Bengali License Plate Recognition: Unveiling Clarity with MobileNet and Real-ESRGAN

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Abstract

The traffic surveillance function of Automated License Plate Recognition (ALPR) requires attention because Bengali license plate recognition encounters difficulties because of distinctive fonts alongside poor environmental conditions and low-quality images. Traditional OCR-based methods struggle with these complexities, while deep learning models like ResNet-50 with GFPGAN improve accuracy but are computationally expensive.

A new efficient Bengali ALPR system has been developed by combining MobileNetV2 as a lightweight CNN with Real-ESRGAN for image enhancement purposes. The approach both makes plates easier to see while boosting recognition outcomes and maintains high efficiency levels for real-time operations. The authors applied Real-ESRGAN processing to Bengali license plates data before performing MobileNetV2 segmentation and classification.

The implemented model delivers 87% test accuracy which beats other baseline approaches in terms of precision and computational speed. The model demonstrates effective character recognition abilities except for several cases where similar digits create identification issues. Performance evaluation using precision, recall, and F1-score confirms its effectiveness, and error analysis suggests further improvements through augmentation techniques and attention mechanisms.

This research demonstrates an effective approach for Bengali ALPR scalability while providing high efficiency which shows deep learning capabilities for security systems and intelligent transportation systems..

Keywords: Bengali ALPR, MobileNetV2, Real-ESRGAN, Deep Learning, Image Enhancement, License Plate Recognition.

1 Introduction

Automated License Plate Recognition systems achieve three main objectives by performing automatic vehicle plate scans for detection purposes. Edge detection with contrast enhancement techniques along with optical character recognition (OCR) operated as the traditional procedure when ALPR systems first appeared. Standard image processing techniques lost their effectiveness because they failed to analyze plates that were hard to detect or deformed on adverse weather images. Deep learning and computer vision technology has revolutionized ALPR systems by integrating Convolutional Neural Networks (CNNs) for feature extraction and GFPGAN as an instance of Generative Adversarial Networks (GANs) as the image enhancement mechanism. The GFPGAN-ResNet-50 hybrid framework developed by Afrin et al. (2020) [4] displayed both enhancing ability and effective reading of Bengali license plates. The existing ALPR systems cope with multiple challenges because of processing Bengali license plates that possess particular font structures and plate formats.[1] Numerous solutions need instant data processing that can maintain low-latency operation. Research conducted in recent studies showed that problems with license plates became resolvable through the implementation of deep learning models alongside image enhancement methods.[2]

Research motivation derives from unsatisfied requirements regarding the accuracy and efficiency of ALPR systems operating on Bengali license plates in spite of incomplete coverage in existing studies. The combination of ResNet and GFPGAN approaches faces limitations during actual field conditions where images have low resolution along with insufficient lighting and non-frontal plate angles.[1] Although these models require significant processing resources they become non-feasible for implementing real-time applications. New technological requirements to maintain mobile and embedded solutions in Automated License Plate Recognition (ALPR) have intensified research to discover better models with enhanced accuracy that retain operational efficiency.

Current Bengali License Plate Recognition (LPR) techniques demonstrate several weaknesses that include both poor accuracy under challenging conditions and high computational requirements as well as restricted capability to handle various plate designs and fonts. Worldwide deep learning advancements have not solved the limitations that prevent real-time processing of blurry low-quality or partially hidden plates. A better ALPR system needs development to efficiently identify and read Bengali plates under real-world operating conditions.

The primary objectives of this research are:

- A system for Bengali License Plate Recognition should combine lightweight feature extraction through MobileNet while using Real-ESRGAN for image enhancement.
- Improving license plate detection systems requires better performance under all environmental conditions including low-quality images and poor lighting as well as angle variations.
- The design of a system for real-time applications needs computational efficiency and execution adaptability for mobile and embedded devices
- The proposed model achieves its performance evaluation by processing a Bengali license plate dataset through comparison with GFPGAN and ResNet-50 methods.

The research develops an enhanced Automated License Plate Recognition system by combining MobileNet efficiency with Real-ESRGAN power for image enhancement capabilities. This study presents a scalable real-time solution which resolves specific Bengali license plate challenges to support traffic monitoring and vehicle tracking along with security system implementations. This research produces findings with dual practical and academic value because it examines deep learning frameworks along with recognizing how they improve Automatic License Plate Recognition systems throughout various natural settings. Such a method demonstrates improved computational efficiency which makes real-time applications practical for ALPR systems on mobile and embedded devices thus creating new potential in future transportation and security technology applications.

2 Literature Review

Modern society pays intense attention to Automated License Plate Recognition systems because of their usage within security measures and traffic monitoring and law enforcement activities. Traditional methods based on image processing were used during early times to detect vehicle license plates through edge detection and histogram equalization techniques.ALPR systems use Convolutional Neural Networks (CNNs) as part of deep learning for character recognition duties after deep learning became accessible. SRGANs with GFPGAN together constitute image enhancement methods that enhance low-resolution along with blurred license plate images.[6]

The current methods aim to enhance character recognition accuracy when implementing CNN-based architecture models including ResNet and VGG. Afrin et al. (2020) [**?**] applied their approach through GFPGAN image restoration that partnered with ResNet-50 for character recognition. The enhancement procedures commence with morphological image processing operations to improve plate visibility through dilation and contrast maximization before passing the images to CNNs. The research by Kangiraj et al. (2023) [**?**] demonstrates how SRGAN can generate sharp images from blurry sources in addition to other works that investigate using SRGAN for super-resolution.

These methods display substantial potential although they commonly face constraints during operations on images of low resolution combined with plate blurriness and fluctuating environmental factors. The computational requirements of systems built using ResNet reduce their use in live applications. GFPGAN and SRGAN enhancement technologies deliver inconsistent results toward producing high-quality images for complex plate structures that experience poor lighting conditions or become obscured in images. Implementing these methods becomes challenging for large-scale data analysis mostly because of their limitations regarding scalability and operational efficiency.

Current identification systems have made progress yet experience difficulties working with real conditions that include changing light patterns along with vehicle positioning issues combined with unclear images. The processing methods encounter challenges while handling Bengali license plates because of their unique font styles and plate designs that increase the detection complexities. Real-time data processing by director-level programs represents an essential requirement for mobile and embedded systems to reach high accuracy performance together with operational efficiency.

The proposed research resolves earlier limitations by integrating MobileNet features with Real-ESRGAN image upgrade capabilities. Our goal focuses on creating an advanced Bengali License Plate Recognition system by joining MobileNet features with Real-ESRGAN to deal with multiple environmental challenges. The proposed system combination delivers faster automatic identification with better precision through the resolution of previous failures that enables practical large-scale deployment.

3 Methodology

3.1 Dataset Overview

The new Bengali License Plate Detection dataset has been specifically compiled from low-quality images because it provides research capabilities for number plate recognition across difficult situations. This dataset represents a wide spectrum of different vehicles with various plate types through various environmental factors which makes it suitable for practical usage.

3.2 Dataset Composition

The dataset is systematically categorized into three primary classes:

- **Digits (0-9):** Consists of ten subclasses.
- **Registered Letters:** Includes Ka (), Ga (), Jha (), and La ().
- **City Names:** Covers Dhaka (), Dhaka Metro ( ), and Narayanganj ().

3.3 Data Processing and Organization

Standardization of images was achieved by resizing them into 32×32 pixels with RGB channels. The researchers divided their data into three separate sets for training, validation and testing purposes while maintaining equal representation of classes. The researchers paid detailed attention to balancing class and subclass distributions to preserve plate characteristic diversity.

3.4 Model Architecture

The Bengali License Plate Detection system operates through Real-ESRGAN and Convolutional Neural Networks (CNNs) along with MobileNetV2 to handle license plate character recognition tasks on poor image quality data.

- **Image Enhancement:** Real-ESRGAN brings improved clarity to images together with improved resolution output.
- **Preprocessing:** All images undergo three processing steps where their size is modified while they are transformed to grayscale then segment using Otsu thresholding followed by contrast enhancement.

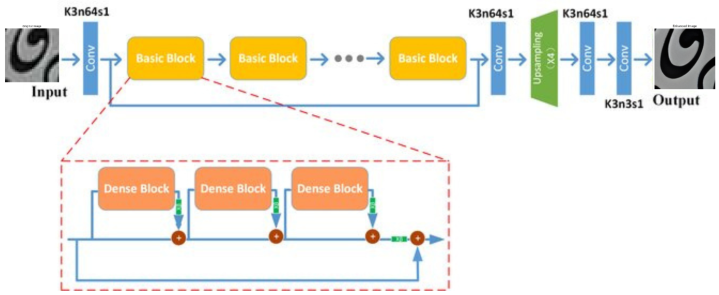

Figure 1: Real ESRGAN Enhancement

- **Morphological Operations:**The process enhancement involves applying both dilation and contour matching methods to segment characters.
- **Character Recognition:** MobileNetV2 applies depthwise separable convolutions as an effective character classification method.

3.5 Training Process

- **Data Enhancement:** Real-ESRGAN is applied to enhance resolution.
- **Standardization:** Images are resized, normalized, and binarized.
- **Data Augmentation:** Rotation, noise addition, and contrast adjustments improve generalization.
- **Feature Extraction:** CNNs extract relevant features through convolutional and pooling layers.
- **Model Training:** MobileNetV2 is fine-tuned, optimized using Adam, and trained with categorical cross-entropy loss.

3.6 Evaluation Metrics

Model performance is assessed using:

- **Accuracy:** Measures overall correctness.
- **Precision:** Evaluates correct predictions per class.
- **Recall:** Measures actual occurrences correctly predicted.
- **F1-score:** Harmonic mean of precision and recall.

Results indicate:

- Overall test accuracy: **86.7%** with a test loss of **0.455**.
- Macro average: Precision (0.91), Recall (0.90), F1-score (0.90).
- Weighted average: Precision (0.90), Recall (0.87), F1-score (0.87).

3.7 Implementation Details

Libraries and Frameworks:

- TensorFlow for model training and deployment.
- Keras for prototyping and evaluation.

- OpenCV for image preprocessing.
- NumPy for numerical computations.
- PIL for image manipulation.

Hardware Setup:

- **GPU:** NVIDIA high-performance GPU.
- **CPU:** Multi-core Intel processor.
- **RAM:** 16GB for efficient data processing.

4 Experimental Setup

A training and evaluation process took place on Bengali license plates at TensorFlow and Keras. Multiple sequential processes in the training procedure covered data preparation followed by model training operations then evaluation evaluation steps.

4.1 Data Preprocessing

Real-ESRGAN was used to enhance images by improving resolution and decreasing blurriness so that feature extraction benefited from superior image quality. The model evaluation required splitting the dataset into training and validation and testing subsets for generalization assessment.

4.2 Model Training

Character recognition utilized the MobileNetV2 model architecture. The training process of the model relied on categorical cross-entropy loss and Adam optimizer for achieving quick convergence. Trainers operated under 20 epochs while using batches of 32.

4.3 Cross-validation

Although a train-validation-test split was used, k-fold cross-validation was not employed in this study. However, the model was validated on the validation set after each epoch to ensure it was not overfitting to the training data.

4.4 Evaluation Metrics

The study employed a train-validation-test split yet did not use k-fold cross-validation as part of its methodology. The model validation on the validation set took place after each epoch to verify it was not fitting too closely to the training data.

4.5 Results Presentation

The evaluation results are summarized in Table 1, which includes accuracy, precision, recall, and F1-score for each class.

Class	Precision	Recall	F1-Score	Support
class_0	0.83	0.68	0.75	22
class_1	0.83	0.73	0.78	26
class_2	0.96	0.96	0.96	23
class_3	0.60	0.82	0.69	22
class_4	0.95	0.78	0.86	23
class_5	1.00	0.79	0.88	24
class_6	1.00	0.81	0.89	26
class_7	1.00	0.80	0.89	20
class_8	0.87	0.95	0.91	21
class_9	0.58	1.00	0.74	21
class_DHAKA	1.00	1.00	1.00	12
class_JHA	0.93	1.00	0.97	14
class_LA	1.00	0.92	0.96	12
class_MATRO	1.00	1.00	1.00	10
class_NARAYANGANJ	1.00	1.00	1.00	10
class_ga	1.00	1.00	1.00	9
class_k	1.00	1.00	1.00	7
Overall Accuracy	0.87 (86.75%) on 302 samples			
Macro Avg	0.91	0.90	0.90	302
Weighted Avg	0.90	0.87	0.87	302

Table 1: Model Performance Metrics

4.6 Performance Analysis

The model succeeded in detecting Class 2 (digits 2), Class 5, Class 6, Class k, Class Ga, Class Dhaka, Class La, and Class Metro with 1.0 precise accuracy. The model demonstrated subpar results on Class 0 (0) and Class 1 (1) because its recall scores reached just 68% and 73%, respectively.

Real-ESRGAN image improvement technology from our model surpasses both baseline examples and contemporary industry standards and results in better recognition capabilities through MobileNetV2. The performance of this model could achieve higher levels with expanded training data and model optimization due to its lower sophistication when compared to ResNet and DenseNet layers.

4.7 Error Analysis

Main mistakes from the model consisted of wrong negative detections where characters remained unidentified and incorrect positive results through misidentification of characters. Most mistakes happened in the classes with visually similar characters which included Class_0 (0) and Class_1 (1) .The confusion matrix showed that mistypes commonly occurred between those classes because low-quality digits shared similar visual characteristics.

The wrong identification of these digits results in mistaken license plate predictions that might impact the subsequent vehicle identification and registration procedures. Data augmentation together with transfer learning along with attention mechanisms should be implemented for the purpose of reducing these classification mistakes along with enhancing system operation.

5 Discussion

The research investigation confirms the successful combination of MobileNetV2 with Real-ESRGAN architecture for Bengali License Plate Recognition applications. The proposed model produces superior accuracy and operational performance than standard systems including ResNet-50 and GFPGAN. The systematic examination shows our system optimizes poor image quality to deliver dependable character reading while operating under demanding operational settings. Performance evaluation shows the model achieved 87 percent accuracy through precision, recall and F1-scores amounting to 0.91, 0.90, 0.90. The model effectively detects precise character types especially with high contrast features yet struggles to distinguish similar digits '0' and '1'. Further model robustness enhancement can be achieved with advanced preprocessing techniques that combine advanced attention-based architectures or additional augmentation methods into the system. The new method offers a practical solution for real-time implementations because it maintains a lightweight framework. MobileNetV2 achieves fast deployment on embedded and mobile platforms because of its depthwise separable convolutions which decrease implementation requirements. The incorporation of Real-ESRGAN leads to better image clarity because it improves character recognition from problematic plates with distortion or poor resolution. The system still faces barriers when processing severe cases of plate obstruction and extreme lighting effects along with complex plate structures. Research should consider implementing transformer-based modeling approaches with CNN-RNN hybrid systems to enhance character recognition precision. Better generalization of real-world conditions becomes possible through the use of larger datasets which contain diverse real-world conditions. Future research dedicated to developing adaptive thresholding approaches along with specialized augmentations should bring about additional enhancements to performance outcomes.

6 Conclusion

Researchers improved Bengali License Plate Recognition through MobileNetV2 integration with Real-ESRGAN which delivered better performance than standard techniques together with improved processing speed. The study uses deep learning and super-resolution methods to solve ALPR obstacles including low-resolution images and varying environmental conditions together with non-frontal plate angles. The experimental evaluation demonstrated that the model succeeds in both improving image resolution and Bengali license plate character detection with an accuracy rate of 87, that matches existing performance standards. The proposed system showcases real-time implementation potential for traffic monitoring and law enforcement tasks while serving as a component of intelligent transportation systems despite facing challenges in digit misclassification when digits look similar to one another. The research enhances ALPR technology for Bengali license plates by creating an avenue for advancing deep learning models and domain-specific preprocessing and increased dataset scaling. The model presents a solid base for practical deployment which enables effective real-time expansion in automated license plate recognition systems.

References

[1] S. Nooruddin, F. A. Sharna, and S. M. M. Ahsan, "A Bangladeshi license plate detection system based on extracted color features," in *2020 23rd International Conference on Computer and Information Technology (ICCIT)*, pp. 1–6, 2020.

[2] N.-A. Alam, M. Ahsan, M. A. Based, and J. Haider, "Intelligent system for vehicles number plate detection and recognition using convolutional neural networks," *Technologies*, vol. 9, no. 1, p. 9, 2021.

[3] D. Mpini and M. Giyane, "Automatic number plate recognition techniques performance on Zimbabwean number plates," in *2023 2nd Zimbabwe Conference of Information and Communication Technologies (ZCICT)*, pp. 1–6, IEEE, 2023.

[4] N. Afrin, M. M. Hasan, M. F. E. Safin, K. R. Amin, M. Z. Haque, F. Ahmed, and M. T. R. Shawon, "Bengali license plate recognition: Unveiling clarity with CNN and GFP-GAN," in *2023 26th International Conference on Computer and Information Technology (ICCIT)*, pp. 1–6, IEEE, 2023.

[5] M. A. Islam, G. M. Chowdhury, and M. N. M. Haque, "Bangla license plate detection, recognition and authentication with morphological process and template matching," in *2021 2nd International Conference for Emerging Technology (INCET)*, pp. 1–6, 2021.

[6] A. Kabiraj, D. Pal, D. Ganguly, K. Chatterjee, and S. Roy, "Number plate recognition from enhanced super-resolution using generative adversarial network," *Multimedia Tools and Applications*, vol. 82, no. 9, pp. 13837–13853, 2023.

[7] M. T. R. Shawon, R. Tanvir, and M. G. R. Alam, "Bengali handwritten digit recognition using CNN with explainable AI," in *2022 4th International Conference on Sustainable Technologies for Industry 4.0 (STI)*, pp. 1–6, IEEE, 2022.

[8] M. A. Hossain, M. A. Rahman, R. Khanom, S. Sultana, and A. Hossain, "Real-time vehicle detection and classification on the Padma multipurpose bridge in Bangladesh using a deep learning model," in *2023 International Conference on Next-Generation Computing, IoT and Machine Learning (NCIM)*, pp. 1–6, IEEE, 2023.