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Enhancing Bangladeshi License Plate Recognition: A YOLOv8 Approach with Roboflow Integration for Accuracy and Speed Optimization

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Abstract: ***Automatic License Plate Recognition (ALPR) systems are indispensable in modern transportation services, offering crucial benefits in traffic management, parking, toll collection, and surveillance. However, implementing ALPR in Bangladesh presents challenges due to the intricacies of Bangla characters and low-resolution CCTV images. Despite ALPR's potential to enhance safety and security, issues such as license plate variations and image quality hinder its effective implementation. This research addresses these challenges by developing a customized YOLOv8 model tailored for recognizing Bengali license plates, with a focus on precise localization, character segmentation, and script deciphering. Leveraging advanced deep learning techniques, the study aims to enhance efficiency and accuracy for applications in law enforcement and traffic management. Through a comprehensive workflow integrating Roboflow and YOLOv8, effective dataset collection, annotation, augmentation, and model training are demonstrated. System evaluation on diverse test datasets confirms the reliable detection and recognition of Bangladeshi license plates, underscoring the model's practical utility and robustness in real-world scenarios. Additionally, the research showcases notable advancements in ALPR technology specific to Bangladesh's unique context. Noteworthy is the model's exceptional performance in detecting license plates from corner angles, even across various vehicle types, as well as its ability to accurately identify plates amid challenging conditions such as broken or obscured plates and low-resolution images. Moreover, the system's proficiency in scenarios with multiple license plates, like those on buses adorned with banners, contributes significantly to improved road safety and traffic management.***

Keywords: Automatic License Plate Recognition (ALPR), Bengali license plates, Deep Learning, YOLOv8, Roboflow, Dataset Annotation, Data Augmentation, Object Detection, Real-world deployment

I. INTRODUCTION

ALPR systems play a crucial role in contemporary transportation services, facilitating traffic control, parking regulation, toll collection, and surveillance on a global scale. However, despite its global prevalence, Bangladesh faces hurdles in ALPR implementation due to the intricacies of Bangla characters and low-resolution CCTV images. While ALPR deployment in cities like Dhaka could mitigate crime and traffic violations, overcoming challenges such as license plate variations and image quality remains crucial for effective implementation.

As of mid-2023, Bangladesh's population stands at approximately 172.95 million people, accounting for 2.15% of the global population and ranking eighth among countries by population [1]. As of August 2021, Bangladesh Road Transport Corporation (BRTC) reported a total of 4,808,715 registered vehicles in the country. [2]. From the year 2019-2022, Bangladesh observed approximately 24,639 deaths due to road accidents (Prothom Alo, 2022) [3].

Bangladesh, with digitization efforts beginning in 2012. These license plates, introduced in 1973, are characterized by retroreflective properties and consist of two lines featuring a combination of alphabets, words, and digits. Commercial plates are distinguished by a vibrant green colour, while private plates are pristine white. Each plate comprises two lines, with the first line indicating the city name, metropolitan status, and vehicle class, while the second line consists of a six-digit numeric sequence. Adhering to Bangladesh Road Transport Authority (BRTA regulations, the license plates must bear Bangla script on flat steel or aluminium plates measuring 524mm x 112mm. The upper line of the plate displays intricate Bangla words and alphabets denoting city areas, while the lower line contains six digits representing the vehicle class number and a unique identification code. Notably, the presence of Matra, a horizontal line atop certain Bangla alphabets, aids in character recognition, particularly for identifying city names and metro indicators. Overall, Bangla license plates exemplify both aesthetic elegance and regulatory compliance.

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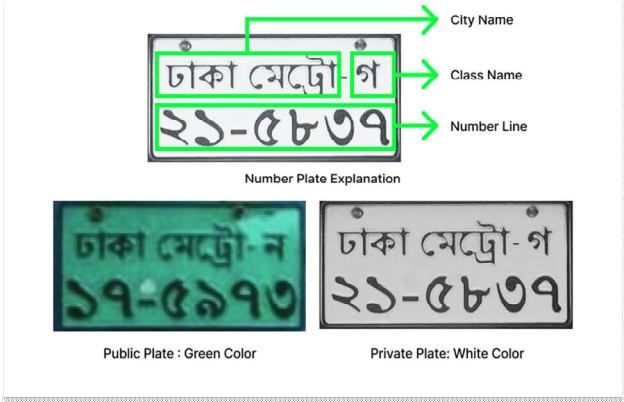


Fig. 1 Bangladeshi Number Plate

Our research aims to develop a YOLOv8 model tailored for recognizing Bengali license plates, addressing the challenges of vehicle license plate recognition in Bangladesh. This involves accurately localizing license plates, segmenting alphanumeric characters, and deciphering Bengali script. By integrating advanced deep learning techniques, we seek to enhance efficiency and accuracy in applications such as law enforcement and traffic management.

A. Existing Challenges

This research faces several existing challenges that underscore its significance and urgency. The burgeoning vehicle usage in Bangladesh, propelled by rapid population growth, exacerbates issues such as vehicle thefts, traffic violations, and accidents. Addressing these challenges requires effective vehicle number plate recognition systems to curb offenses and identify perpetrators. Moreover, the country's ongoing infrastructural projects, particularly in urban centers like Dhaka, contribute to pollution levels, necessitating enhanced measures for understanding and mitigating the environmental impact of vehicle emissions. Despite these pressing concerns, insufficient research has been conducted to develop robust solutions tailored to Bangladesh's unique context, highlighting the need for this study to fill the existing gap and provide valuable insights for future endeavors. Furthermore, overcoming challenges like recognizing plates in low-resolution images and on moving vehicles adds complexity to the research, emphasizing the importance of innovative approaches to tackle these obstacles effectively.

B. Research Objective

In this research, we aim to develop an advanced Automatic License Plate Recognition (ALPR) system tailored specifically for Bangladeshi license plates. The primary objective is to achieve accurate and efficient detection, localization, and recognition of license plates in real-time. Leveraging deep learning techniques, particularly YOLOv8, and integrating Roboflow for dataset annotation and augmentation, our goal is to address unique challenges faced in Bangladesh, including the complexities of Bangla characters and low-resolution CCTV images. Additionally, we aim to solve specific issues encountered in real-world scenarios. Firstly, by sourcing 90% of the training data from angular perspectives, we aim to excel in detecting license plates from corner angles across various vehicle types. Secondly, we seek to overcome challenges posed by the prevalent condition of Bangladeshi vehicles, often featuring broken or obscured license plates, by developing a system capable of accurately identifying license plates amidst such obstacles, including low-resolution images or adverse conditions like dust-covered plates. Lastly, our objective is to ensure exceptional performance in scenarios where multiple license plates are present, such as buses adorned with banners, by reliably detecting and identifying the correct license plate, thereby contributing significantly to improved road safety and traffic management. Through these endeavors, we aspire to provide valuable insights and methodologies to advance ALPR technology, with a strong emphasis on practical deployment in real-world contexts.

C. Key Features and Innovations

Key features and innovations of the proposed workflow include a comprehensive approach to dataset collection, annotation, and augmentation for Bangladeshi license plate detection and recognition. Leveraging Roboflow's labeling tools facilitates accurate annotation of license plate regions, while data augmentation enhances dataset diversity, ensuring robust model performance across various scenarios.

Exporting the labeled dataset in YOLOv8-compatible format streamlines model training, with fine-tuning tailored for accuracy. Integration of the trained model into applications enables real-time license plate detection, further augmented by Optical Character Recognition (OCR) for character recognition. System performance evaluation using a separate test dataset ensures reliability, culminating in the deployment of the integrated system for real-world license plate tasks. This holistic workflow combines cutting-edge tools and methodologies to achieve efficient and accurate Bangladeshi license plate detection and recognition.

II. LITERATURE SURVEY

A. *Literature Review*

Bangla license plate recognition systems employ sophisticated methodologies and cutting-edge techniques to accurately process and identify license plate data [4]. These systems encompass various modules, including pre-processing stages, character recognition algorithms, and vehicle registration authentication protocols. Notably, Convolutional Neural Networks (CNNs) play a central role in these systems, facilitating the detection and segmentation of Bengali license plate numbers with exceptional precision [5]. Moreover, template matching methods are employed to enhance character recognition accuracy [6], while Deep Convolutional Neural Network (DCNN) models are increasingly utilized for real-time recognition of both license plates and characters, ensuring swift and efficient processing [7]. The integration of advanced algorithms such as YOLO (You Only Look Once) and customized segmentation techniques has significantly enhanced the accuracy of license plate detection and localization, particularly tailored to the unique characteristics of Bangladeshi license plates [8].

Furthermore, the utilization of comprehensive datasets like NumtaDB, comprising an extensive collection of numerical images, provides invaluable resources for training CNN models and refining recognition algorithms [9]. Image processing methodologies, including transformations to the HVC color space, block division techniques, and histogram equalization, further optimize image contrast and streamline character segmentation processes [10]. In parallel, the application of efficient morphological operations and Sobel edge detection methods contributes to the precise identification of number plates, ensuring robust recognition performance across diverse scenarios [11].

Advanced feature extraction techniques, such as Discrete Cosine Transform (DCT) and Linear Discriminant Analysis (LDA), are instrumental in enhancing plate recognition accuracy, enabling nuanced analysis and classification of license plate data [12]. Furthermore, automatic number plate recognition (ANPR) systems demonstrate versatile applications, ranging from vehicle owner identification to multilingual character recognition, thereby highlighting the broad utility of these technologies in various domains [13].

The proposed algorithm, which integrates LDA and DCT feature extraction techniques, represents a significant leap forward in achieving higher recognition accuracy and efficiency [14]. Additionally, the successful implementation of number plate detection algorithms relies heavily on the availability of effective hardware and software components, underscoring the critical importance of robust infrastructure in supporting these sophisticated systems [15].

B. *Background Study*

The field of Automatic License Plate Recognition (ALPR) has witnessed significant advancements in recent years, driven by the increasing demand for efficient traffic management systems. Various research endeavors have been undertaken to develop robust ALPR systems tailored to specific regions and languages, including Bengali-speaking areas such as Bangladesh.

Onim et al. [16] introduced BLPnet, an end-to-end Deep Neural Network (DNN) model designed explicitly for ALPR with a focus on Bengali characters. This model offers a computationally efficient solution, incorporating a cascaded architecture for accurate vehicle region detection. Leveraging a Convolutional Neural Network (CNN)-based Bengali OCR engine, BLPnet achieves impressive license plate recognition accuracy of 95% with enhanced speed.

Saif et al. [17] presented an ALPR system dedicated to Bangla license plates, employing Convolutional Neural Networks (CNNs) for both license plate detection and number recognition. Their system achieved an impressive accuracy of 99.5% on 200 images and demonstrated real-time processing capabilities.

Al Nasim et al. [18] proposed a hybrid approach for ALPR focused on Bangladeshi vehicles, integrating the YOLO model for license plate detection and a CNN model for character recognition. This approach ensures accurate and automated license plate detection, addressing various applications such as tracking and billing systems.

Rahman et al. [19] highlighted the dominance of Convolutional Neural Networks (CNNs) in computer vision and machine learning, introducing a CNN-based Bangla License Plate Recognition System (BLPRS) with improved accuracy suitable for various applications.

Pervej et al. [20] presented an efficient method for real-time computer vision-based recognition of Bangla vehicle license plates, demonstrating promising results with a recognition accuracy of 96.62%.

Dhar et al. [21] outlined a system design for implementing ALPR specifically tailored for Bangladeshi License Plates, achieving remarkable accuracy in recognition through stages of plate detection, shape verification, tilt correction, and character recognition using CNNs.

Haque et al. [22] addressed the challenge of ALPR systems functioning effectively with low-resolution license plate images, proposing an approach utilizing Enhanced Super Resolution Generative Adversarial Networks (ESRGANs) to upscale LR images and enhance recognition performance.

Ahmed et al. [23] proposed a cascaded architecture leveraging YOLOv7 for license plate detection and a custom Bangla OCR engine for character recognition, achieving high accuracy in both tasks and showcasing potential for enhancing road safety and traffic management.

Hasan and Alam [24] developed a multi-stage deep learning pipeline for Automatic Bangla License Plate Recognition, achieving significant improvements in accuracy and computational efficiency compared to previous methods.

Sarif et al. [25] introduced an end-to-end license plate recognition system tailored for Bangladeshi vehicles, achieving high accuracy in character recognition and contributing to the development of a diversified dataset for further research.

Rahman et al. [26] presented a real-time end-to-end ALPDR system for Bangladeshi vehicles, demonstrating high accuracy in license plate detection, segmentation, and recognition across diverse environmental scenarios.

Onim et al. [27] introduced a YOLOv4-based object detection model trained for detecting Bangladeshi vehicle license plates, operating at an average of 14 frames per second on real-time video footage.

Nasim et al. [28] focused on fog-resilient Bangla car plate recognition using the Dark Channel Prior (DCP) fog-dehazing technique, showcasing potential for enhancing transportation safety in challenging conditions.

Chowdhury et al. [29] implemented an ALPR system powered by ResNet50 for Bangla License Plate Detection and OCR, achieving high accuracies and precision with minimal error rates.

Tusar et al. [30] detailed the implementation of an ALPR system using MATLAB Image Processing Toolbox and ResNet50, demonstrating high accuracy in license plate detection and character recognition.

These research endeavors collectively contribute to the advancement of ALPR systems tailored for Bengali-speaking regions, addressing various challenges and demonstrating promising results for real-world applications.

III. RESEARCH METHODOLOGY

Our proposed methodology leverages YOLOv8, the latest iteration of Ultralytics' renowned real-time object detection and image segmentation model. YOLOv8 stands at the forefront of deep learning and computer vision advancements, delivering unmatched speed and accuracy. Its streamlined architecture ensures versatility across diverse applications and seamless integration with a range of hardware platforms, spanning from edge devices to cloud APIs.

Roboflow offers a comprehensive framework for creating computer vision models without the need for hand-labeling images. By utilizing big, slow foundation models to train small, fast supervised models, Roboflow ensures efficient model development and deployment. Its production-ready inference server supports various model architectures and fine-tuned models, making it easy to deploy computer vision solutions. With secure role-based access, Roboflow ensures data safety while enabling organizations to augment labeling capacity internally or through Roboflow Labeling. Committed to strict security and privacy standards, Roboflow provides a range of advantages, including open-source availability and user-friendly design tailored to individuals with varying technical expertise. Whether for personal or professional use cases, Roboflow equips users with the tools needed to label, train, and deploy computer vision solutions effectively.

By leveraging the capabilities of Roboflow alongside the power of YOLOv8, a comprehensive solution for Bangladeshi license plate detection and recognition can be developed. Roboflow streamlines the process by offering an intuitive interface for dataset creation, annotation, and augmentation, ensuring a diverse and well-labeled dataset. This dataset can then be seamlessly integrated with YOLOv8, taking advantage of its state-of-the-art object detection capabilities. Through fine-tuning and training on the annotated dataset, the YOLOv8 model can be optimized for accurate license plate detection in various conditions.

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Furthermore, by implementing OCR for character recognition on the detected license plates, the system can achieve full license plate recognition functionality. The integrated solution holds promise for applications in traffic management, security, and law enforcement, offering a robust and efficient way to handle Bangladeshi license plate tasks.

A. Workflow

To integrate Roboflow with YOLOv8 for Bangladeshi license plate detection and recognition we will follow this workflow on Fig. 1:

1) Collect a diverse dataset of Bangladeshi license plate images.
2) Annotate license plate regions using Roboflow's labeling tools.
3) Enhance dataset diversity through Roboflow's data augmentation.
4) Export the labeled dataset in YOLOv8-compatible format.
5) Train the YOLOv8 model on the dataset, fine-tuning for accuracy.
6) Integrate the trained model into your application for real-time detection.
7) Implement Easy-OCR for character recognition on detected license plates.
8) Evaluate system performance with a separate test dataset.
9) Deploy the integrated system for real-world license plate tasks.

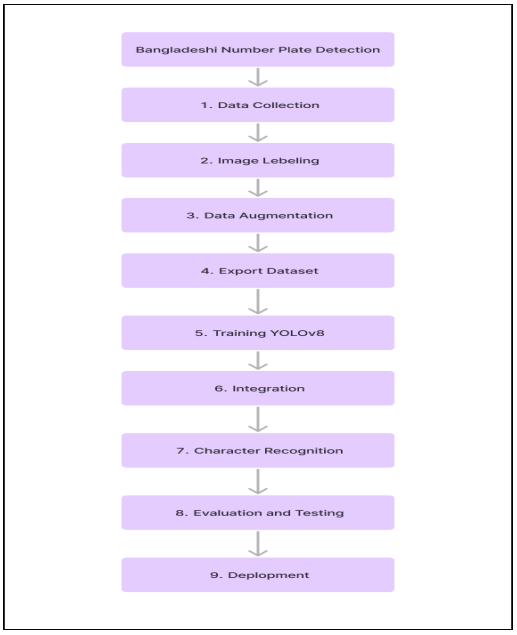


Fig. 1 Work Steps

B. Data Collection:

With meticulous care, we assembled a dataset featuring images showcasing Bangladeshi license plates, meticulously crafted to ensure its richness and diversity, thereby enhancing the robustness of our models. Employing a multifaceted approach, we utilized cameras stationed along roadsides and public areas, alongside capturing images using smartphone cameras, as illustrated in Fig. 2.

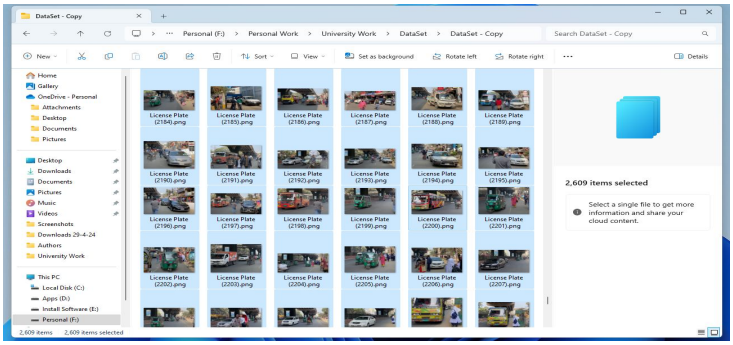


Fig. 2 Data collection

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Our emphasis on diversity extended to capturing images under varying lighting conditions, angles, and backgrounds. Particularly noteworthy was our focus on acquiring images from diverse angles, thereby enriching the dataset with a plethora of perspectives. This rigorous data collection methodology forms the cornerstone for training computer vision models adept at detecting and recognizing Bangladeshi license plates. In total, our dataset comprises approximately 2600 images, meticulously curated and stored within our local environment, poised to fuel our model development endeavors.

C. Image Labeling:

Use Roboflow's labeling tools to annotate the license plate regions in the dataset. This step involves drawing bounding boxes around the license plates and labeling them accordingly.

1) *Create Account to Roboflow:* To begin, creating an account on Roboflow is the first step, followed by establishing a new workspace. Within the workspace, selecting a suitable plan is essential, with options ranging from various plans depicted in Fig. 3, where we opted for the sandbox plan for its complimentary features.

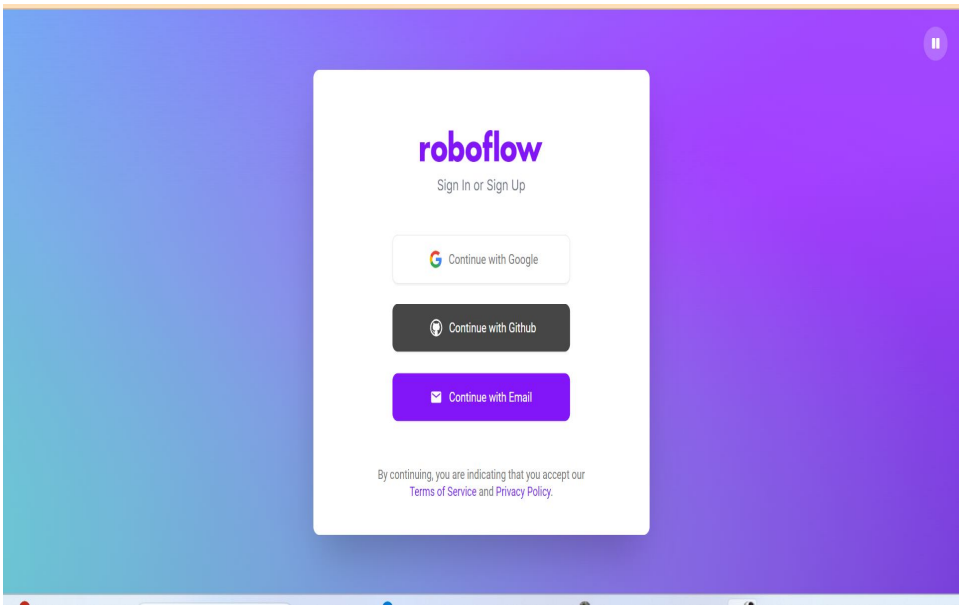


Fig. 3 Crate Account on Roboflow

2) *Create a New Project:* After completing the initial setup, the next step involves creating a new project, guided by the steps depicted in Fig. 4.

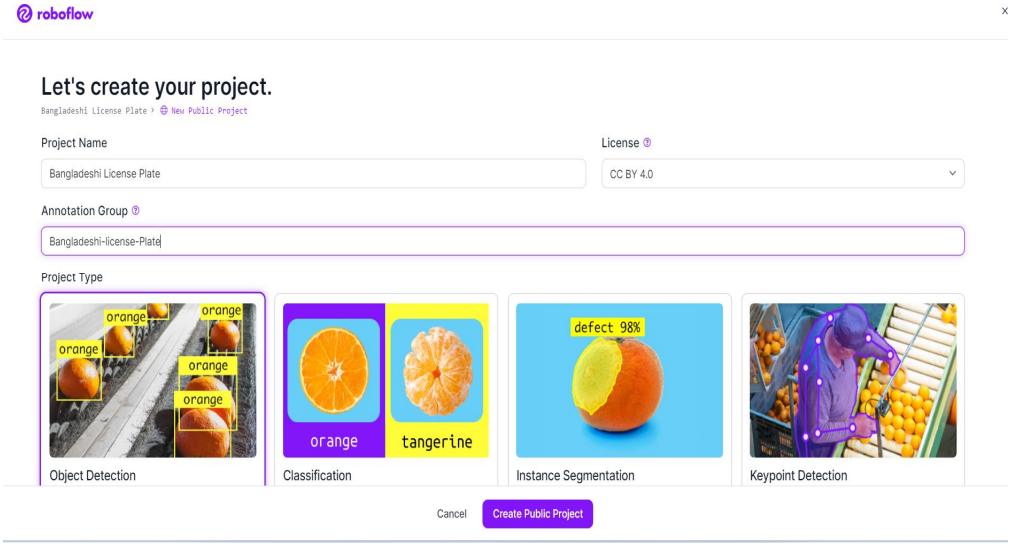


Fig. 4 Creating a New Project

3) *Upload the Data:* Following that, our dataset, totaling 2600 images, was uploaded, initiating the annotation process. We then proceeded to partition the dataset into train, test, and validate sets, as demonstrated in Fig. 5. Upon completion, we clicked the "Save and Continue" button to proceed to the next step.

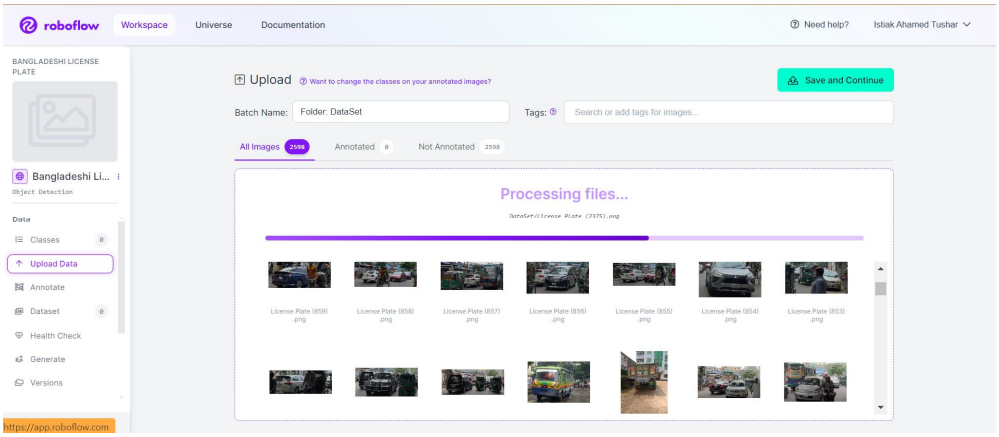


Fig. 5 Upload Data

4) *Data Labeling or annotation:* In this stage, we meticulously labeled our data one by one using Roboflow's advanced tools, which streamlined the process shown on Fig. 6. Employing rectangle boxes, we labeled various types of Bangladeshi number plates for cars, CNG vehicles, buses, large and small trucks, and the unique Leguna transport.

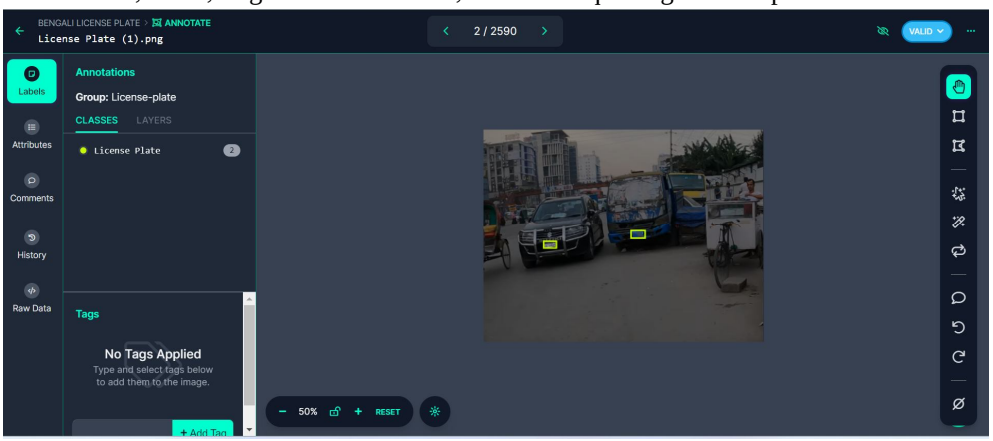


Fig. 6 Data Labelling

While we aimed to label all number plates, we refrained from labeling very distant ones to prevent confusion during model training with smaller objects like billboards or banners commonly seen beside roads.

5) *Save Data for Augmentation:* After completing these steps, we meticulously prepared our labeled data and saved it, paving the way for the next crucial phase: data augmentation. In the upcoming steps, we will leverage data augmentation techniques to further enhance the diversity and richness of our dataset, thereby optimizing our model's performance and robustness in real-world scenarios.

D. Data Augmentation

Leveraging Roboflow's advanced data augmentation features, we significantly enhanced the diversity of our dataset through various techniques shown on Fig. 7. This included rotation, flipping, scaling, and adding noise, aimed at simulating diverse real-world scenarios. To thoroughly assess the impact of these augmentations on model performance, we meticulously applied three distinct augmentation sets, each tailored to introduce different variations in the image context. Furthermore, we systematically adjusted the distribution of data across the training, testing, and validation sections to ensure comprehensive model evaluation and robustness assessment.

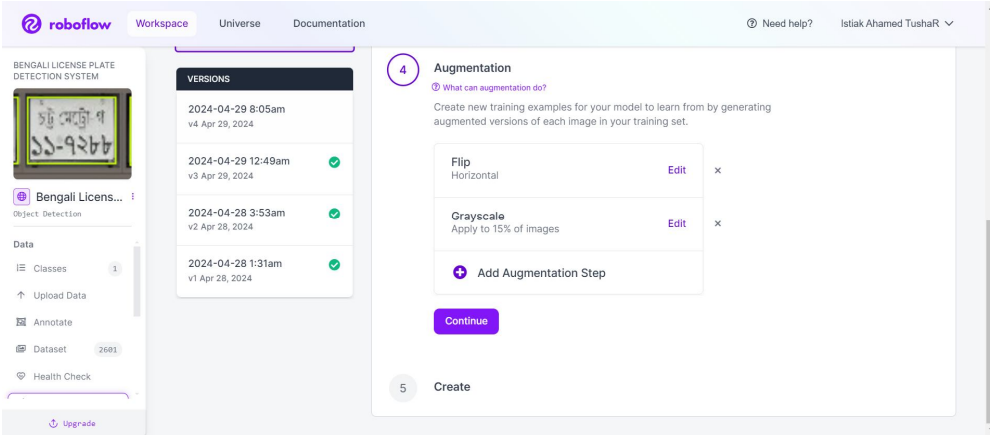


Fig. 7 Data Augmentation

E. Export Dataset

Export the labeled dataset from Roboflow in a format compatible with YOLOv8, such as YOLO darknet format (`.txt` files with coordinates and class labels) Fig. 8.

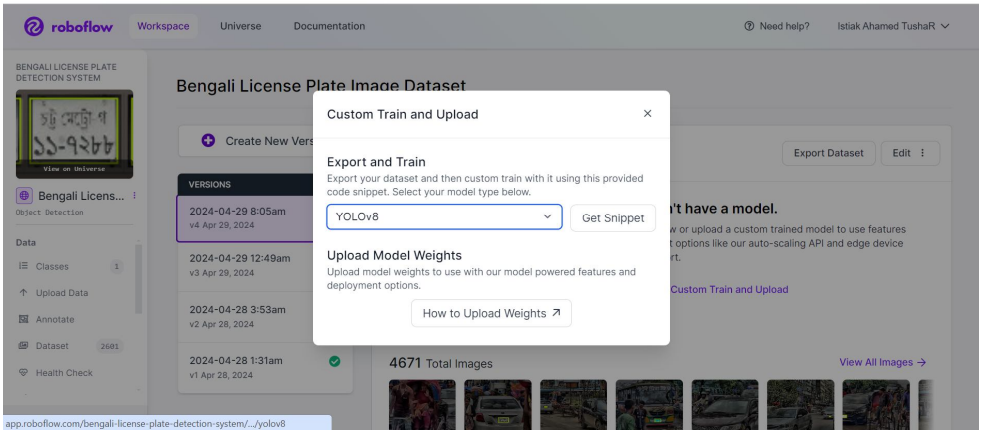


Fig. 8 Export Dataset in YOLOv8 Format

F. Training YOLOv8

We employed the exported dataset to train the YOLOv8 model for license plate detection, harnessing the capabilities of Roboflow for seamless integration. While YOLOv8 can typically be trained using frameworks like PyTorch or TensorFlow, Roboflow provided us with the flexibility to train our model directly on YOLOv8. This enabled us to explore the platform's performance enhancements and evaluate its impact on detection accuracy. Through fine-tuning the model on the Bangladeshi license plate dataset, we aimed to achieve significant improvements in detection accuracy, leveraging the robust training capabilities of YOLOv8 to adapt the model to our specific requirements.

G. Integration

Integrating the trained YOLOv8 model with our application or system for license plate detection is the next crucial step. This process entails setting up an inference pipeline capable of processing incoming images or video streams in real-time and accurately detecting license plates. Leveraging tools like PyCharm and other virtual environments, we seamlessly import our trained model from Roboflow into our project for further refinement. Upon importing the model, we utilize its capabilities to detect license plates from both images and videos, followed by segmentation of the plates from the vehicle. To integrate our model effectively, we can utilize the provided code snippet showcased in Fig. 9, facilitating smooth integration into our application or system for real-world deployment.

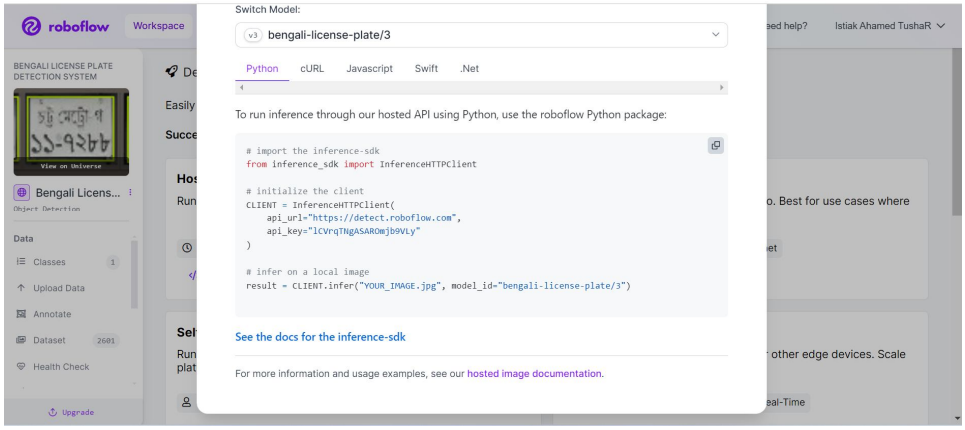


Fig. 9 Integration Process

H. Character Recognition

Utilizing EasyOCR for Bengali text recognition, we successfully identified and recognized Bangla license plates, leveraging the preceding steps of object detection with YOLOv8 and extraction of Regions of Interest (ROIs). The comprehensive dataset curated through meticulous collection methods ensured a diverse range of images, capturing various lighting conditions, angles, and backgrounds. With the OCR capabilities of EasyOCR supporting over 70 languages and accommodating different fonts and text styles, we achieved accurate and efficient recognition of Bangla characters on license plates. This integration seamlessly worked within our Python application, demonstrating robust performance and excelling in OCR benchmarks. Through the systematic process of object detection and OCR analysis, EasyOCR provided reliable results, contributing to the effectiveness of our license plate recognition system.

I. Evaluation and Testing:

To assess the effectiveness of the combined system in detecting and recognizing Bangladeshi license plates, we conducted evaluations on a distinct test dataset, rigorously testing its performance across various scenarios. Through iterative fine-tuning of the model and algorithms based on evaluation results, we refined the system to optimize its accuracy and reliability. Our testing encompassed diverse image and video datasets, including real-world scenarios captured via CCTV cameras. Remarkably, the model showcased consistent and efficient performance across different situations, angles, places, and environmental conditions. The results, as depicted in Fig. 10, underscored the system's capability to accurately detect and recognize license plates, affirming its practical utility and robustness in real-world applications.

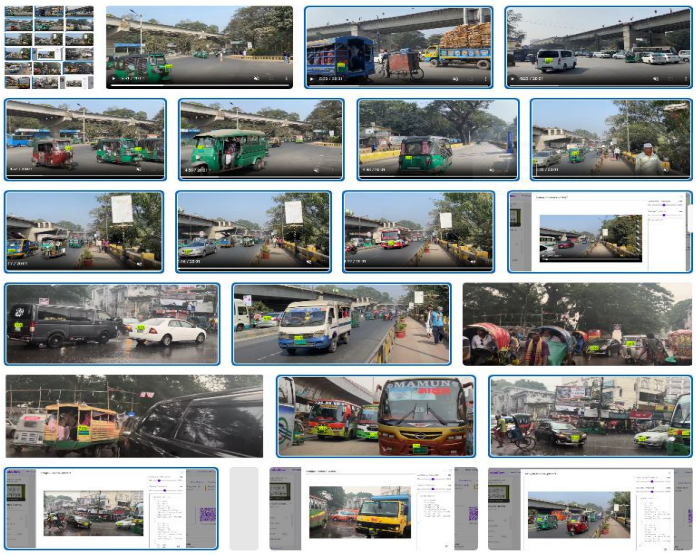


Fig. 10 Testing picture of model on Image, Video and CCTV Footage

J. Deployment

The development process of our system commenced with meticulous dataset curation, gathering images of Bangladeshi license plates from various sources to ensure diversity in conditions and contexts. Through robust annotation and segmentation using Roboflow, the dataset was prepared for YOLOv8 model training, augmented for enhanced diversity and accuracy. Integration into our application facilitated real-time license plate detection, with PyCharm serving as the seamless platform for model deployment. Extensive testing validated the model's efficiency across diverse scenarios, confirming its reliability in detecting and recognizing license plates with precision. These results underscored the system's practicality and potential for deployment in real-world applications such as traffic management and security systems.

IV. RESULT AND DISCUSSION

We meticulously crafted three distinct datasets through the augmentation of our collected data, employing techniques such as rotation, flipping, scaling, and noise addition to emulate diverse real-world scenarios. Each dataset was meticulously tailored to introduce unique variations in the image context, allowing for a comprehensive assessment of their impact on model performance. Moreover, we systematically adjusted the distribution of data across the training, testing, and validation sections to ensure thorough model evaluation and robustness assessment. The results of our tests, including model performance based on the type of dataset and augmentation, as well as the segmentation of data into training, testing, and validation sets, are summarized comprehensively in TABLE 1, providing valuable insights into the effectiveness of our approach.

TABLE I

	Information and Result for prepared dataset		
	Dataset 1	Dataset 2	Dataset 3
Size of Dataset	Total Images: 2601 Train Set: 1820 Valid Set: 521 Test Set: 260	Total Images: 7091 Train Set: 6735 Valid Set: 253 Test Set: 103	Total Images: 5595 Train Set: 5074 Valid Set: 521 Test Set: 260
Preprocessing	Auto-Orient: Applied Resize: Stretch to 640x640	Auto-Orient: Applied	Auto-Orient: Applied Auto-Adjust Contrast: Using Adaptive Equalization
Augmentations	No augmentations were applied.	Rotation: Between -15° and +15° Grayscale: Apply to 15% of images Bounding Box: Rotation: Between -15° and +15° Bounding Box: Shear: ±10° Horizontal, ±10° Vertical Bounding Box: Brightness: Between -15% and +15% Bounding Box: Noise: Up to 0.34% of pixels	Flip: Horizontal, Vertical Grayscale: Apply to 15% of images
Training Model	Model Type: Roboflow 3.0 Object Detection (Fast) (YOLOv8) Checkpoint:COCO	Model Type: Roboflow 3.0 Object Detection (Fast) (YOLOv8)	Model Type: Roboflow 3.0 Object Detection (Fast) (YOLOv8)

		Checkpoint: COCOn	Checkpoint:bengali-license-plate/1 (Model created by Dataset 1)
Result	mAP: 94.0% Precision: 89.4 Recall: 90.8%	mAP: 94.7% Precision: 94.7% Recall: 86.7%	mAP: 94.8% Precision: 94.5% Recall: 87.9%

During the training of the YOLOv8 model, the generated training graph provides essential insights into its performance metrics, including Mean Average Precision (mAP), Box loss, Class loss, and Object Loss, as depicted in Fig. 11. This graph enables a comparative analysis of Dataset 1, 2, and 3, offering a detailed understanding of the model's behavior across different datasets.

Examining the training graph for Dataset 1, we observe consistent and favorable trends in performance metrics. The mAP values reflect the model's ability to achieve high precision and recall rates, indicating its proficiency in accurately detecting and recognizing license plates. Concurrently, the Box loss, Class loss, and Object Loss demonstrate stable and minimal fluctuations, signifying effective optimization and convergence during the training process.

Comparatively, analyzing the training graphs for Dataset 2 and 3 allows for assessing the model's adaptability to varying data distributions and conditions. Any discrepancies or deviations in performance metrics between datasets provide valuable insights into the model's robustness and generalization capabilities.

Overall, the comparative analysis facilitated by the training graph aids in understanding how the YOLOv8 model responds to different datasets, thereby guiding further refinement and optimization efforts. By identifying trends and patterns in performance metrics across datasets, we can make informed decisions to enhance the model's efficacy and suitability for real-world ALPR applications.

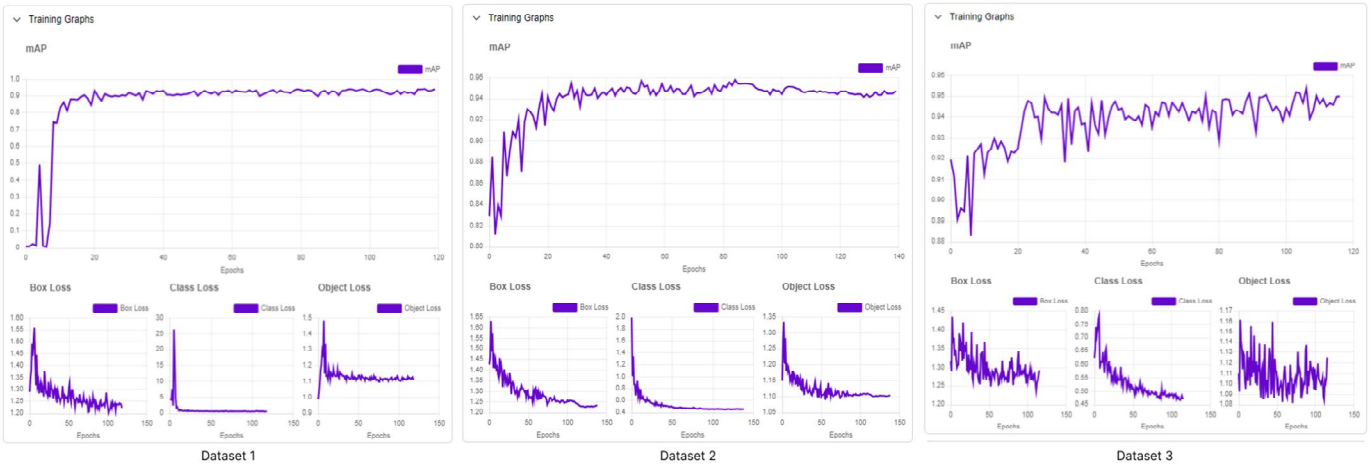


Fig. 11 Tanning Graphs for Dataset 1, Dataset 2 and Dataset 3

After training the YOLOv8 model, we meticulously evaluated its performance using a combination of matrices and graphs derived from the training process showcases the comprehensive metrics obtained from post-testing on Roboflow, offering valuable visual insights into the model's proficiency, particularly when subjected to real-world testing conditions. In the results discussion for Dataset 1, following the training of the YOLOv8 model, we conducted meticulous evaluations to assess its performance. Utilizing a combination of matrices and graphs derived from the training process, we obtained comprehensive metrics, as illustrated in Fig. 11. These metrics, obtained from post-testing on Roboflow, provide valuable visual insights into the model's proficiency, particularly when subjected to real-world testing conditions.

Regarding the first point, the model's exceptional performance in detecting license plates from corner angles, especially evident in Dataset 1, underscores its robustness. This proficiency in corner-side detection, derived from a significant portion of angular data during training, demonstrates the model's adaptability to diverse vehicle orientations commonly encountered in real-world scenarios. Moreover, Dataset 1's results also highlight the model's capability to accurately identify license plates amidst challenging conditions prevalent in Bangladeshi settings.

Despite the common occurrence of broken or obscured license plates, the model exhibits consistent accuracy, showcasing its resilience to such obstacles. This capability extends to scenarios involving low-resolution images, dust-covered plates, and other adverse conditions, further validating the model's effectiveness in practical applications.

Lastly, the model's performance on Dataset 1 reaffirms its ability to handle situations with multiple license plates, as often encountered on vehicles like buses adorned with banners. Even amidst cluttered environments, the model reliably distinguishes and identifies the correct license plate, underscoring its potential for enhancing road safety and traffic management.

In conclusion, the evaluation results for Dataset 1 serve as a testament to the YOLOv8 model's efficacy and suitability for real-world ALPR applications in Bangladesh. The model's exceptional performance, as evidenced by comprehensive metrics and visual representations, validates its reliability and underscores its potential to address the unique challenges posed by Bangladeshi license plates in diverse operational environments.

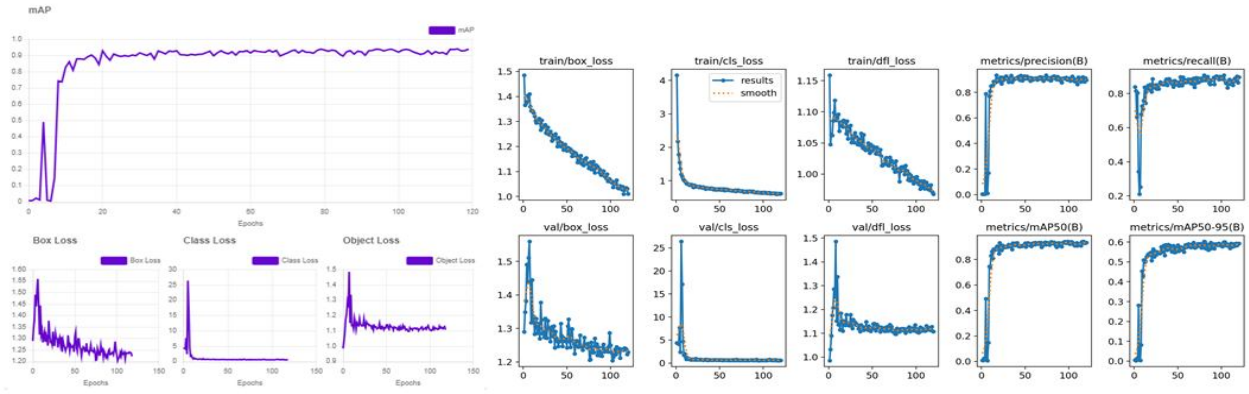


Fig. 12 Training process graph for dataset 1

V. CONCLUSION

In summary, this research introduces a comprehensive framework tailored for developing a highly effective Automatic License Plate Recognition (ALPR) system specifically designed for Bangladeshi license plates. By leveraging advanced deep learning techniques like YOLOv8 and harnessing the capabilities of Roboflow for dataset annotation and augmentation, a robust solution has been crafted capable of accurately detecting and recognizing Bangladeshi license plates in real-time. The methodology employed emphasizes three key points:

Firstly, 90% of the data utilized in training was sourced from angular perspectives, enabling the model to excel in detecting license plates from corner angles across various vehicle types.

Secondly, given the prevalent condition of Bangladeshi vehicles, often featuring broken or obscured license plates, the system's ability to discern and accurately identify license plates amid such challenges is noteworthy. Even amidst low-resolution images or adverse conditions, such as dust-covered plates, the model exhibits remarkable proficiency.

Lastly, the model demonstrates exceptional performance in scenarios where multiple license plates are present, as commonly seen on buses adorned with banners. Despite the cluttered environment, the system reliably detects and identifies the correct license plate, contributing significantly to improved road safety and traffic management.

In conclusion, this research offers valuable insights and methodologies to enhance ALPR technology, specifically addressing the unique challenges posed by Bangladeshi license plates. Its potential for real-world deployment in traffic management, security, and law enforcement applications signifies a substantial contribution to advancing road safety not only in Bangladesh but also in similar contexts worldwide.

VI. FUTURE WORK

Future work in this research direction could focus on several key areas to advance the capabilities and practicality of the developed ALPR system for Bangladeshi license plates. Firstly, there's potential for enhanced model training by continually refining and optimizing the YOLOv8 model to achieve greater detection accuracy and robustness across varying environmental conditions and vehicle types. Dataset expansion is another avenue, where including a more diverse range of license plate images captured under different circumstances could bolster the model's generalization capabilities. Refining localization and segmentation techniques could further improve the system's ability to accurately identify and extract license plate regions from complex backgrounds.

Exploring the integration of multimodal information, such as vehicle speed and context data, could enrich the system's understanding and decision-making capabilities. Additionally, optimizing real-time performance and ensuring compliance with evolving regulatory standards are critical considerations. Field testing in real-world scenarios and designing user-friendly interfaces would provide valuable insights into system performance and facilitate widespread adoption. Addressing these aspects would refine the ALPR system's effectiveness and adaptability for various applications in traffic management, law enforcement, and urban planning contexts.

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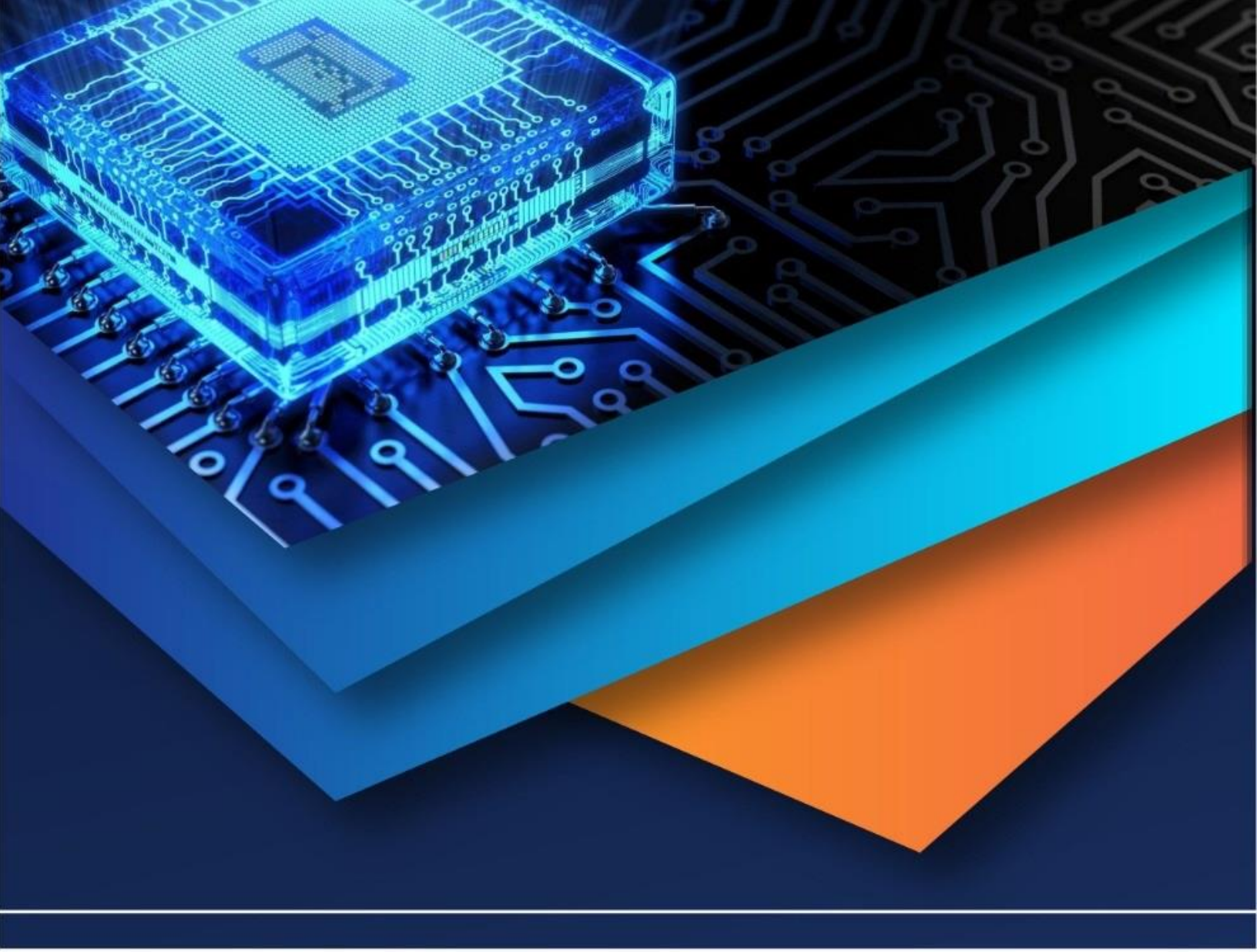
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