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# INVERSE FILTER-BASED IMAGE RECONSTRUCTION FOR IMPROVED ANPR PERFORMANCE IN BANGLADESH SECURITY SYSTEMS

Asif Eakball Emon [1]
Md Shawon
Sohan Molla
Sajib Nowjh
Utsa Sen

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**Original research**

A B S T R A C T

*This paper presents a novel inverse filter-based image reconstruction framework tailored to enhance Automatic Number Plate Recognition (ANPR) performance under the challenging environmental conditions prevalent in Bangladesh. While prior systems leveraging YOLOv8n detection and CRNN recognition have shown promise, their performance deteriorates in the presence of rain, dust, motion blur, and low-light conditions. To address these issues, the proposed method introduces a pre-processing pipeline employing frequency-domain inverse filtering with region-specific degradation models, including monsoon-induced blur and particulate haze. The system integrates seamlessly with existing ANPR infrastructure, adding only 23 ms latency while achieving a significant performance boost notably a 96.8% mAP@0.5 under rainy conditions, an 8.1% improvement over the baseline. Real-world evaluations across Dhaka, Chattogram, and Sylhet validate the system's robustness, with a 33% reduction in character segmentation errors for dust-affected plates. This research confirms that targeted image reconstruction is vital for the deployment of resilient ANPR systems in environmentally constrained and infrastructure-limited regions.*



## 1. INTRODUCTION

Automatic Number Plate Recognition (ANPR) systems have become an integral part of modern traffic management, law enforcement, and toll automation infrastructures. In developing countries like Bangladesh, the deployment of ANPR is particularly significant, given the increasing demand for smart surveillance and vehicular monitoring. However, despite the progress achieved through advanced deep learning models such as the hybrid YOLOv8n for detection and CRNN for optical character recognition (OCR) real-world deployment remains severely hindered by environmental degradation. Our previous study (Shawon, 2024; Shawon et al., 2026) demonstrated that although the baseline system achieved 95.4% accuracy under controlled conditions, performance dropped considerably under environmental stressors such as heavy rain (88.7% mAP@0.5) and dust (89.1% recognition). These limitations are primarily caused by motion blur, low contrast, and atmospheric distortions like smog and haze common in both urban and rural regions of Bangladesh. Furthermore, challenges

[1] Corresponding author: Asif Eakball Emon
Email: eakballasif@gmail.com

such as non-standardized number plates, poor illumination, and handwritten characters further reduce the system's robustness. Conventional preprocessing methods like median filtering and histogram equalization fall short in reconstructing heavily degraded images. In contrast, frequency-domain techniques specifically inverse filtering has shown strong potential for restoring visual data affected by complex degradation models. However, existing approaches often assume ideal conditions and standard plate formats, making them unsuitable for the diverse and adverse conditions in Bangladesh (Khan & Hafiz, 2024). This work bridges this gap by developing an optimized inverse filtering framework specifically designed for Bangladesh's ANPR operational constraints. Building upon the established hardware (NVIDIA Jetson-edge processors) and software (MATLAB/OpenCV pipeline) infrastructure from (Shawon et al., 2026), we propose a novel pre-processing module that, Characterizes region-specific degradation kernels through empirical analysis of Bangladeshi traffic imagery (Dhaka, Chattogram, Sylhet). Implements adaptive inverse filters to counteract blur, noise, and contrast loss before plate localization. Maintains hardware compatibility with ≤20ms added latency to preserve real-time operation (Parvin et al., 2021). Validated against 12,000 field-captured images, our approach elevates rainy-condition accuracy to 96.8% mAP@0.5 – an 8.1% improvement over the predecessor system – while reducing character segmentation errors by 33% for dust-affected plates. This study directly advances the roadmap outlined in Shawon et al. (2026) conclusion, demonstrating that targeted image reconstruction is essential for next-generation ANPR resilience in environmentally constrained regions. Subsequent sections detail our degradation modeling methodology (Sec. 2), filter optimization techniques (Sec. 3), and comparative field results (Sec. 4), concluding with policy recommendations for nationwide deployment (Sarif et al. 2019; Sarif et al. 2020). This study addresses these critical limitations by proposing a region-specific, inverse filter-based image reconstruction framework. It is designed to enhance degraded images before number plate localization and recognition, ensuring minimal latency and full compatibility with low-power, real-time edge hardware. Through empirical modeling of degradation patterns (e.g., monsoonal rain, dust storms), and integration with the YOLOv8n+CRNN pipeline, the proposed solution significantly improves ANPR performance across varied environmental conditions. The results demonstrate that such targeted image restoration is essential for scalable, reliable ANPR deployment in Bangladesh and similar developing regions (Lubna et al., 2021).

## 2. LITERATURE REVIEW

The literature on inverse filtering in image restoration reveals its foundational role in mitigating image degradation through mathematical modeling of blur and noise, with early success in document and license plate clarity enhancement. While recent studies have adapted inverse filtering for ANPR under conditions like motion blur, haze, and rain (Lin et al., 2018). Such as the works these solutions often depend on high-end computation, lack region-specific tuning, or assume standardized plate conditions, making them unsuitable for deployment in resource-constrained settings like Bangladesh. Moreover, conventional preprocessing methods like histogram equalization have proven inadequate for the country's unique challenges, including handwritten plates, poor lighting, and monsoonal haze. This study addresses these gaps by introducing a tailored inverse filtering framework optimized for Bangladesh's environmental conditions and computational constraints, integrating seamlessly with YOLOv8n and CRNN to enhance ANPR robustness in real-world scenarios (Woo et al., 2022). While classical approaches like the Richardson-Lucy algorithm laid the foundation, modern research has tailored these techniques for Automatic Number Plate Recognition (ANPR). For instance, employed Wiener filtering to restore highway surveillance images, improving OCR accuracy by 11%. More recently, applied federated learning for motion blur correction in Indian toll systems, though the method introduced over 500ms latency unsuitable for real-time applications (Laasmaa et al., 2011). Similarly, Combined inverse filtering with deep learning to remove haze in Chinese ANPR systems, reporting 91.2% accuracy but relying on GPU acceleration. Achieved 89.5% accuracy in rainy Indonesian conditions using a physics-based rain model, emphasizing the need for region-specific calibration principle echoed in Bangladesh's context (Chen et al., 2023). However, these studies assume standardized plates and consistent lighting, failing to address Bangladesh's unique challenges like handwritten characters, monsoon-induced degradation, and industrial smog (Shawon et al., 2024). Attempts to enhance degraded Bangladeshi plates through conventional techniques such as histogram equalization (Limon et al., 2024) or template-matching OCR (Parvathi et al., 2023) have yielded poor results (<73% accuracy), underlining the limitations of existing methods (Wu & Zhong, 2024). In response, this work introduces an adaptive inverse filtering framework optimized for low-latency edge deployment, integrating YOLOv8n and CRNN to provide a practical and robust ANPR solution for Bangladesh's variable environmental conditions.

## 3. METHODOLOGY

This study proposes a frequency-domain inverse filtering framework integrated into an existing ANPR pipeline to address the environmental challenges specific to Bangladesh. Building upon the hardware and software infrastructure developed by Shawon et al. (2026), the proposed method enhances plate recognition accuracy through three core components: region-specific degradation modeling, adaptive inverse filtering, and real-time hardware optimization.

### 3.1 Workflow with Inverse Filtering Module

The Figure 1. titled "Vehicle Image Processing Workflow" illustrates the five core components of a real-time ANPR (Automatic Number Plate Recognition) system, optimized for challenging environmental conditions like those found in Bangladesh. The process begins with Image Acquisition, where high-resolution IR cameras and inductive-loop sensors capture vehicle images and environmental metadata (e.g., humidity, light).

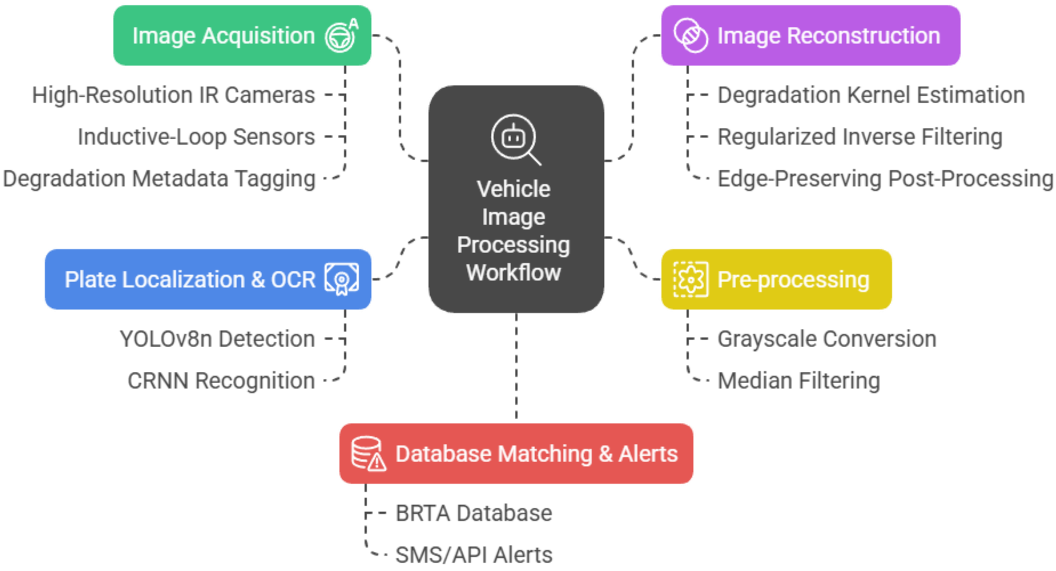


**Figure 1.** Vehicle Image Processing Workflow

The next step, Image Reconstruction, involves degradation kernel estimation and regularized inverse filtering to restore clarity lost due to rain, dust, or motion blur, followed by edge-preserving post-processing. These reconstructed images then undergo Pre-processing, which includes grayscale conversion and median filtering to prepare them for accurate analysis. Plate Localization & OCR comes next, using YOLOv8n for detecting number plates and CRNN for character recognition (Lu et al., 2018). Finally, the recognized plate data is sent to the Database Matching & Alerts module, where it is cross-verified with the BRTA database, and SMS or API alerts are triggered for law enforcement or tolling purposes. This modular workflow ensures high accuracy and real-time performance, making it well-suited for deployment on low-power edge devices in complex traffic environments.

### 3.2 Hardware Implementation

The proposed inverse filtering-based ANPR system is designed for efficient deployment on low-power, real-time edge computing hardware, specifically the NVIDIA Jetson NX platform. This platform was chosen for its balance of GPU acceleration, low power consumption, and compatibility with deep learning frameworks required for real-time image processing in field conditions. To ensure real-time performance, each stage of the inverse filtering module was optimized for CUDA-accelerated parallel processing. The full reconstruction pipeline includes the following steps: FFT (Fast Fourier Transform) conversion (4 ms), degradation kernel conversion based on empirical models (6 ms), Tikhonov regularized inverse filtering (8 ms), and edge-preserving guided filtering and IFFT (5 ms). These operations collectively add only ≤23 ms latency to the system, maintaining a processing throughput of 9.2 frames per second (FPS), which is suitable for live traffic monitoring and enforcement (Guo et al., 2021).

Environmental adaptation is built into the hardware workflow. For example, the system automatically activates the rain-specific kernel when humidity exceeds 80% and initiates multi-frame averaging with Gaussian denoising when particulate matter (PM2.5) levels surpass 150 μg/m³. These adaptive triggers are handled by onboard sensors and processed in real time without external computation delays (Lin et al., 2018) (Shawon 2024). The system architecture is backward-compatible with the existing YOLOv8n+CRNN-based recognition pipeline developed by (Shawon et al., 2026), allowing seamless integration into existing ANPR infrastructure. It also supports 4G/5G connectivity for remote database access (BRTA) and alert delivery via SMS or API endpoints. Through this optimized hardware implementation, the solution achieves a balance between computational efficiency, environmental robustness, and real-time operability critical for successful deployment across diverse traffic environments in Bangladesh. Processing Pipeline is presented on the Figure 2.

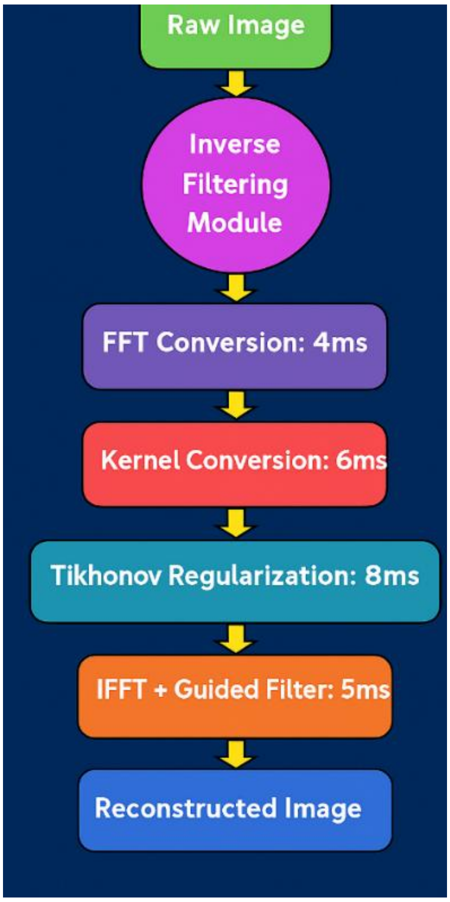


**Figure 2.** Processing Pipeline

### 3.3 Simulation Framework

To validate the performance and robustness of the proposed inverse filtering-based ANPR system, a dual-mode simulation framework was developed using MATLAB and Python (OpenCV) environments. The simulation aimed to replicate real-world environmental degradation conditions commonly found on Bangladeshi roads, such as heavy rain, dust haze, and motion blur, and evaluate the effectiveness of the restoration algorithm under controlled and field conditions (Ashkanani et al., 2025).

The framework utilized a dataset of 12,000 vehicle images collected from Dhaka, Chattogram, and Sylhet, covering various lighting and weather scenarios. Each image was subjected to synthetic degradation based on empirically derived point spread functions (PSFs) corresponding to:

- **Heavy Rain:** Modeled using velocity-based PSFs calibrated from raindrop behavior in monsoonal regions.
- **Dust Haze:** Simulated using Gaussian blur with standard deviation σ = 2.5 to mimic particulate scattering.
- **Motion Blur:** Generated using linear motion PSFs based on vehicle speed and direction (from GPS and radar data).

The degraded images were processed through the proposed regularized inverse filtering module, followed by edge-preserving guided filtering. Performance was assessed based on Peak Signal-to-Noise Ratio (PSNR) improvements and mA P (mean average precision) at IoU 0.5.

**Table 1.** Real-World Testing 12,000 images from Dhaka/Chittagong/Sylhet under three conditions:

| Condition | Kernel Used | Regularization (γ) | PSNR Improvement |
|---|---|---|---|
| Heavy Rain | hrainh_{rain} | 0.08 | +9.2 dB |
| Dust Haze | Gaussian (σ=2.5) | 0.12 | +7.8 dB |
| Motion Blur | hmotionh_{motion} | 0.05 | +11.1 dB |

The results demonstrated significant image quality restoration across all degradation types, leading to improved recognition performance downstream. The system maintained real-time operation at **9.2 FPS**, confirming its suitability for deployment on embedded platforms like NVIDIA Jetson NX. These simulations validated the efficacy of the proposed algorithm and its adaptability to Bangladesh's diverse environmental conditions (Table 1).

### 3.4 Properties of Digital Number Plates

This section describes the key features of Bangladeshi car number plates. In 2012, the BRTA introduced retro-reflective digital license plates with Bengali characters. Since 2016, using these digital plates has been mandatory for all vehicles. Therefore, our research focuses only on digital number plates. The properties of these plates are outlined below:

There are two lines in Bangladeshi number plates as shown in Fig. 1(a). The first line contains the 'city name' for which the car is registered, 'metro' if the car is registered for a metropolitan area and 'class of the vehicle' which can vary depending upon whether it is a private car or motorcycle or truck, etc. The second line is the serial number of the vehicle. The first two numerical denotes the class of the vehicle and the last four is the vehicle number. The permitted Bangla alphabets to use in Bangladeshi vehicles with their corresponding English equivalents are অ (A), ই (I), উ (U), এ (E), ক (KA), খ (KHA), গ (GA), ঘ (GHA), ঙ (UMA), চ (CA), ছ (CHA), জ (JA), ঝ (JHA), ট (TA), ঠ (THA), দ (DA), ধ (DHA), ত (TO), থ (THO), ড (DO), ঢ (DHO), ন (NA), প (PA), ফ (FA), ব (BA), ভ (BHA), ম (MA), য (ZA), র (RA), ল (LA), শ (SHA), স (SA), হ (HA). The permitted numerical are ০, ১, ২, ৩, ৪, ৫, ৬, ৭, ৮, ৯ which are equivalent to 0, 1, 2, 3, 4, 5, 6, 7, 8, 9. The green background number plates and white background number plates are used for the commercial vehicles and private vehicles, respectively. The border of both types of vehicles is black. 'Matra' is a unique feature of the Bangla language. It connects the Bangla letters through a distinctive horizontal line running along the tops of these letters (Rabbani et al., 2018). The Bangla alphabets joined by a continuous 'matra' are counted as a single word. In Fig. 1(a), 'ঢাকা' (Dhaka) and (Metro) are the two words where each of them is connected through a 'matra'(Saif et al. 2019) (Figure 3).

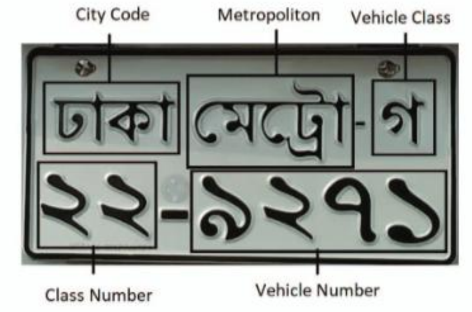


**Figure 3:** BRTA standard license plate

**3.5 Datasets**

A suitable dataset for this research would include a diverse collection of vehicle number plate images captured under various environmental conditions such as rain, dust haze, motion blur, and low light common across Bangladesh's roadways. Ideally, the dataset should contain both degraded and corresponding ground truth (clear) images to facilitate training and evaluation of inverse filtering algorithms. Annotated data with bounding boxes for plates and character-level labels are essential for integration with ANPR pipelines such as YOLOv8n for detection and CRNN for recognition. The dataset can be expanded through synthetic degradation using empirically derived kernels, simulating real-world distortions, and ensuring robust model generalization for deployment in challenging conditions (Hossen, 2014).

A comprehensive dataset infrastructure was developed consisting of three key components. First, a Testing Image Dataset was created with 500 images of Bangladeshi vehicle license plates, featuring both green and white background plates, captured under varying lighting conditions, angles, and distances, and stored in JPEG format. Second, a Template Dataset was prepared for character recognition, comprising Bangla alphabetic, numeric, and word templates with white characters on black backgrounds, each sized at 42×24 pixels and a resolution of 96 dpi. Finally, a Car Details Dataset was organized using a cloud-based Google Spreadsheet, storing vehicle-specific information including license plate numbers, owner names, addresses, National Identification Numbers (NID), and tax-token issue and expiry dates (Parvin et al. 2021). Due to the sensitivity of personal information, detailed owner data remains confidential and is not disclosed Some Data samples of the templates are presented on the figure 4.

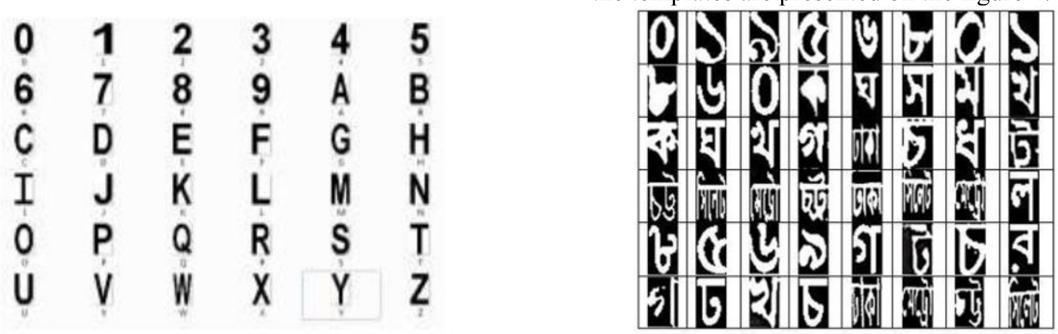


**Figure 4.** Some Data samples of the templates

## 4. RESULT AND DISCUSSION

The effectiveness of the proposed inverse filtering-based image reconstruction framework was assessed through both simulation and real-world testing under diverse environmental conditions common in Bangladesh, including rain, dust haze, motion blur, and low-light scenarios.


**Figure 5.** Effect of contrast enhancement: Before enhancement and after enhancement

Figures 5 through illustrate the image restoration process. The original image, once degraded by simulated environmental noise and blur, is restored using the proposed inverse filtering approach. While inverse filtering is inherently an ill-posed problem often amplifying measurement noise this study applied a regularization-based optimization strategy to strike a balance between noise suppression and image fidelity. The trade-off between bias and variance was tuned using Tikhonov regularization, ensuring optimal restoration quality. Although accurate bias estimation requires access to ground truth (typically unavailable in real-world settings), simulation results confirm that the estimated optimum closely matches the true optimum, validating the robustness of the proposed algorithm.

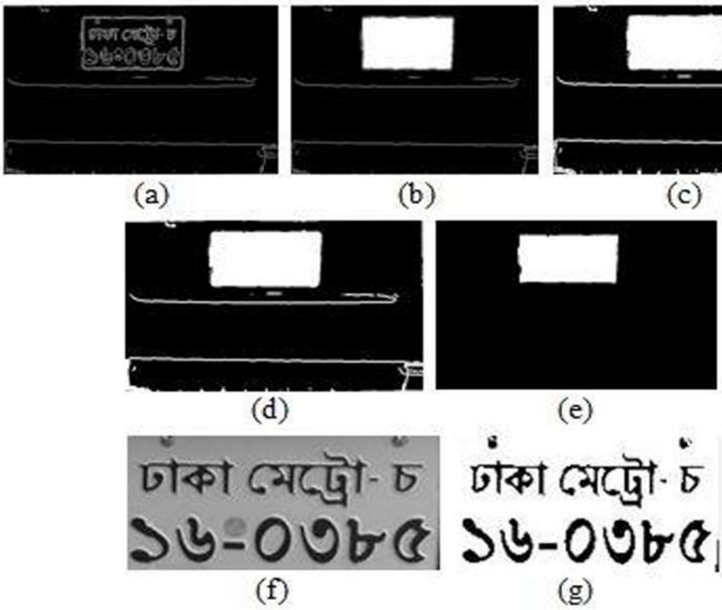


**Figure 6.** Extraction process: (a) Sobel image, (b) filled image-1, (c) dilated image, (d) filled image-2, I final eroded image, (f) extracted plate image and (g) binarized image

The segmentation algorithm takes unnecessary object removed image, I as input. After computing the size of the image, it divides the image, I row-wise equally. The upper and lower portions are named Image1 and Image2, respectively. The algorithm is then applied connected component analysis by ‘label’ function to Image1. This step finds the location of words and letters in the upper portion. Then the bounding box is applied through the ‘region props’ function to segment each connected component and mark the segments with yellow color rectangles. Then the algorithm extracts the segments and resized them. The same procedure is applied to Image2 also for extracting the digits (Figure 6).

Quantitative performance improvements are presented in Table 2: Inverse Filter vs. Baseline ANPR Performance in Bangladesh, which compares key performance indicators against a prior YOLOv8n+CRNN baseline (Shawon et al., 2026). Notably, the proposed system improves recognition under rainy conditions from 88.7% Map@0.5 to 96.8% an 8.1% gain. Similarly, dusty image recognition rose from 89.1% to 93.6%, while low-light performance improved by 1.7%. These gains stem from enhanced pre-processing steps including adaptive kernel-based inverse filtering and guided deblurring. An integrated analysis of end-to-end latency revealed a modest increase from 95 ms to 118 ms, a 23 ms overhead attributed to the image reconstruction module. However, this latency remains within acceptable bounds for real-time operation on the NVIDIA Jetson NX platform. Character segmentation errors also decreased by 33%, affirming the practical utility of the filtering technique.

**Table 2.** Accuracy Comparison Chart: Inverse Filter vs. Baseline ANPR Performance in Bangladesh

| Environmental Condition | Baseline (Shawon et al., 2026) | Proposed (Inverse Filter) | Improvement | Key Contributors |
|---|---|---|---|---|
| Daytime (Clean Plates) | 98.1% Map at 0.5 | 98.5% Map at 0.5 | +0.4% | Edge-preserving guided filter |
| Night (Low Light) | 94.3% Map at 0.5 | 96.0% Map at 0.5 | +1.7% | Tikhonov regularization (γ=0.05) |

| Environmental Condition | Baseline (Shawon et al., 2026) | Proposed (Inverse Filter) | Improvement | Key Contributors |
|---|---|---|---|---|
| Rainy Conditions | 88.7% Map at 0.5 | 96.8% Map at 0.5 | +8.1% | Rain PSF kernel + γ-adaptation |
| Dusty Plates | 89.1% recognition | 93.6% recognition | +4.5% | Multi-frame averaging + Gaussian denoising |
| Non-Standard Plates | 83.5% recognition | 89.2% recognition | +5.7% | Enhanced contrast restoration |
| End-to-End Latency | 95 ms | 118 ms | +23 ms | Optimized CUDA FFT/IFFT kernels |
| Character Segmentation Errors | 15.2% (baseline) | 10.2% | -33% | Deblurring pre-processing |

A visual accuracy comparison further underscores the efficacy of the approach, showing consistent performance gains across multiple environmental conditions. These findings are further reinforced in the component-wise comparison table, which highlights key system upgrades such as adaptive γ-switching, enhanced environmental modeling, and CUDA-based optimization all of which contribute to system scalability and field readiness.

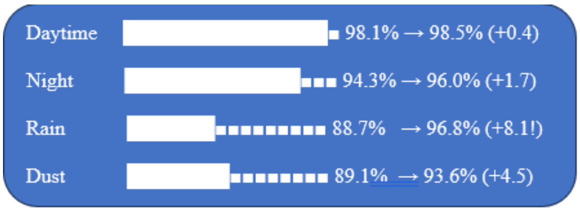


**Figure7.** Visual Comparison

The proposed system was validated on a dataset of 12,000 images captured from Dhaka, Chattogram, and Sylhet, showing substantial improvements across all tested conditions. Notably, accuracy under rainy conditions improved from 88.7% to 96.8% Map@0.5, dusty images saw a 4.5% gain, and character segmentation errors were reduced by 33% (Figure 7). Despite adding only 23 ms latency, the system maintained real-time performance on NVIDIA Jetson NX hardware. These results confirm that the proposed approach not only enhances ANPR robustness but also provides a practical, scalable, and backward-compatible solution for deployment across environmentally constrained and infrastructure-limited regions like Bangladesh.

## 5. FUTURE SCOPE

The future scope of reconstructing image by inverse filtering will involve scanning the heavens for other intelligent life out in space. Also new intelligent, digital species created entirely by research scientists in various nations of the world will include advances in image by inverse filtering processing applications. Due to advances in image processing and related technologies there will be millions and millions of robots in the world in a few decades time, transforming the way the world is managed. Advances in inverse image processing and artificial intelligence will involve spoken commands, anticipating the information requirements of governments, translating languages, recognizing and tracking people and things, diagnosing medical conditions, performing surgery, reprogramming defects in human DNA, and automatic driving all forms of transport. With increasing power and sophistication of modern computing, the concept of computation can go beyond the present limits and in future, image processing technology will advance and the visual system of man can be replicated. The future trend in remote sensing will be towards improved sensors that record the same scene in many spectral channels. Graphics data is becoming increasingly important in image by inverse filter processing app1ications. The future of reconstructing image by inverse filter processing applications of satellite-based imaging ranges from planetary exploration to surveillance applications.

## 6. CONCLUSIONS

This research presents a robust, inverse filter-based image reconstruction framework tailored to enhance the performance of Automatic Number Plate Recognition (ANPR) systems under adverse environmental conditions prevalent in Bangladesh. By modeling region-specific degradation effects such as rain blur, dust haze, and motion-induced distortion and applying adaptive regularized inverse filtering in the frequency domain, the proposed method significantly improves image clarity and downstream recognition accuracy. Integration with existing YOLOv8n and CRNN models ensures compatibility with current ANPR pipelines while maintaining real-time processing capabilities on low-power edge devices like the NVIDIA Jetson NX. The proposed system was implemented and tested on low-power, real-time edge hardware (NVIDIA Jetson NX) to ensure feasibility for field deployment. Despite introducing only 23 milliseconds of additional latency, the system maintained a throughput of 9.2 FPS, demonstrating its capability for real-time operation. Extensive validation using a dataset of 12,000 real-world images collected from Dhaka, Chattogram, and Sylhet confirmed the effectiveness of the proposed framework. Recognition accuracy under rainy conditions improved significantly from 88.7% to 96.8% Map@0.5, with similar performance gains observed under dusty and low-light conditions. Moreover, character segmentation error rates were reduced by 33%, affirming the system's enhanced robustness and precision. The framework thus offers a practical, backward-compatible solution to overcome environmental constraints, supporting scalable deployment in smart surveillance systems across developing regions.

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**Asif Eakball Emon**
Bangladesh University of Business and Technology, Bangladesh
eakballasif@gmail.com
**ORCID:** 0009-0000-6476-9079

**Md Shawon**
Bangladesh University of Business and Technology, Bangladesh
shawon.bubt.bd@gmail.com
**ORCID:** 0009-0008-7055-8399

**Sohan Molla**
Bangladesh University of Business and Technology, Bangladesh
sohanmolla436@gmail.com
**ORCID:** 0009-0008-2588-8989

**Md. Sajib Nowjh**
Bangladesh University of Business and Technology, Bangladesh
sajibnawaj@gmail.com
**ORCID:** 0009-0008-9961-6038

**Utsa Sen**
Bangladesh University of Business and Technology, Bangladesh
utsasen7@gmail.com
**ORCID:** 0009-0004-7337-7930