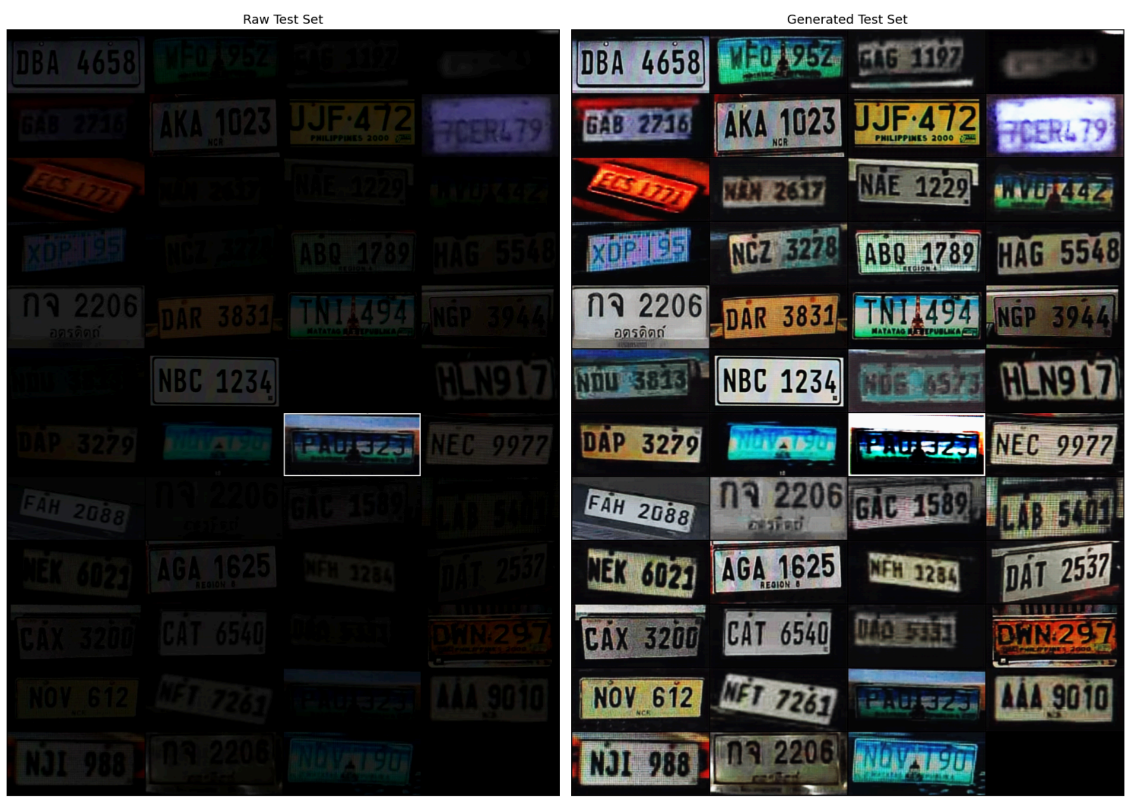


Figure 42. Low Light Test Set. (a) Raw Test Set (b) Generated Test Set

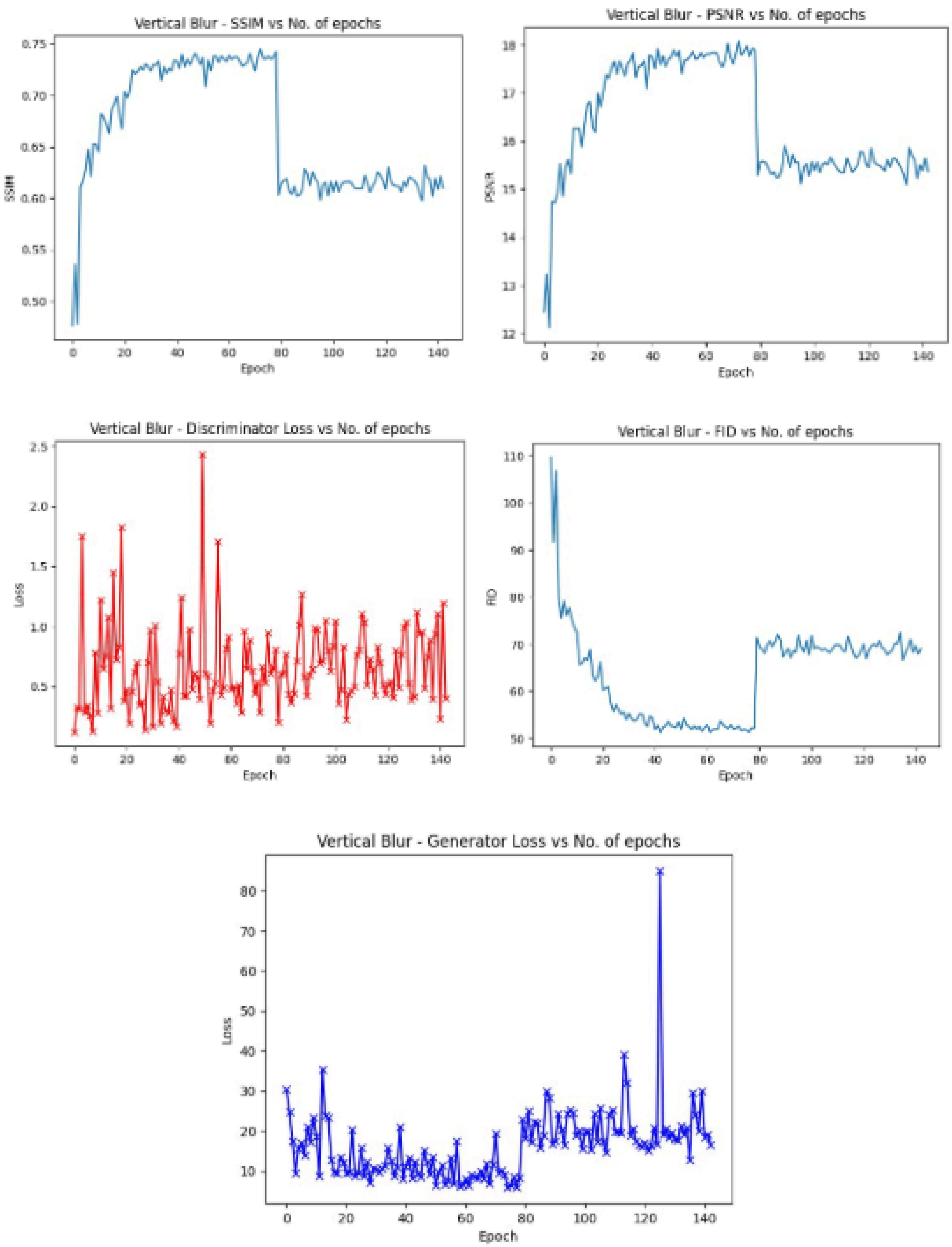


Figure 43. Vertical Blur Visualizations

The vertical motion blur model underwent two separate training stages: an initial 80-epoch training phase using the original vertically blurred dataset, followed by a 65-epoch fine-tuning phase on a new dataset containing shorter-kernel vertical blur. This change in dataset explains the noticeable jump in the performance graphs, as the model adapted to a different blur severity during fine-tuning. Despite this adjustment, the model continued to struggle with vertically distorted characters. Compared to horizontal blur, vertical blur caused more pronounced artifacts and deformation, particularly affecting the vertical strokes of characters. As a result, the model often confused letters such as “H” and “M” or “E” and “F,” confirming that vertical motion blur is more destructive to structural information and leads to reduced reconstruction accuracy.

Figure 44. Vertical Blur Test Set. (a) Raw Test Set (b) Generated Test Set

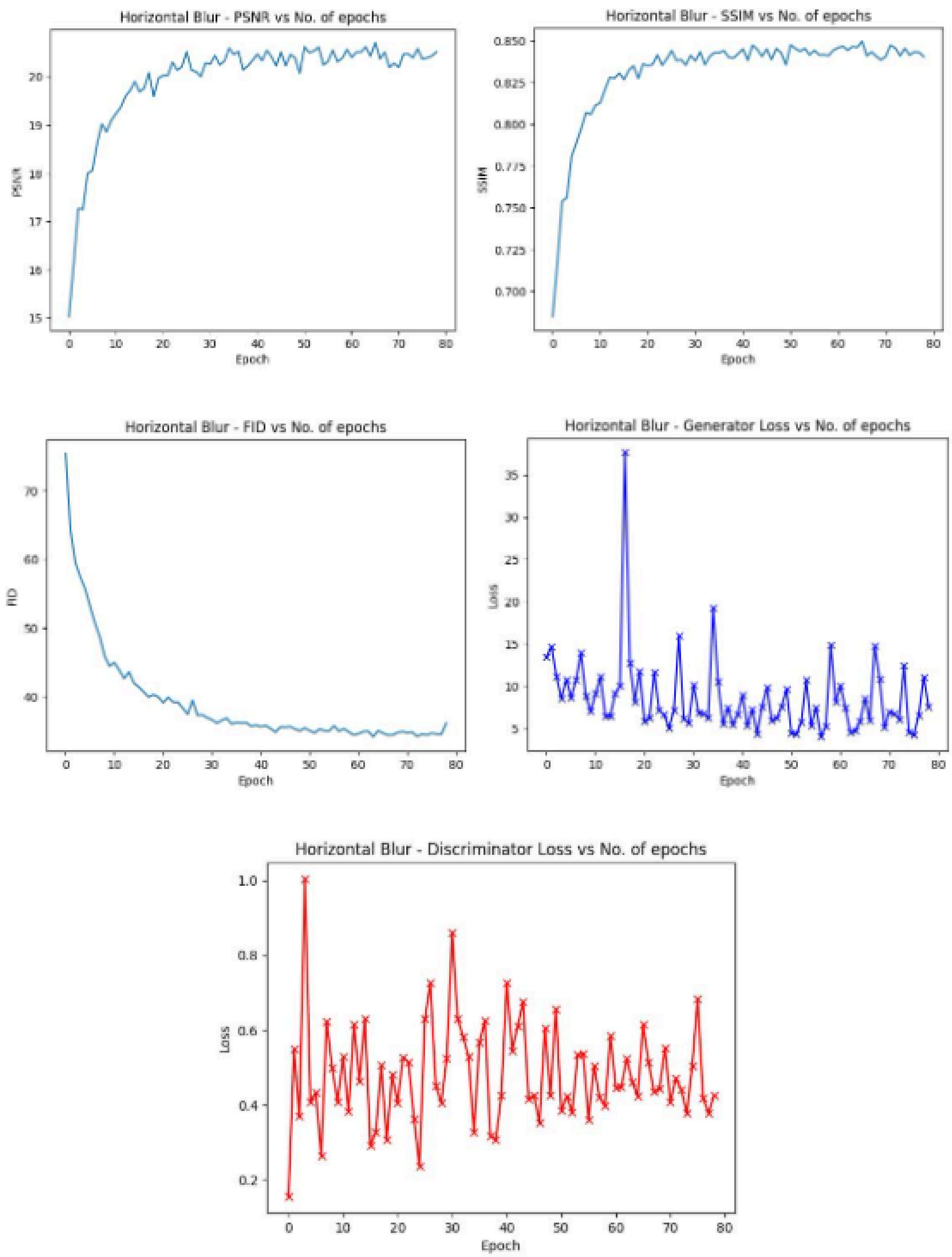


Figure 45. Horizontal Blur Visualizations

The horizontal motion blur model demonstrated the strongest overall performance among all distortion-specific models. Its restorations appeared visually sharp and closely aligned with the ground truth, showing effective recovery of character edges and spacing, particularly on license plates with clear fonts. The model successfully reduced streaking and maintained structural accuracy, which contributed to more realistic and legible outputs. However, in cases of severe horizontal smudging where fine details were completely lost, the model struggled to reconstruct the affected regions accurately. Despite this limitation, the results indicate that the horizontal blur model was the most robust in preserving structure and achieving natural-looking restorations.

Figure 46. Horizontal Blur Test Set. (a) Raw Test Set (b) Generated Test Set

Appendix J: Model Performance Metrics

CNN Classifier / Qualifier Metrics

Accuracy

Accuracy measures the overall proportion of correct predictions out of all predictions made, calculated as:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

This metric provides a general overview of model correctness, indicating how frequently the classifier makes correct decisions. However, in datasets with class imbalance, accuracy alone can be misleading; therefore, it was evaluated alongside precision, recall, and F1-score.

Precision

Precision evaluates the correctness of positive predictions for each class and is expressed as:

$$Precision = \frac{TP}{TP + FP}$$

It measures how often the classifier's positive predictions are actually correct, minimizing false positives in scenarios such as automated enforcement. High precision indicates that the model rarely misclassifies other plate types as a given category.

Recall

Recall, also known as sensitivity, measures the model's ability to identify all actual positive instances and is computed as:

$$\boldsymbol{Recall} = \frac{\boldsymbol{TP}}{\boldsymbol{TP} + \boldsymbol{FN}}$$

High recall ensures that the classifier captures all relevant license plates, reducing the number of missed detections and improving enforcement accuracy.

F1-score

The F1-score combines precision and recall into a single metric, defined as:

$$\boldsymbol{F1} = \boldsymbol{2} \times \frac{\boldsymbol{Precision} \times \boldsymbol{Recall}}{\boldsymbol{Precision} + \boldsymbol{Recall}}$$

This harmonic mean balances both false positives and false negatives, making it a reliable metric in class-imbalanced datasets. A high F1-score indicates consistent performance across different license plate categories.

Confusion Matrix

The confusion matrix visualizes correct and incorrect predictions across all classes. It provides detailed insights into specific misclassifications, revealing which classes the model confuses most frequently. Both raw and normalized confusion matrices were analyzed to guide model improvement and better understand classification behavior in Philippine plate types.

GAN Reconstruction Metrics

Fréchet Inception Distance (FID)

FID measures the similarity between the feature distributions of generated images and real images using an Inception network. Lower FID values indicate higher image realism and diversity. This metric evaluates the perceptual quality of reconstructed images, ensuring that the GAN generates deblurred license plates that closely resemble authentic ones.

Structural Similarity Index (SSIM)

SSIM quantifies perceived image quality based on luminance, contrast, and structural similarities between the original and reconstructed images. It ranges from 0 to 1, where higher values represent better structural preservation. In this study, a higher SSIM indicated that the GAN maintained the essential visual structure of license plates, which was critical for text recognition accuracy.

Peak Signal-to-Noise Ratio (PSNR)

PSNR evaluates the fidelity of reconstructed images compared to their originals, expressed as:

$$\boldsymbol{PSNR = 10\log_{10}\left(\frac{MAX_I^2}{MSE}\right)}$$

where $MAXI$ is the maximum possible pixel value and MSEMSEMSE is the mean squared error. Higher PSNR indicates better reconstruction quality and lower noise, contributing to clearer and more readable plate images.

Render Speed

Render speed measures the average processing time per image, typically reported in seconds per image. Lower render speeds indicate faster reconstruction and are crucial for real-time deployment in resource-constrained Philippine enforcement systems. The evaluation included both mean and median render times to ensure reliability of performance measurements.

CRNN Recognition Metrics

Character Error Rate (CER)

CER quantifies the rate of incorrectly recognized characters by computing the normalized Levenshtein distance between the predicted and ground truth sequences:

$$CER = \frac{Insertions + Deletions + Substitutions}{Number\ of\ characters\ in\ ground\ truth}$$

Lower CER values indicate fewer character-level errors, reflecting higher recognition precision. This metric is particularly important for understanding model performance in distinguishing visually similar characters.

Word Accuracy Rate (WAR)

WAR evaluates the percentage of license plates that were completely recognized without any character errors. It is defined as:

$$WAR = 1 - WER$$

Where WER is the Word Error Rate. A higher WAR indicates better end to end recognition performance, showing that the CRNN accurately identified full license plate strings, which is a critical requirement for traffic enforcement and record systems.

All metrics were computed on the designated test set to ensure unbiased evaluation. For fairness and reproducibility, each metric was calculated under consistent preprocessing conditions (normalized image inputs and uniform resolution). Performance results were reported as mean values with standard deviations where applicable. For the GAN metrics (FID, SSIM, PSNR), all computations followed standard evaluation protocols using 10,000 generated samples. The evaluation was conducted on a consistent hardware setup, and all metric implementations were based on standard libraries (PyTorch, NumPy, and SciPy)

Appendix K: Supplementary Results

K.1 Comparative Performance of ResNet Architectures

In the paper, the researchers reported ResNet18 trained from scratch as the optimal distortion classifier, achieving 96.2% test accuracy. This section provides a comprehensive comparison of several ResNet variants from ResNet18 up to ResNet50 and covers the trade-offs and impacts of pretraining on the performance of the models.

Table 7

Performance Metrics Across ResNet Variants

Model	Accuracy	Parameters
ResNet18 (Scratch)	96.2%	11.1M
ResNet18 (Pretrained)	95.2%	11.1M
ResNet34 (Scratch)	95.7%	21.3M
ResNet34 (Pretrained)	91.9%	21.3M
ResNet50 (Scratch)	95.2%	23.5M

The evaluation of ResNet architectures for distortion classification provides insights into model selection for LiPAD's lightweight design. The ResNet18 (Scratch) model emerged as the optimal solution, achieving 96.2%

accuracy with only 11.1M parameters, outperforming all other variants while maintaining low computational overhead. Notably, pretrained models consistently underperformed their scratch-trained counterparts. ResNet18 (Pretrained) achieved 95.2% accuracy, while ResNet34 (Pretrained) recorded the lowest accuracy of 91.9%, despite sharing the same architecture as their scratch equivalents. These results suggest that there is a domain mismatch between ImageNet's general features and the features and patterns required to classify distortions in LiPAD's target domain.

Deeper architectures also failed to deliver better accuracy despite being deeper models. ResNet34 (Scratch) reached 95.7% accuracy but required nearly double the parameters (21.3M) of ResNet18, representing only a marginal 0.5% improvement. Similarly, ResNet50 trained from scratch matched the pretrained ResNet18 in accuracy but demanded 23.5M parameters, double that of the ResNet18 model, without providing accuracy advantages. The results of the comparison show that increased depth and parameters do not inherently enhance performance for the distortion classification task, especially when computational efficiency is prioritized.

K.2 Supplementary Results for GAN Deblurring Models

Three GAN architectures were evaluated for distortion-specific deblurring: Autoencoder, Residual Attention U-Net, and Real-ESRGAN v4+. The Residual

Attention U-Net showed superior performance across all distortion types, while the alternatives exhibited underwhelming performance.

Table 8

Autoencoder Performance Metrics

Distortion Type	Generator Parameters	Discriminator Parameters	Mean PSNR	Mean SSIM	FID
Low Light	16.6M	140K	15.33	0.723	34.17
Horizontal Blur	16.6M	140K	19.04	0.756	39.84
Horizontal Blur	29M	6M	16.82	0.733	63.90

(a) (b) (c) (d)

Figure 47. Autoencoder results. (a) low-light input, (b) autoencoder output, (c) horizontal blur input, and (d) autoencoder output

The Autoencoder architecture showed moderate to promising quantitative metrics for horizontal blur but failed in perceptual quality. Despite moderate SSIM values, human visual inspection of the test set revealed otherwise; the outputs were either as distorted as the inputs or even more distorted. The 29M-parameter model even underperformed its shallow counterpart, indicating that increased complexity without architectural refinement exacerbates overfitting. For the low light results, it resulted in a decently performing model throughout the test set.

Table 9

Real-ESRGAN v4+ Performance

Model	Fine-tuning Iterations	Fine-tuning Time	Peak PSNR
Real-ESRGAN v4+	80,000	7hr 40m	21.83 @ 54,000 iter

(a) (b)

Figure 48. Real-ESRGAN v4+ results. (a) low-quality input, (b) Real-ESRGAN v4+ output

Real-ESRGAN v4+ achieved the highest PSNR but failed the human perception evaluation. During testing, the model merely enlarged blurry images without restoring the structural content of the images, producing outputs with magnified artifacts. The model's inability to recover text-specific features made it unsuitable for license-plate deblurring.

Appendix L: Ethical Approval

Appendix M: Reviewed Paper Annotations

Generative Adversarial Networks

Gong, H., Feng, Y., Zhang, Z., Hou, X., Liu, J., Huang, S., & Liu, H. (2024). A Dataset and Model for Realistic License Plate Deblurring. *ArXiv.org*. https://arxiv.org/abs/2404.13677

The paper introduced a method to improve the detection of motion-blurred license plates. It presented the License Plate Blur (LPBlur) dataset, which specifically captured two conditions of a license plate: a blurred and a sharp image. The paper also proposed the License Plate Deblurring Generative Adversarial Network (LPDGAN) that incorporates feature fusion, text reconstruction, and partition discriminator modules. The authors provided the topics with step-by-step techniques for readers to follow the proposed process of gathering the data and developing the model.

Sereethavekul, W., & Ekpanyapong, M. (2023). Adaptive lightweight license plate image recovery using deep learning based on generative adversarial network. *IEEE Access, 11*, 26667–26685. https://doi.org/10.1109/ACCESS.2023.3255641

This paper proposed how a GAN can be used for adaptive lightweight license plate image recovery in traffic monitoring systems. This paper also discussed the importance of recovering degraded license plate images, and it also introduced the License Plate Recovery GAN (LPRGAN) model, along with its supporting detection and validation systems. The LPRGAN model was demonstrated to show how it solves multiple degradation problems such as low bitrate, low light, and motion blur. More emphasis is put on the superior performance of LPRGAN for real-time processing on resource-constrained devices compared to conventional single-task restoration approaches such as CNNs and Transformers.

Kabiraj, A., Pal, D., Ganguly, D., Chatterjee, K., & Roy, S. (2022). Number plate recognition from enhanced super-resolution using generative adversarial network. *Multimedia Tools and Applications*. https://doi.org/10.1007/s11042-022-14018-0

This paper discussed how an Enhanced Super Resolution Generative Adversarial Network (ESRGAN) can help in improving number plate recognition from low-resolution images. In addition, the researchers also introduced the basic concept of ESRGAN and its modifications, such as the replacement of batch normalization with Residual in Residual Dense Blocks (RRDB). The rest of the paper is focused more about the workflow of combining ERSGAN-based image enhancement with an Optical Character Recognition (OCR) framework and how it performs compared to other methods like ProSR and SRGAN in terms of accuracy of character detection and recognition.

Pan, Y.-J., Tang, J., & Tjahjadi, T. (2024). LPSRGAN: Generative adversarial networks for super-resolution of license plate image. *Neurocomputing*, 127426. https://doi.org/10.1016/j.neucom.2024.127426

The study presented LPSRGAN, a new super-resolution algorithm based on GAN that enhances the recognition of low-resolution license plates by reconstructing them into high-resolution and readable images. The researchers developed a novel n-stage random combination degradation model to simulate realistic degradation from actual real-world images and it was optimized using perceptual OCR loss to preserve character clarity. The proposed system was tested on a custom LicensePlateDataset 10K and achieved a notable improvement in recognizing license plates and it was also shown in the paper that it can generalize to a real captured image.

Hamdi, A., Chan, Y. K., & Koo, V. C. (2021). A New Image Enhancement and Super Resolution technique for license plate recognition. *Heliyon*, *7*(11), e08341. https://doi.org/10.1016/j.heliyon.2021.e08341

This study proposed the Double Generative Adversarial Networks for Image Enhancement and Super Resolution (D_GAN_ESR) for improving current LPR technologies. Additionally, it discussed how current LPR technologies are affected by low-quality images and motion blurs from low-end surveillance and analogue cameras. The paper presents a proposed model which consists of two generators, one specialized in filtering and one for super-resolution, together with their corresponding discriminator. The results were presented in the latter part of the paper, which showed better accuracy and performance compared to the existing LPR systems.

Boby, A., & Brown, D. (2022). Improving Licence Plate Detection Using Generative Adversarial Networks. *Lecture Notes in Computer Science*, 588–601. https://doi.org/10.1007/978-3-031-04881-4_47

This paper examined how to overcome license plate detection in real-world scenarios where images are usually noisy, occluded, or poorly lit and discussed shortcomings of existing license plate recognition systems that typically require clear, high-quality images. As a solution to the presented limitations, the researchers proposed a deep learning solution, which is mainly based on two main technologies: You Only Look Once (YOLO) as an object detector and Generative Adversarial Networks (GANs), in particular ESRGAN, which is an image upscaling and reconstruction from a low-quality image. Furthermore, the training with different datasets was also discussed in this paper, aiming to enhance performance in different conditions.

Jadhav, A., & Aradhya, M. (2024). Clearview: Real-time traffic signal and license plate recognition. *World Journal of Advanced Engineering Technology and Sciences*, *13*(1), 100–111. https://doi.org/10.30574/wjaets.2024.13.1.0375

The study introduced Clearview, an Android app designed to improve Intelligent Transportation Systems (ITS) that has an ability to recognize license plates even with inclement weather conditions, which usually impair the visibility of traditional ITS. It also presented the technologies the researchers used to develop the system, including GAN, YOLOv4, SSD (Single Shot MultiBox Detector), and Tesseract OCR, all working together to achieve the functionality of Clearview.

Furthermore, the proposed application achieved over 90% accuracy in detection tasks and performed well on its purpose.

Cheng, Y., & Chen, P. (2023). Using Generative Adversarial Network Technology for Repairing Dynamically Blurred License Plates. *The Sixth International Symposium on Computer, Consumer and Control (IS3C 2023). Department and Graduate Institute of Information and Communication Engineering.* https://doi.org/10.1109/is3c57901.2023.00042

This study proposed the use of GAN to effectively deblur dynamically blurred license plate images better than traditional image processing methods. The proposed solution enhanced the accuracy of GAN by ensuring the consistency of the image size and only clear and readable license plates in the dataset, additionally pairing each license plate with their corresponding generated blurred plate version to ensure model accuracy. Furthermore, in the training data the images were processed using histogram equalization to ensure pixel value uniformity in images to improve GAN restoration. This proposed solution achieved a 95% restoration rate with a dataset of license plates with a blur of 85% or more.

Convolutional Neural Network

Wang, M. (2024). Unleashing the power of Convolutional Neural Networks in license plate recognition and beyond. *Applied and Computational Engineering*, *52*(1), 69–75. https://doi.org/10.54254/2755-2721/52/20241252

This paper explores the use of Convolutional Neural Networks (CNN) in license plate recognition systems. The paper proposed a tri-layered CNN architecture; Convolutional Layers, Pooling Layers, and Fully Connected Layers with use of Tensor flow, MATLAB and a STM32MP157 embedded chip for license plate recognition. This paper emphasizes the importance of CNN as an effective image recognition algorithm for license plate recognition, although it has its limitations, such as occlusion issues, illumination and angle variation, and diversity of license plates.

Mhatre, A., Sharma, P., & Maurya, A. (2023). Deep learning based automatic vehicle license plate recognition system for enhanced vehicle identification. *International Journal on Recent and Innovation Trends in Computing and Communication, 11(9)*, 10-20. https://doi.org/10.17762/ijritcc.v11i9.8112

This paper discussed the importance of automatic vehicle license plate recognition (AVLPR) systems in vehicle identification. It also discussed the limitations of traditional license plate recognition techniques. The paper presented the reasons for using deep learning and Convolutional Neural Networks (CNN) in AVLPR systems and introduced the Lightweight Parallel CNN model as their approach. This paper also included important phases of their approach, including license plate localization, segmentation, feature extraction, and classification.

Jin, X., Tang, R., Liu, L., & Wu, J. (2020). Vehicle license plate recognition for fog-haze environments. *IET Image Processing*, *15(6)*, 1273–1284.

https://doi.org/10.1049/ipr2.12103

This paper presented a method to improve vehicle license plate recognition in fog-haze environments. It also introduced the License Plate Recognition method for Fog-Haze environments (LPRFH). The paper also discussed an approach to dehaze images and detect license plates: Joint Further-dehazing and Region-extracting Model (JFRM), which is based on Object Detection Convolutional Neural Network (ODCNN), and Super-Resolution Convolutional Neural Network (SRCNN).

Ch.M. Shruthi, Vemullapalli Ramachandra Anirudh, Rao, P. B., Shankar, B. S., & Pandey, A. (2023). Deep Learning based Automated Image Deblurring. *E3S Web of Conferences*, *430*. https://doi.org/10.1051/e3sconf/202343001052

In this paper, image deblurring was discussed as a part of computer vision to restore sharp images from blurred ones. In addition, the paper also presented limitations due to camera motion and defocus blur in traditional methods and presented a solution to these limitations. In the paper, the proposed solution includes the use of deep learning such as CNNs and autoencoders. The researchers also found that the advancements in image deblurring can have a great impact on a number of fields, including medical imaging, forensics and surveillance.

Nascimento, V., Laroca, R., & Menotti, D. (2024). Super-Resolution Towards License Plate Recognition. *Proceedings of the 37th Thesis and*

Dissertation Contest, (pp. 78-87). Porto Alegre: SBC. doi:10.5753/ctd.2024.1999

The work discussed the use of an attention-based super resolution (SR) to aid license plate recognition from low-resolution surveillance video. It introduced a convolutional neural network composed of subpixel convolution layers and a Pixel Level Three Fold Attention Module (PLTFAM) to enhance image reconstruction, further supported by a perceptual loss function incorporating OCR features. The goal of the paper is to enhance the accuracy of OCR in forensic settings and validate the results through a series of experiments. Moreover, this paper also contributed to the field by offering their implementation and datasets publicly.

Sahil N, Ganesh, S., Krishnan, S., & Kalyani P. (2022). Image Deblurring for CCTV Captured Images of Fast Moving Vehicles. *Lecture Notes in Electrical Engineering*, 93–102. https://doi.org/10.1007/978-981-16-9089-1_8

This paper studied the problem of blurry CCTV footage from fast moving vehicles, a problem that makes it difficult to identify license plates in traffic surveillance. The limitations of license plate recognition using CCTV footage were presented in this paper, due to the problems of motion, camera shake and out of focus conditions that cause image clarity to degrade. In this paper, with these limitations, a system was introduced to restore distorted images using U-Net and ResNet, accurately locate the license plates using YOLOv4, and read the characters using a Convolutional Neural Network (CNN) to assist in real-world traffic monitoring.

Fang D. & Daisheng Z. (2024).Spatial correction and Deblurring fusion algorithm for vehicle
license plate images based on deep learning. *International Journal of Modeling, Simulation, and Scientific Computing 2024 15:05.* https://doi.org/10.1142/S1793962324500454

This study discussed the problem of motion blur and spatial distortion in recognizing license plates for ALPR systems. The paper also discussed the limitations of single-purpose image reconstruction algorithms, which often handle either correction or deblurring of images independently. As a solution to these limitations, the researchers presented the 4xSTN + DSC15 + DSK algorithm as a unified approach solution in correcting spatial distortions, as well as deblurring license plate numbers within a single model.

Li, L., Sang, N., Yan, L., & Gao, C. (2019). Motion-blur kernel size estimation via learning a convolutional neural network. *Pattern Recognition Letters*, *119*, 86–93. https://doi.org/10.1016/j.patrec.2017.08.017

This paper discussed the problem of estimating motion blur kernel size, which is a key parameter in restoring clear images from blurry images, and is usually done manually and inefficiently. It presented a way to automate this process using a convolutional neural network (CNN) to improve the performance of existing image deblurring techniques. This study also pointed out the difficulty of the trial and error approaches in the traditional deblurring and suggests a more systematic, data driven solution. The purpose of the paper is to enhance collaboration between technical algorithms and practical image restoration needs to make deblurring more effective and accessible.

Yasha, B. P., & Fadhillah, N. (2024). Enhanced Vehicle Identification: A Machine Learning Approach to Number Plate Recognition. *International Journal of Research Publication and Reviews*, 2501–2505. https://doi.org/10.55248/gengpi.5.0624.1502

This research looked into how traditional number plate recognition systems often fail when faced with various weather conditions and illuminations, thus making them less useful for managing traffic or helping law enforcement. In order to address this limitation, the researchers introduced a solution using machine learning to make vehicle identification sharper and more flexible. The proposed model relied heavily on Convolutional Neural Networks (CNNs), which are great at processing images and recognizing license plates more effectively. Toward the end, the paper compared the proposed approach against the conventional method of plate recognizing and resulted in a better performance across a range of conditions and metrics.

Shazan, A., & Amit Kr., J. (2022). Image Deblurring using CNN and Its Application in Vehicles Licence Plate Detection. *Jaypee University of Information Technology, Solan, H.P.* http://ir.juit.ac.in:8080/jspui//xmlui/handle/123456789/3676

The study proposed a solution to the problem of traditional intelligent traffic systems, where they often fail to recognize plate numbers due to blurred and noisy images. This paper presented the solution by developing a model using

CNNs and autoencoders to deblur, detect, and recognize license plate numbers. The approach resulted in high accuracy for plate extraction, character segmentation, and character recognition, even when validated through unseen and real-world data.

> Gómez, K., Nair, A., Abhinand, C. B., Jishnu, K. S., Rahul, K., & Binny, S. (2024). AI-Enhanced Camera Systems for Real-Time Identification of Expired Vehicle Pollution and Insurance via License Plate Recognition. *Deleted Journal*, *2*(12), 3585–3590. https://doi.org/10.47392/irjaem.2024.0528

The framework was introduced in the paper to automate the vehicle compliance monitoring system using license plate recognition and deep learning methods such as CNNs, YOLOv5, and OCR models. The problem that the paper wanted to solve is the inefficiency in identifying vehicles with expired pollution certificates and insurance in real time and reducing the manual methods. The proposed system also integrated edge computing and centralized databases and reached high accuracy and fast processing time per vehicle under optimal conditions.

> Rossi, G., Fontani, M., & Milani, S. (2021). *Neural Network for Denoising and Reading Degraded License Plates* (pp. 484–499). Springer, Cham. https://doi.org/10.1007/978-3-030-68780-9_39

The study presented a neural network-based system to improve the recognition of severely degraded license plates, which is a problem for law enforcement in interpreting low-quality images from CCTV or personal devices. The researchers presented a two-stage approach with CNNs: one network denoises the input image, and the second recognizes the characters. The system was tested on a synthetic dataset based on Italian license plates and validated with real-world data and achieved an average character classification accuracy of 93%.

Shim, S.-O., Imtiaz, R., Habibullah, S., & Alshdadi, A. A. (n.d.). Optimizing Deep Learning for Efficient and Noise-Robust License Plate Detection and Recognition. *International Journal of Advanced Computer Science and Applications*. https://doi.org/10.14569/ijacsa.2024.0150461

The study presented an optimized deep learning framework for license plate recognition designed for noisy and real-world environments. The proposed system used a Convolutional Autoencoder (CAE), InceptionResNetV2 architecture, and Bidirectional LSTM/CRNN for denoising, feature extraction, and character decoding, respectively. Datasets like Saudi license plates were tested on the proposed system, and the results were higher detection accuracy and recognition accuracy than methods mentioned in the related literature of the paper.

Wang, Z., Jiang, Y., Liu, J., Gong, S., Yao, J., & Jiang, F. (2021). Research and Implementation of Fast-LPRNet Algorithm for License Plate Recognition. *Journal of Electrical and Computer Engineering*, *2021*, 1–11. https://doi.org/10.1155/2021/8592216

The study developed a two-component system for real-time vehicle license plate recognition (VLPR) tailored to Bangla license plates in Bangladesh. YOLOv8 was implemented to detect plates from video streams and designed a custom Convolutional Neural Network (CNN) to identify characters, addressing the shortcomings of international VLPR systems for Bangla script. Using a substantial image dataset, they worked to improve applications such as traffic monitoring, toll collection, parking management, and security across Bangladesh. The researchers compared their approach with previous methods, examined challenges posed by Bangla's complex script and environmental variables, and suggested future enhancements, including the integration of diverse datasets and exploration of advanced neural architectures. The system was viewed as a foundation for broader practical use, particularly in the context of smart city development.

Bappy, Md. H., & Talukder, K. H. (2024). Real-Time Vehicle License Plate Recognition (VLPR) Using Deep CNN. *International Journal For Multidisciplinary Research*, *6*(3). https://doi.org/10.36948/ijfmr.2024.v06i03.20897

This paper introduced a two-component Vehicle License Plate Recognition (VLPR) system specifically designed for Bangla license plates, using YOLOv8 for real-time detection and a custom Convolutional Neural Network (CNN) for character recognition. The system was trained with a dataset of more than 33,000 images and attained a detection rate of 97.30% and a character recognition rate of 98.10%. The work tackled the specific complexities of Bangla script and environmental changes, surpassing conventional techniques and previous CNN-based techniques for Bangladeshi number plates, and made substantial contributions to automatic traffic surveillance by providing high accuracy and real-time processing. It had potential use in toll collection, security, and traffic management. The authors also suggested future improvements, including merging various datasets and novel architectures like Transformers, to further enhance robustness and usability.

Khan, S., Vohra, S., Siddique, S. A., Abro, A. A., & Ebrahim, M. (2024). *A Computer Vision-Based Vehicle Detection System Leveraging Deep Learning*. 1–7. https://doi.org/10.1109/khi-htc60760.2024.10482163

This study developed an integrated system that combined computer vision and deep learning to enhance vehicle detection and number plate recognition for traffic surveillance and management. TThe system consists of two main modules. One applies deep learning algorithms, such as convolutional neural networks (CNNs) and object detection models, to identify and track vehicles in real-time from images or video, even in difficult lighting and weather conditions. The other combines optical character recognition (OCR) with deep learning to extract alphanumeric characters from detected license plates, making it adaptable to various plate designs and locations. The researchers tested the system using real-world scenarios and benchmark datasets, aiming to provide a scalable, customizable solution for intelligent transportation applications like congestion analysis and safety enforcement. They highlighted the system's potential to improve traffic management and security, positioning it as a step forward in innovative transportation technologies.

Brillantes, A. K., Billones, C. D., Jr., Amon, M. C., Cero, C., Jose, J. A. C., Billones, R. K. C., & Dadios, E. (2019). Philippine License Plate Detection and Classification using Faster R-CNN and Feature Pyramid Network.

2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM). IEEE. https://doi.org/10.1109/HNICEM48295.2019.9072930

This study developed an Automatic License Plate Recognition (ALPR) system for Philippine license plates using Faster R-CNN, a CNN-based model, combined with Feature Pyramid Network (FPN) and ResNet-101. The system achieved 82.6% precision in detecting Philippine plates, addressing challenges in vehicle identification for law enforcement and traffic management. The use of Faster R-CNN makes it relevant to the study, as it demonstrates CNN effectiveness in Philippine contexts. However, its performance could be improved with newer models like YOLO, and deblurring techniques could enhance its applicability to fast-moving vehicles in resource-constrained settings.

Amon, M. C. E., Brillantes, A. K. M., Billones, C. D., Jr., Jose, J. A., Sybingco, E., Dadios, E., Fillone, A., Lim, L. G., & Bandala, A. (2019). Philippine License Plate Character Recognition using Faster R-CNN with InceptionV2. *2019 IEEE 11th International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment, and Management (HNICEM)*. IEEE. https://doi.org/10.1109/HNICEM48295.2019.9072930

This study focused on character recognition of Philippine license plates using Faster R-CNN with InceptionV2, a CNN-based architecture, achieving 83.895% accuracy. It addressed challenges posed by variations in Philippine plate designs (1981, 2003, 2014 series) and environmental factors, making it highly relevant for traffic management and law enforcement in the Philippines. The CNN approach aligns with the study’s focus on AI-powered recognition, though integrating deblurring techniques could improve its performance for blurred images from fast-moving vehicles in resource-constrained environments.

Jose, J. A. C., Billones, C. D., Jr., Brillantes, A. K. M., Billones, R. K. C., Sybingco, E., Dadios, E. P., Fillone, A. M., & Lim, L. A. G. (2021). Artificial Intelligence Software Application for Contactless Traffic Violation Apprehension in the Philippines. *Journal of Advanced Computational Intelligence and Intelligent Informatics, 25*(4), 410–415. https://doi.org/10.20965/jaciii.2021.p0410

This study developed a contactless traffic violation apprehension system for Metro Manila using Faster R-CNN with Inception V2, a CNN-based model, to detect number coding violations. It automated law enforcement processes, improving traffic management in the Philippines. The use of Faster R-CNN aligns with the study’s focus on AI-powered LPR, though the lack of performance metrics suggests a need for further evaluation. Adding deblurring methods could enhance its effectiveness for fast-moving vehicles in resource-constrained environments.

GAN & CNN Hybrid

Kukreja, V., Kumar, D., Kaur, A., Geetanjali, & Sakshi. (2020). GAN-based synthetic data augmentation for increased CNN performance in Vehicle Number Plate Recognition. *2020 4th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*. https://doi.org/10.1109/iceca49313.2020.9297625

This paper dealt with the problem of parking management by presenting the issue of identifying vehicle number plates in automated systems. It analyzed how poor image quality and noise often led to errors in recognizing license plates, which in turn impacts parking efficiency and security. An automatic vehicle number plate recognition (AVNPR) system was introduced to simplify parking and reduce human involvement in the study. The paper presented a novel implementation of two hybrid models: Generative Adversarial Networks (GAN) to improve image quality and Convolutional Neural Networks (CNN) to accurately recognize plates. The approach proposed resulted in an improved performance in real-world scenarios such as parking lots and traffic enforcement.

Other Recovery Methods

AlHalawani, S., Benjdira, B., Ammar, A., Koubaa, A., & Ali, A. M. (2024). DiffPlate: A Diffusion Model for Super-Resolution of License Plate Images. *Electronics*, 13(13), 2670. https://doi.org/10.3390/electronics13132670

This study introduced a novel Diffusion Model called DiffPlate that is specifically designed for license plate super-resolution. The proposed approach intends to improve low-resolution images of license plates obtained from surveillance cameras for practical traffic applications. The study used Diffusion Models and applied U-Net architecture as the main technology to achieve the researcher's goal. The paper also discusses the limitations of the proposed approach, DiffPlate, which requires heavy computation power and hence affects its real-world usability.

License Plate Detection and Character Detection

Balia, R., Barra, S., Carta, S., Fenu, G., Podda, A. S., & Sansoni, N. (2021). *A Deep Learning* (pp. 211–226). *Springer, Cham.*

https://doi.org/10.1007/978-3-030-86970-0_16*Solution for Integrated Traffic Control Through Automatic License Plate Recognition*

This study proposed a traffic control using Automatic License Plate Recognition (ALPR) solution for traffic management in Smart Cities using deep learning. The paper suggests the use of bullet cameras to capture license plates which were then processed in the module. There are two main components: an ALPR module for capturing license plates and risk estimation module using the Faster R-CNN model, which was trained using synthetic video data to predict traffic anomalies, while the ALPR applies YOLO and Tesseract to capture vehicle plates efficiently. This solution demonstrates the power of applying deep learning in real-world traffic enforcement and management in smart urban cities.

Jain, L., & Vashisht, G. (2024). Automatic License Plate Recognition with CNN Method in Machine Learning. *International Journal For Multidisciplinary Research*. https://doi.org/10.36948/ijfmr.2024.v06i01.11930

This study discussed the use of deep learning techniques in tracking individual vehicles. To tackle this issue, the paper proposed the use of Convolutional Neural Network (CNN) in object detection for license plates and Simple OCR for character recognition. In preprocessing, the images were converted into grayscale to reduce the variety of data in each image. While in the detection process, OpenCV find Contours was used to spot the region of interest. For the character recognition, Tesseract Optical Character Recognition (OCR) was used to decipher the text. This paper concludes that this model can be used for foreign licenses although the accuracy will not be as accurate for Indian Licence Plates, considering their diverse format.

Ali, Q. A. (2024). An Efficient System for Detecting Multiple Traffic Violations and Recognizing License Plates Using Video Processing and Deep Learning. *International Journal of Electrical and Electronic Engineering and Telecommunications*, *13*(5), 406–414. https://doi.org/10.18178/ijeetc.13.5.406-414

This study looked into deep learning solutions in reducing traffic violations. Proposed to develop a system that automatically detects traffic violations and license plates of moving vehicles using technologies such as You Only Look Once (YOLO) detection algorithm that used Convolutional Recurrent Neural Networks (CRNN) algorithm is identifying license plates, wherein each license plates are recognized through the use of Optical Character Recognition (OCR). The proposed system demonstrated an applicable real-time detection for traffic violations with a 98% accuracy, on the other hand it accurately recognized license plates with a 98% success rate.

Nirmala, B., Nithya, S., Vidhiya, R., Sunalini, K. K., Kumar, B. H., & Varadharajan, B. (2023). Intelligent system for vehicles license plate recognition using a hybrid model of GAN, CNN, and ELM. Proceedings of the 2023 2nd International Conference for Innovation in Technology (INOCON), Bangalore, India, 1-6. https://doi.org/10.1109/INOCON57975.2023.10101051

This study suggested the need for license plate recognition systems to be improved due to the increasing number of vehicles. The proposed system is composed of Generative Adversarial Networks (GAN) with Convolutional Neural

Networks (CNN) and an Extreme Learning Machine (ELM), wherein GAN was used as a discriminator and to improve the ability of the model to differentiate valid and invalid features to help the CNN which was used for feature extraction in recognizing license plate and with the use of ELM, the system would perform classification faster and more efficiently as it reduced training time. This paper concluded with a 98.9% success rate in recognizing license plates.

Patakamudi, S., Tejaswi, D. S., Khan, M. A., Saishree, M., Rachapudi, V. B., & Anguraj, D. K. (2024). Real-time number plate detection using AI and ML. 1–6. https://doi.org/10.56294/gr202437

This study proposed a real-time license plate verification system that rapidly identifies vehicle plate numbers through the combination of artificial intelligence (AI) and machine learning (ML) techniques, wherein the system used Region-based Convolutional Neural Networks (RCNN) and RCNN algorithms for real-time detection of license plates. The advanced RCNN replaced the selective search algorithm with a Regional Proposal Network (RPN) that generated region proposals directly from the convolutional feature maps. The study concluded that the results significantly advanced the study for license plate recognition in the field of intelligent transportation systems, as the system had a 95% success rate with a minimal processing time for 110-115 ms.

Mahalakshmi, S., & Dheeba, J. (2024). Robust Approach of Automatic Number Plate Recognition System using Deep CNN. *Journal of Machine and Computing*, 853–860. https://doi.org/10.53759/7669/jmc202404079

The study proposed an effective method in recognizing license plates from digital images, with a focus on high accurate recognition. To achieve this, the proposed solution was to use Deep Convolutional Neural Networks (DCNN) to enhance precision, recall, and processing speed while reducing error rates in the automatic number plate recognition (ANPR). Additionally, the training dataset was 100 images of vehicles with their plate number, but the input data were gray-scaled beforehand to improve the accuracy of the model. The paper concluded with an astonishing 99% accuracy in detection and 93% success rate for recognition of plate numbers.

Convolutional Recurrent Neural Network

Liu, Y., Jin, L., Lai, S., & Yang, X. (2023). License plate recognition system in unconstrained scenes via a new image correction scheme and improved CRNN. *Journal of Electronic Imaging*, *32*(5), 053033. https://doi.org/10.1117/1.JEI.32.5.053033

This study developed a license plate recognition system for unconstrained scenes, addressing challenges like large-angle deflections and blur to enhance real-time traffic surveillance. The system utilized YOLOv5l for detection, AFF-Net for segmentation and angle correction, perspective transformation, and an improved SC-CRNN with channel attention for recognition. Transfer learning was applied using the CCPD dataset, and a custom CTPSD dataset of 5,500 images was used for testing. The proposed system achieved a detection precision of 98.35% and a recognition accuracy of 99.16%, demonstrating robustness despite limited data. This work is highly relevant to my LiPAD pipeline (YOLO → GAN → Angle Correction → CRNN), as it incorporates similar components like YOLO for detection, angle correction via AFF-Net, and an enhanced CRNN for recognition, offering insights into handling unconstrained environments like those in the Philippines.

Xu, F., Chen, C., Shang, Z., Peng, Y., & Li, X. (2024). A CRNN-based method for Chinese ship license plate recognition. *IET Image Processing*, *18*(1), 298–311. https://doi.org/10.1049/ipr2.12949

This study proposed a CRNN-based method for recognizing Chinese ship license plates (SLPs) in marine environments, tackling challenges such as fog, tilt, and low resolution. The system employed an improved Dark Channel Prior (DCP) for defogging, Hough Transform (HT) for tilt correction, data augmentation, Adaptive Histogram Equalization (AHE), Image Edge Padding (IEP), CRNN for text recognition, and Edit-Distance (ED) for correction, using a dataset of 4,759 SLP images. The method achieved a recognition accuracy of 92.93%, outperforming alternatives like CnOCR (73.74%), paddleOCR (74.53%), and DenseNet (79.80%). This study is relevant to my LiPAD pipeline, particularly for its use of CRNN for recognition and HT for angle correction, which aligns with my system's angle correction and recognition stages. The defogging and image enhancement techniques could also inform my GAN-based preprocessing step for handling degraded Philippine CCTV images.

Sun, H., Fu, M., Abdussalam, A., Huang, Z., Sun, S., & Wang, W. (2019). License plate detection and recognition based on the YOLO detector and CRNN-12. In S. Sun (Ed.), *Signal and information processing, networking and computers: Proceedings of the 4th International Conference on Signal and Information Processing, Networking and Computers (ICSINC)* (pp. 66–74). Springer. https://doi.org/10.1007/978-981-13-1733-0_9

This study developed an end-to-end system for Chinese car license plate detection and recognition in complex environments, addressing challenges like uneven lighting and tilt. It utilized YOLOv2 and YOLOv3 for detection and CRNN-12 (a 12-layer CNN + 2-layer bidirectional GRU + CTC loss) for recognition, trained on datasets of 7,386 images for detection and 71,790 for recognition. The system achieved a detection IOU of 0.8406 with YOLOv3 and a recognition accuracy of 98.86% with CRNN-12, with real-time speeds (0.021s for detection, 0.052s for recognition). This work is directly relevant to my LiPAD pipeline, as it uses YOLO for detection and CRNN for recognition, mirroring my system's structure. The high accuracy and speed provide a benchmark for my system, though I need to incorporate angle correction and GAN-based preprocessing to handle Philippine-specific challenges like blur and shadows.

Tee, K. F. (2019). *License Plate Recognition Using Convolutional recurrent Neural Network* (Doctoral dissertation, UTAR).

This study developed a lightweight, segmentation-free Automatic License Plate Recognition (ALPR) system for Malaysian license plates, aiming to improve on Soo's (2017) CRNN model by making it end-to-end trainable, smaller, and capable of recognizing two-row plates. The system used EAST for text detection and a custom CRNN (7-layer CNN + 2 bidirectional LSTMs + CTC loss) for recognition, trained on 25,720 images and tested on LPR44 (409 samples), LPR45 (553 samples), and Open Environment Dataset (2,533 samples). The proposed CRNN achieved 99.27% accuracy on LPR44, 93.49% on LPR45, and 78.80% on the Open Environment Dataset, with a prediction time of less than 1 second and a smaller architecture (5.5M parameters vs. 1.9B in Soo's model). It successfully handled two-row plates but struggled with lowercase letters and shadows. This study is highly relevant to my LiPAD pipeline, as its lightweight CRNN design and high accuracy inform my recognition stage, while its challenges with shadows highlight the importance of my GAN-based preprocessing step for Philippine CCTV images.

Bensouilah, M., Zennir, M. N., & Taffar, M. (2021). An ALPR system-based deep networks for the detection and recognition. *ICPRAM 2021 - 10th International Conference on Pattern Recognition Applications and Methods*, 204–210.

This study developed an end-to-end ALPR system for Algerian license plates, addressing the challenge of non-standardized plate designs by avoiding segmentation. The system employed YOLOv3 (with Darknet-53 and MobileNet backbones) for detection and an improved CRNN for recognition, using a VGG-12 CNN for feature extraction, two bidirectional GRU layers (instead of LSTM) for sequence labeling, and CTC loss. The LPA Dataset (2019) included 3,408 images for detection and 2,179 license plates for recognition, collected in Draria, Algeria, and augmented with online images. The system achieved a detection precision of 99% and recall of 97% with YOLOv3 (0.050s/image), while MobileNet-YOLOv3 was faster at 0.032s/image. The CRNN with BGRU achieved a recognition accuracy of 92% (CER: 0.99%, WAR: 7.94%), outperforming baseline models like the original CRNN and Wu-DenseNet. This study is highly relevant to my LiPAD pipeline, as it uses YOLO for detection and CRNN for recognition, aligning with my system's structure. The lightweight MobileNet-YOLOv3 option supports my focus on efficiency in resource-constrained Philippine settings, and the CRNN's high accuracy informs my recognition stage, though I need to incorporate my GAN-based deblurring step to handle motion blur and other degradations specific to Philippine CCTV images.

Reviews of different methods in ALPR

Khan M. M., Ilyas, M., Khan I. R., Alshomrani S., & Rahardja S. (2023). License Plate Recognition Methods Employing Neural Networks. *IEEE Access*, *11*, 73613–73646. https://doi.org/10.1109/access.2023.3254365

The paper reviewed state-of-the-art deep neural network methods for LPR systems and compared them with the performance of traditional feature-based methods. The new methods are composed of CNNs, residual recurrent networks (RNNs), and long-short-term-memory (LSTM) networks. The study also discussed the limitations and strengths of the reviewed DNN methods. The performance of the different DNNs was measured on different datasets, and it was shown that CNNs and LSTMs achieved finer character recognition, while YOLO is faster in processing time.

Shashirangana, J., Padmasiri, H., Meedeniya, D., & Perera, C. (2020). Automated License Plate Recognition: A Survey on Methods and Techniques. *IEEE Access*, *9*, 11203–11225. https://doi.org/10.1109/access.2020.3047929

This paper provided a comprehensive review of the methods and techniques used in ALPR systems, ranging from the paper's consideration of traditional computer vision techniques to modern deep-learning techniques. The researchers analyzed over 100 studies from the past two decades, focusing on both multi-stage and single-stage ALPR approaches. The survey also discussed the shift from traditional computer vision techniques to deep learning-based techniques and compared their assessed accuracy and generalization metrics. In the latter part of the paper, requirements for practical ALPR benchmarks to guide future research and development were proposed.

Sajol, H. C., Santos, J. C., Agustin, L. M., Zafra, J. J., & Teogangco, M. (2022). OCULAR: Object Detecting CCTV using a Low-Cost Artificial Intelligence System with Real-Time Analysis. *AIP Conference Proceedings, 2502*(1), 050007. https://doi.org/10.1063/5.0109030

This study developed a low-cost ALPR system for a Philippine university using YOLO, a CNN-based model, achieving 95.33% accuracy in detecting Philippine plates. It enhanced security by automating plate detection, addressing manual inefficiencies. The system's low-cost nature and high accuracy make it highly relevant to the study's resource-constrained environments. Including deblurring techniques and higher-resolution cameras could further improve its performance for real-time traffic regulation in the Philippines.

Reyes, R. C., Cepe, E. M., Guerrero, N. D., Sevilla, R. V., & Montesines, D. L. (2021). Deep Inference Localization Approach of License Plate Recognition: A 2014 Series Philippine Vehicle License Plate. *2021 International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, 257–259. IEEE. https://doi.org/10.1109/ICCIKE51210.2021.9410765

This study developed a license plate detection system for the 2014 series Philippine vehicle license plates using YOLOv3, a CNN-based model, achieving 96.21% mAP. It addressed challenges of multiple plate versions in the Philippines, supporting applications like traffic enforcement and toll collection. The high accuracy of YOLOv3 makes it relevant to the study, demonstrating CNN effectiveness in Philippine LPR. However, its limited dataset size suggests that larger datasets and deblurring methods could enhance its robustness for real-world, resource-constrained scenarios.

Coching, J. K., Valenzuela, I. J. C., Fillone, A. M., Yeung, S. G., Concepcion, R. S., II, Billones, R. K. C., & Dadios, E. P. (2024). Data Modeling and Integration for a Parking Management System with License Plate Recognition. *ICO 2023, LNNS 1169*, 351–360. Springer Nature

Switzerland AG. https://doi.org/10.1007/978-3-031-73224-6_34

This study proposed a YOLOR-based License Plate Recognition (LPR) system for a Parking Management System in the Philippines, achieving 76.41% mAP@0.5 for Philippine plates. YOLOR, a CNN-based model, was used for detection, combined with EasyOCR for character recognition. The system addressed unique Philippine plate variations, enhancing smart parking applications. Its relevance to the study lies in its CNN application in a Philippine context, though extended training and deblurring techniques could improve accuracy for resource-constrained traffic regulation scenarios.

Appendix N: Communication

Consultation forms

ANGELES UNIVERSITY FOUNDATION
Angeles City

College of Computer Studies
School College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Alfonso, Aljunalei; Cruz, Jansen; Laylo, Wrenz Ivan; Salem, Jamaica
Course / Year / Section: BSCS 3-A
Date: April 02, 2025

Reason for Providing Academic Counseling

✓ Topic consultation
✓ Resources (Data Sets, Interview)
✓ Restrictions
✓ Features of data sets

Action Taken by the Faculty:

- ☐ For follow-up (When? Time?) ______
- ☐ For remedial class (When? Time?) ______
- ☐ For referral to GCC (When? Time?) ______
- ✓ Others, please specify: Thesis Consultation

Melissa M. Pantig — 04/02/2025
Signature of Faculty above Printed Name — Date

NOTED:
DR. LILIBETH TIMBOL-CUISON — 04/08/2025
Dean, AUF-CCS
Dean of Faculty Concerned — Date

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

AUF-FORM OVPAA-41
JUNE 02, 2014, REV.01

ANGELES UNIVERSITY FOUNDATION
Angeles City

College of Computer Studies
School College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Alfonso, Aljunalei; Cruz, Jansen; Laylo, Wrenz Ivan; Salem, Jamaica
Course / Year / Section: BSCS 3-A
Date: April 10, 2025

Reason for Providing Academic Counseling

Letter of Intent
Chapter 1 review
Chapter 2 review

Action Taken by the Faculty:

- ☐ For follow-up (When? Time?) ____________
- ☐ For remedial class (When? Time?) ____________
- ☐ For referral to GCC (When? Time?) ____________
- ☑ Others, please specify: Thesis Consultation

Melissa M. Pantig — 4/10/2025
Signature of Faculty above Printed Name — Date

NOTED:

DR. LILIBETH TIMBOL-CUISON
DEAN, CCS
Dean of Faculty Concerned — 4/10/25
Date

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

AUF-FORM-OVPAA-41
JUNE 02, 2014, REV.01

ANGELES UNIVERSITY FOUNDATION
Angeles City

College of Computer Studies
School College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Cruz, Jansen C.; Alfonso, Aljuwaki; Laylo, Wrenz Ivan; Salem, Jimmica
Course / Year / Section: BSCS 3-A
Date: April 12, 2025

Reason for Providing Academic Counseling

✓ Chapter 1, 2, and 3 Review

Action Taken by the Faculty:

- ☐ For follow-up (When? Time?) ______
- ☐ For remedial class (When? Time?) ______
- ☐ For referral to GCC (When? Time?) ______
- ☐ Others, please specify: ______

Melissa M. Pauling — 04/12/25
Signature of Faculty above Printed Name — Date

NOTED:
DR. LILIBETH TIMBOL-CUISON
Dean, AUF-CCS
Dean of Faculty Concerned — 2 1 APR 2025
Date

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

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JUNE 02, 2014, REV.01

ANGELES UNIVERSITY FOUNDATION
Angeles City

COLLEGE OF COMPUTER STUDIES
School College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Alfonso, Aljunalei M.
Jansen Cruz
Jamaica Salem
Wrenz Ivan Laylo

Course / Year / Section: BSCS 3-A

Date: April 20, 2025

Reason for Providing Academic Counseling

Chapter 3 Review

Action Taken by the Faculty:

- ☐ For follow-up (When? Time?) ____________
- ☐ For remedial class (When? Time?) ____________
- ☐ For referral to GCC (When? Time?) ____________
- ☐ Others, please specify: ____________

Melissa M. Pantig
Signature of Faculty above Printed Name

04/20/2025
Date

NOTED:

DR. LILIBETH TIMBOL-CUISON
Dean, AUF-CCS
Dean of Faculty Concerned

2 1 APR 2025
Date

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

AUF-FORM-OVPAA-41
JUNE 02, 2014, REV.01

ANGELES UNIVERSITY FOUNDATION
Angeles City

College of Computer Studies
School College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Alfonso, Ajjunalei; Cruz, Jansen; Laylo, Wrenz Ivan; Salem, Jamaica
Course / Year / Section: BSCS 3-A
Date: May 27, 2025

Reason for Providing Academic Counseling

Revisions on ODRF

Additional recommendations on system flowchart

Action Taken by the Faculty:

- ☐ For follow-up (When? Time?) ____
- ☐ For remedial class (When? Time?) ____
- ☐ For referral to GCC (When? Time?) ____
- ☑ Others, please specify: thesis consultation

Melissa A. Pantig
Signature of Faculty above Printed Name

05/27/2025
Date

NOTED:

~~DR. LILIBETH TIMBOL-CUISON~~
Dean ~~of~~ Faculty Concerned

05/27/2025
Date

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

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JUNE 02, 2014, REV.01

ANGELES UNIVERSITY FOUNDATION
Angeles City

CCS
School College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Alfonso, Aljundei; Cruz, Jansen; Laylo, Wenz Ivan; Salem, Jamaica
Course / Year / Section: BSCS 4-A
Date: August 04, 2025

Reason for Providing Academic Counseling

Rechecking of Chapter 4 draft
Consultation on write-up of Models in Chapter 4

Action Taken by the Faculty:

- ☐ For follow-up (When? Time?) ______
- ☐ For remedial class (When? Time?) ______
- ☐ For referral to GCC (When? Time?) ______
- ☐ Others, please specify: ______

Signature of Faculty above Printed Name — Date: 8/4/2025

NOTED:
DR. LILYBETH TIMBOL-CUISON
Dean of Faculty Concerned — Date: 8/11/25

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

AUF-FORM-OVPAA-41
JUNE 02, 2014, REV 01

ANGELES UNIVERSITY FOUNDATION
Angeles City

CCS
School College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Alfonso, Aljunaki; Cruz, Jansen; Laylo, Wrenz Ivan; Salem, Jamaica
Course / Year / Section: BSCS 4-A
Date: August 14, 2025

Reason for Providing Academic Counseling
Consultation about the WebApp

Action Taken by the Faculty:
- ☐ For follow-up (When? Time?) ____________
- ☐ For remedial class (When? Time?) ____________
- ☐ For referral to GCC (When? Time?) ____________
- ☐ Others, please specify: ____________

Melissa MS Pantig
Signature of Faculty above Printed Name — Date

NOTED:
DR. LILIBETH TIMBOL-CUISON
Dean, AUF-CCS
Dean of Faculty Concerned — Date 08/08/2025

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

AUF-FORM-OVPAA-41
JUNE 02, 2014, REV 01

ANGELES UNIVERSITY FOUNDATION
Angeles City

CCS
School College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Alfonso, Ajumalei; Cruz, Jansen; Layla, Wrenz Ivan; Sulem, Jamaica
Course / Year / Section: BSCS 4A
Date: August 28, 2025

Reason for Providing Academic Counseling

Invitation for External Panel
Status of Website
Chapter I Consultation

Action Taken by the Faculty:

- ☐ For follow-up (When? Time?) ______
- ☐ For remedial class (When? Time?) ______
- ☐ For referral to GCC (When? Time?) ______
- ☐ Others, please specify: ______

Melissa M. Pantig
Signature of Faculty above Printed Name

Date

NOTED:
DR. LILIBETH TIMBOL-CLISON
Dean, AUF-CCS
Dean of Faculty Concerned

08/28/2025
Date

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

AUF-FORM-OVPAA-41
JUNE 02, 2014, REV 01

ANGELES UNIVERSITY FOUNDATION
Angeles City

CCS
School/College

ACADEMIC ADVISING / CONSULTATION FORM

Name of Student: Alfonso Almodal, Cruz Janen, Lanzo Vicente, Salem Jamaica
Course / Year / Section: BSCS 4A
Date: 09-15-2025

Reason for Providing Academic Counseling

Conference paper review
Presentation details
Title update

Action Taken by the Faculty:

- ☐ For follow-up (When? Time?) ____________
- ☐ For remedial class (When? Time?) ____________
- ☐ For referral to GCC (When? Time?) ____________
- ☐ Others, please specify: ____________

Melissa M. Fontz
Signature of Faculty above Printed Name

9/15/2025
Date

NOTED:
DR. LUBETH TIMBOL-CUISON
Dean, AUF-CCS
Dean of Faculty Concerned

9/15/25
Date

(to be accomplished in triplicate/distributed appropriately: Student, Faculty, Office referred to)

AUF-FORM-OVPAA-41
JUNE 02, 2014, REV 01

Letter of Intent

ANGELES UNIVERSITY FOUNDATION
Angeles City

College of Computer Studies

April 11, 2025

PLTCOL DARYL O. GONZALES
Chief TEU,
Angeles City Police Office
New City Hall Compound, Brgy. Pulung Maragul, Angeles City

Subject: Request for Interview Appointment on Traffic Management and Vehicle Identification

Dear Sir:

Greetings!

We are third-year students from the **College of Computer Studies at Angeles University Foundation**, currently pursuing **Bachelor of Science in Computer Science (BSCS)**. We are conducting a research study titled **"LiPAD: AI-Powered Philippine License Plate Deblurring and Recognition for Effective Traffic Regulation and Law Enforcement in Resource-Constrained Environments"**

As part of our study, we would like to request an appointment with you or a representative from your office to help us gain insight into how traffic enforcement is managed in Angeles City, specifically in situations where license plates are unclear or blurred due to motion or poor image quality. We are interested in how these challenges affect vehicle identification and violation processing, what technologies or practices are currently in place to address them, and how deblurring technology like ours could support and enhance license plate recognition in actual traffic scenarios.

We also hope to share with you the goal of our project, which is to improve the clarity of blurred license plates using modern AI technology and support law enforcement efforts. Additionally, we would be grateful for any insights or suggestions you may have that could further strengthen our study.

We greatly appreciate the opportunity to speak with you at your most convenient time. Thank you very much for considering our request.

Respectfully,

Alfonso, Aljunalei M. | alfonso.aljunalei@auf.edu.ph | **+63 945 185 2002**
Cruz, Jansen C. | cruz.jansenc@auf.edu.ph | **+63 921 723 8199**
Laylo, Wrenz Ivan M. | laylo.wrenzivan@auf.edu.ph | **+63 956 593 5944**
Salem, Jamaica E. | salem.jamaica@auf.edu.ph | **+63 999 854 1937**

Pcpl Gerald Dungca

Noted by:

MS. MELISSA M. PANTIG, MCS
BSCS Program Chair
College of Computer Studies
Angeles University Foundation

PSMS Jerick Det B Jimenez
04/11/2025 2:50 p.m

Technical Panel Invitation Letter

ANGELES UNIVERSITY FOUNDATION
Angeles City
COLLEGE OF COMPUTER STUDIES

October 21, 2025

Mr. Arn Lagazo
Command Center Supervisor
City Government of Angeles City, Pampanga
City Hall Building, Pulung Maragul, Angeles City

Dear **Mr Lagazo,**

Greetings in Peace!

We, the undersigned, are fourth-year students taking up Bachelor of Science in Computer Science in the College of Computer Studies at the Angeles University Foundation. We are writing to formally invite you to serve as an external panelist for our upcoming thesis defense.

Our thesis, titled "LiPAD: Lightweight AI-Powered Philippine License Plate Deblurring and Recognition using Convolutional Neural Network, Convolutional with Recurrent Neural Network, and Generative Adversarial Networks Models", explores the development of LiPAD (License Plate Advanced Deblurring), a lightweight, self-aware deep-learning system designed to restore poor-quality Philippine vehicle license plate images degraded by low resolution blur, vertical-blur, horizontal-blur, and low-light blur, thus providing a viable and efficient solution for assisting the local traffic enforcement in acquiring clear license plates, we believe your insights and feedback would be incredibly valuable to the discussion and evaluation of our work.

The defense is scheduled to take place on October 28 at 3PM in the Research Lab of Emmanuel Y. Angeles Center for Learning and Innovation Building. Joining us and contributing to this significant milestone in our academic journey would be an honor.

Please let us know if you are available to participate. We are happy to provide any additional information or materials you may need in advance. Thank you for considering our invitation, and we look forward to the possibility of your participation.

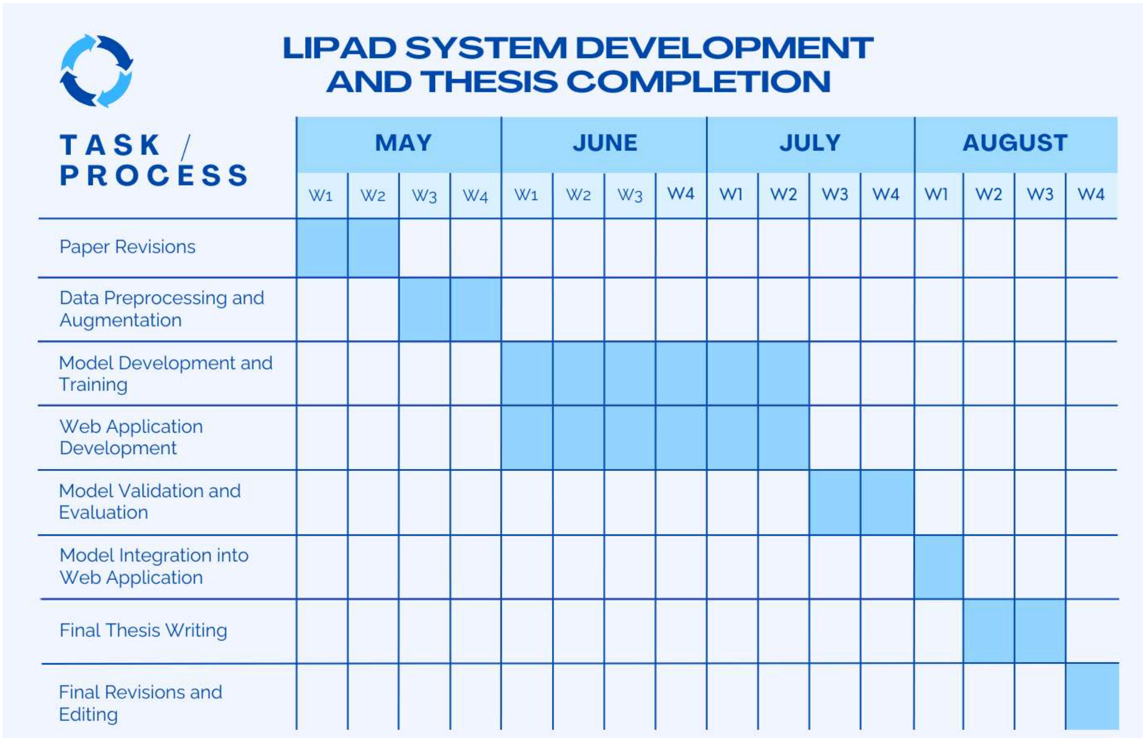
Warm regards,

Alfonso, Aljunalei M.
Cruz, Jansen C.
Laylo, Wrenz Ivan M.
Salem, Jamaica E.

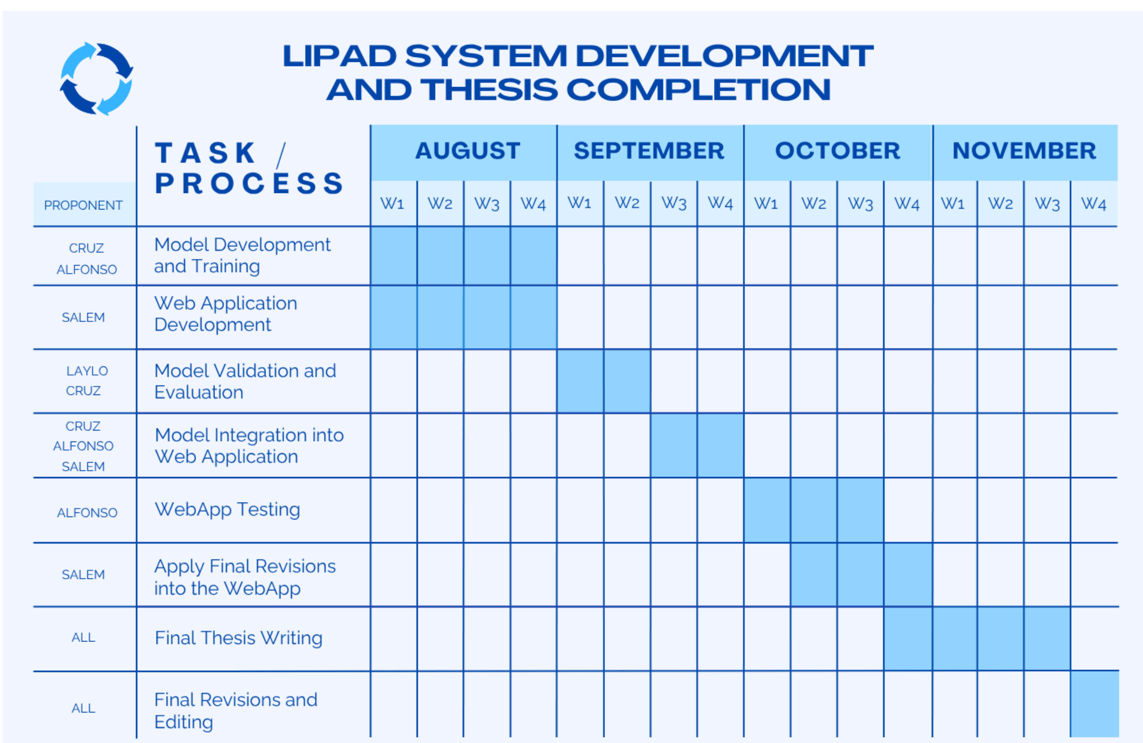
Noted by:

Melissa M. Pantig, MCS
Research Adviser
AUF-CCS

Appendix O: Gantt Chart



Updated Gantt Chart



Appendix P: Biography