

License Plate Detection and Privacy-Aware Masking in Surveillance Imagery

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Abstract: *This study presents a novel approach to License Plate Recognition (LPR) and Masking, focusing on utilizing OpenCV and cascade classifiers as opposed to deep learning techniques. The methodology involves training cascade classifiers to detect license plate regions, followed by image preprocessing techniques to refine the detected areas. The proposed system offers a privacy-focused license plate masking feature, allowing for the obscuring or blurring of license plates in images and videos to protect sensitive information. Experimental results showcase the system's efficacy in accurately identifying license plates in various environments. Notably, deep learning techniques are intentionally omitted, and the study relies solely on image processing methods. The privacy feature successfully balances data utility and confidentiality by safeguarding private data while maintaining overall visual data usefulness. In conclusion, the integration of OpenCV, cascade classifiers, and privacy preservation techniques yields a comprehensive solution for License Plate Recognition and Masking, suitable for applications in security, surveillance, and privacy-conscious scenarios.*

Keywords — *Masking, OpenCV, cascade classifiers, image preprocessing, sensitive information, privacy preservation, security, surveillance.*

I. INTRODUCTION

License Plate Recognition (LPR) has emerged as a crucial technology with a wide range of applications such as traffic management, traffic analysis, parking management, security, media, research, location-based services, and compliance with privacy regulations. It ensures privacy in public spaces, prevents unauthorized tracking, safeguards personal data, respects individual rights, and upholds ethical standards in data handling and sharing, and security surveillance. This paper introduces an innovative approach to License Plate Recognition and Masking, leveraging the power of OpenCV and cascade classifiers. Using OpenCV and image processing for license plate detection and masking offers advantages in terms of simplicity, efficiency, transparency, and privacy compared to deep learning-based approaches. It allows for accurate and robust detection, customization, and adaptability to specific requirements, making it a suitable

choice for real-time applications, resource-constrained environments, and scenarios where privacy and interpretability are paramount concerns. The integration of these techniques enables accurate license plate detection and a privacy-focused masking feature.

The proposed methodology employs cascade classifiers, which are a type of machine-learning technique designed for object detection. These classifiers use a sequence of progressively more complex filters to identify specific features in images. In contrast, CNNs are deep learning architectures that automatically identify pertinent characteristics from data. CNNs excel in recognizing complex patterns and hierarchical features, which can be advantageous in various recognition tasks, including LPR.

A. Computational Requirements

Cascade classifiers are computationally efficient and well-suited for real-time applications due to their relatively low computational demands. They are capable of achieving good performance on relatively simple tasks like license plate detection. On the other hand, CNNs, especially deep and complex architectures, demand significant computational resources, enhancing their suitability for situations requiring great precision is paramount, and computational cost is not a limiting factor.

B. Use case scenarios

The proposed methodology is ideal for scenarios where accuracy in license plate detection is required while maintaining computational efficiency, such as surveillance systems, traffic monitoring, and parking management. The privacy-centric license plate masking feature also aligns well with these scenarios by providing an added layer of privacy protection. CNNs, on the other hand, thrive at challenging recognition tasks that call for the learning of nuanced patterns from big datasets. They are frequently employed for tasks that need high levels of accuracy, like image classification, object detection, and even license plate recognition in situations with challenging conditions, like varying lighting and angles.

However, the proposed system holds distinct advantages. It features a privacy-focused license plate masking mechanism, seamlessly integrates OpenCV for real-time processing, and allows tailored cascade classifier training for enhanced accuracy. Its potential for versatile object detection further broadens its application scope beyond license plates, setting it apart from [1]'s approach. The proposed system's emphasis is on privacy, OpenCV integration, customization, and broader application.

II. LITERATURE SURVEY

The author [1] presents a comprehensive approach to automating license plate detection and masking. It introduces various algorithms for license plate and car detection, utilizing techniques like Histogram of Oriented Gradients (HOG) and the Caffe framework. The methodology also hints at applying similar procedures for face detection. Notably, the absence of a license plate dataset prompts a discussion on dataset creation. The system is implemented in Python 2.7 on Linux, making it compatible with diverse hardware configurations. The proposed technique achieves an 86.95% accuracy in license plate detection. Additionally, the paper emphasizes its simplicity, running efficiently on a 16GB RAM Linux machine. The approach's versatility is highlighted, as it can potentially extend to detecting other objects, demanding tailored image training. Utilizes broader context of object recognition and privacy-focused image processing.

OpenCV and image processing simplifies and accelerates masking with efficient real-time processing, reliability, and community support. Its flexibility, GPU utilization, and compatibility make it a superior choice compared to custom methods.

The author [2] presents a comprehensive framework for License Plate Detection using computer vision techniques, with a focus on automating the identification and recognition of license plates in digital images. The process encompasses various stages, including image processing, number pad localization, character truncation, and Optical Character Recognition (OCR) techniques. The proposed approach employs the K-NN algorithm and Python programming, harnessing the OpenCV library for efficient image processing. The technology finds versatile applications in security, highway speed detection, and automatic charging systems. The paper outlines the entire process, from capturing license plate images to segmentation, OCR, and acquiring the recognized plate number. Notably, the proposed system simplifies the workflow compared to complex approaches, achieving optimized recognition results without the need for custom OCR algorithms. This simplification benefits from image processing and OpenCV, ensuring accuracy and efficient performance. The system holds the

capability for real-time usage and the potential for seamless integration with access control systems, further amplifying its practicality in various scenarios.

This author [3] presents a novel approach for Automatic License Plate Detection (ALPD) using computer vision techniques in Intelligent Transportation Systems (ITS). The proposed algorithm combines Faster R-CNN with digital image processing to accurately detect vehicles' license plates in images. The process involves initially detecting vehicles in the input image through Faster R-CNN and subsequently analyzing the located vehicle with a robust License Plate Localization Module (LPLM).

The LPLM module utilizes color segmentation and processes the HSV image to accurately detect license plates in the provided input image. It further employs morphological filtering and dimension analysis to precisely locate the license plate. The effectiveness of the algorithm is demonstrated through rigorous testing on the challenging PKU datasets, and the results show that it outperforms recently developed methods by achieving high accuracy in license plate detection with significantly reduced execution time. The proposed method demonstrates great feasibility for security and target detection applications, making it a valuable contribution to the field of Automatic License Plate Detection. With its efficient combination of Faster R-CNN and digital image processing techniques, this approach holds promising potential for enhancing Intelligent Transportation Systems and improving the recognition rate of ALPD systems

This author [4] presents an image-to-text conversion system that extracts text information from license plate images. The strategy employs various stages of image processing using the CV2 OpenCV library in Python to overcome the shortcomings of existing image processing applications. After processing, the Tesseract OCR is utilized to extract text from the processed images. The authors emphasize the importance of variable levels of image processing to optimize results for different images.

Comparative analysis of the algorithm on different sample images of license plates demonstrates that the optimum output varies from stage to stage for each photo. The authors acknowledge the need to develop another algorithm to sort and predict the optimum output. The paper concludes by suggesting future improvements, including the use of Neuro-Fuzzy networks to train the system for recognizing valid license plate number combinations and reducing errors. This system does not involve masking of number plates and recognition of multiple number plates hence complicated images will be hard to process.

The author [5], a novel technique for image segmentation is introduced, specifically aimed at extracting the Region of

Interest (ROI) from images. In this context, the ROI pertains to the vehicle license plate. To effectively identify and isolate the license plate, an innovative Sliding Concentric Window (SCW) algorithm is developed for performing the segmentation task. The proposed approach involves acquiring vehicle images, followed by the application of the SCW algorithm to precisely delineate the ROI. Subsequently, Morphological Image Processing methods, namely erosion, and dilation, are employed to precisely localize the license plate. However, it's noted that in certain instances, the proposed method erroneously identifies other image areas as the ROI, even though they are not license plates. Additionally, the model offers insight into the mask used during the license plate localization process. It's acknowledged that the proposed model encounters challenges when attempting to detect license plates in images containing natural backgrounds. While performing well when the input images are primarily focused on the license plate region, the algorithm struggles when faced with images featuring varying illumination conditions. In such cases, the algorithm generates outputs in which multiple segments of the image are erroneously identified as the ROI.

The author [6] introduces a novel Indian License registered number plate detection and recognition approach, structured into three phases: pre-processing, detection, and recognition. The pre-processing stage employs image-processing techniques like morphological transformation, Gaussian smoothing, and Gaussian thresholding. Number plate segmentation is achieved through contour application, filtering based on character dimensions, and spatial localization. For region of interest filtering and de-skewing, the K-nearest neighbor algorithm is employed for character recognition. The model utilizes color edge mapping, HIS-based color transformation methods, and fuzzy aggregation for number plate extraction. Although the approach achieves a 93.7% accuracy, it overfits numerous fonts, impacting generalization. Achieving a balanced consideration of various fonts is essential, as too many or too few fonts can adversely affect predictions. Notably, the study underscores the effectiveness of simpler models like K Neighbors over sophisticated ones, due to the limited data available for training.

The author [7] represents a template-matching technique that involves comparing a given license plate image with predefined templates of characters and digits. The method capitalizes on the distinctive features of characters, allowing for accurate identification. The study emphasizes the significance of license plate recognition in various applications, such as traffic management and law enforcement. The template matching technique is relatively simple to implement and computationally efficient. It can provide satisfactory results for recognizing license plate

numbers in controlled environments. The method is robust to some degree of noise and distortion in the license plate images. It can handle variations in lighting and minor occlusions. One drawback of the template matching technique is its limited flexibility in handling variations in font style, size, and orientation. This can lead to reduced accuracy in scenarios where license plate designs deviate from the predefined templates.

The study contributes to the field of license plate recognition by showcasing the effectiveness of the template-matching technique. While it offers simplicity and efficiency, it may encounter challenges in handling diverse license plate designs.

The authors [8] explore the utilization of convolutional neural networks (CNNs) for efficient and accurate license plate detection. They employ state-of-the-art object detection frameworks like YOLO (You Only Look Once) and Faster R-CNN to localize license plates within images. Subsequently, the paper delves into license plate recognition (LPR), employing CNNs and possibly recurrent neural networks (RNNs) to segment and recognize characters on the detected plates. The study acknowledges the significance of pre-processing steps such as image enhancement and perspective correction in enhancing the robustness of the proposed system.

The specific details about the dataset used, experimental setup, and quantitative outcomes are not included in this brief overview. The research underscores the potential of deep learning in advancing license plate detection and recognition technology, addressing real-world challenges in the domain. Further expansion of the paper could involve comparative analysis with other methodologies, addressing potential limitations, and proposing avenues for future research in improving the system's performance under diverse environmental conditions.

The author [9] proposes a robust approach utilizing deep learning techniques for accurate license plate recognition in challenging environments. It explores novel neural network architectures tailored to non-standard conditions, enhancing detection and classification accuracy. The paper emphasizes transfer learning strategies, adapting pre-trained models to unique scenarios to improve recognition rates. The author [9] concentrates on feature extraction from distorted plates, enhancing pattern recognition in diverse lighting and weather conditions, and proposes a real-time recognition method employing convolutional neural networks for rapid and reliable identification. The proposed system focuses on optimizing neural network hyper-parameters and training techniques, ensuring robust performance in varying non-standard environments.

The author [10] covers advancements like convolutional neural networks (CNNs) and recurrent neural networks (RNNs) in LPR, emphasizing their accuracy improvements. The authors discuss fusion techniques, combining information from multiple sources to enhance recognition reliability. The paper underscores the advantages of LPR systems. They enable efficient automated vehicle monitoring and reduce manual intervention. LPR enhances law enforcement by enabling quick identification of vehicles involved in criminal activities. Additionally, it streamlines toll collection processes and aids in traffic management through real-time data analysis. The author [10] acknowledges certain drawbacks of LPR systems. Environmental factors such as poor lighting, weather conditions, and vehicle speed can affect recognition accuracy. Variations in license plate formats and fonts pose challenges, leading to recognition errors. Privacy concerns also arise due to the potential misuse of captured data.

The author [11] emphasizes a back-to-basics methodology, investigating fundamental factors influencing detection accuracy. They apply DOE principles to optimize CNN parameters, enhancing robustness across diverse environments. The paper's strength lies in its systematic approach, ensuring precise license plate detection. The integration of CNN and DOE contributes to higher accuracy, particularly under challenging conditions. Optimized parameters improve real-time processing, enhancing traffic management and law enforcement tasks. The study focuses primarily on license plate detection, potentially requiring further research to incorporate character recognition. While effective in various scenarios, extreme environmental factors could impact performance. Additionally, the methodology's applicability to non-standard plate formats or languages may require investigation.

The author [12] explores how Tesseract OCR offers the advantages of open-source accessibility, making it cost-effective and easily adaptable. It accurately extracts characters from license plates, aiding law enforcement and traffic management. The system benefits from Tesseract's continuous development and community support, ensuring updates and improvements. Tesseract's performance can be sensitive to image quality, affecting recognition in challenging conditions like poor lighting or plate distortion. Multilingual plates and non-standard fonts may also pose challenges. Despite its capabilities, Tesseract's recognition accuracy might not match more specialized OCR solutions in complex scenarios, which is the drawback of the proposed system. In summary, the system leverages Tesseract OCR's accessibility and accuracy for license plate recognition, with considerations for image quality and diverse plates.

III. PROBLEM STATEMENT

License plates serve as crucial identifiers of vehicles and their proprietors, encapsulating sensitive personal data. People anticipate the safeguarding of their private information, particularly within public domains. The omnipresence of surveillance cameras and the ease of image capture render individuals susceptible to unauthorized tracking of their daily movements. License plates often correlate with registered vehicle owners, facilitating potential malevolent actors in gathering personal details. This unauthorized tracking heightens the risks of identity theft and fraudulent activities. Masking license plates holds ethical importance and is imperative for cultivating a digital landscape where individuals experience a sense of safety and security in the contemporary information era. It upholds individuals' privacy rights, mitigates the potential for malicious intent, reinforces personal security, and ensures adherence to stringent data protection regulations.

IV. PROPOSED SYSTEM AND ARCHITECTURE

The proposed system consists of two main stages: license plate detection, and license plate masking as shown in Fig.1.

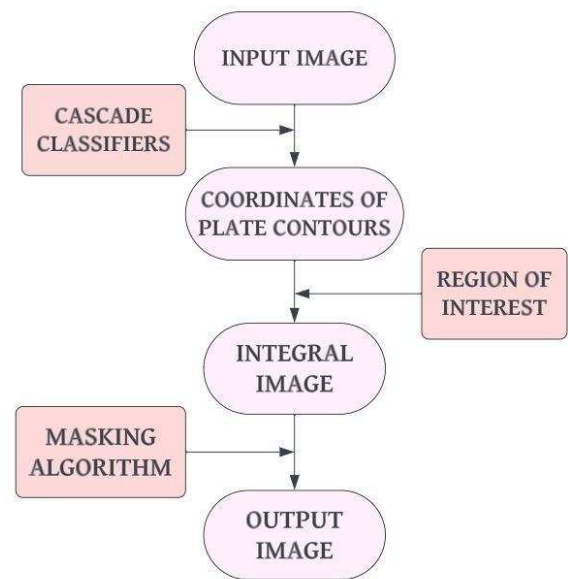


Fig.1 Architecture Block Diagram

1. License Plate Detection:

Cascade classifiers, a variant of machine learning-based object detection, are employed to detect license plates. The algorithm used in implementing this model is the Viola-Jones object detection algorithm, which is a widely used technique for real-time object detection. It utilizes a cascade of classifiers, each consisting of multiple stages. Each stage contains several weak classifiers that collectively work together to classify whether a region contains the object of interest (in this case, a license plate). The algorithm starts by preprocessing the image using an integral image (also known as a summed area table). An integral image is a way to

efficiently compute the sum of pixel intensities within any rectangular region of an image. Given an original image pixel value $I(x, y)$ at position (x, y) , the integral image $S(x, y)$ is calculated recursively as follows-

$$S(0, y) = I(0, y)$$

$$S(x, 0) = I(x, 0)$$

$$S(x, y) = S(x-1, y) + S(x, y-1) - S(x-1, y-1) + I(x, y)$$

Let rectangle with the top-left corner at $(x1, y1)$ and the bottom-right corner at $(x2, y2)$

$$\text{Sum} = S(x2, y2) - S(x1-1, y2) - S(x2, y1-1) + S(x1-1, y1-1) - (1)$$

At each stage, the classifier examines a sub-region of the image using Haar-like features (simple rectangular filters that are applied to the integral image to compute features that can distinguish between different object parts.) including two-rectangle features which is a difference of the sum of pixel intensities in two adjacent rectangles and three-rectangle Feature which is difference between the sum of pixel intensities in two outer rectangles and one central rectangle. and compares them to predefined threshold values. The key idea is that these features can capture various aspects of local image patterns, such as edges, lines, and contrasts. By combining multiple Haar-like features, you can build a more complex representation of the image's texture and patterns. If a region passes a stage's classifier, it proceeds to the next stage. If it fails, the region is discarded as not containing the object. This algorithm uses a machine learning technique called AdaBoost to select a subset of the most discriminative Haar-like features and build a strong classifier. AdaBoost assigns weights to training images and iteratively trains weak classifiers (based on individual Haar-like features) to minimize the classification error. The selected weak classifiers are combined into a strong classifier. The classification function at each stage can be represented as:

$$H(x) = \text{sign}(\sum(\alpha_i * h_i(x))) \quad - (2)$$

where,

$H(x)$ is the final classification decision.

α_i is the weight assigned to the weak classifier $h_i(x)$

$h_i(x)$ is the decision of the weak classifier based on a Haar-like feature.

2. License Plate Masking:

To safeguard individual privacy, the system employs a masking technique to obscure the detected license plate. A simple masking technique is applied to replace the license plate area with a uniform background, rendering the plate's content unreadable. This step is crucial to prevent sensitive information from being exposed. For each detected license plate (x, y, w, h) representing the top-left corner coordinates, width, and height. The region containing the license plate is marked as the Region of Interest (ROI). A black rectangle is drawn around the detected plate (ROI) using OpenCV. effectively blurring the plate area. The masked license plate

area is superimposed onto the original image ensuring that the original context remains intact while safeguarding personal information.

Masking number plates using a combination of OpenCV and cascade classifiers offers several advantages in terms of privacy, security, and efficient processing.

Masking number plates using OpenCV allows for the anonymization of sensitive information in images and videos. This ensures that the identities of individuals, including vehicle owners, are protected from unauthorized tracking or surveillance. Cascade classifiers are optimized for quick object detection, making them suitable for real-time applications. They can swiftly identify the regions of interest (number plates) in an image or video frame, enabling efficient processing and response.

Cascade classifiers require relatively fewer computational resources compared to more complex techniques like deep learning. This makes them suitable for applications with limited computing power or real-time constraints. Due to their efficiency and simplicity, cascade classifiers are particularly useful for real-time applications. A comprehensive toolset for image processing and manipulation is offered by OpenCV. Combining cascade classifiers with OpenCV allows for easy integration with other computer vision tasks, such as object tracking or face recognition. Cascade classifiers can be fine-tuned for specific object detection tasks. This adaptability makes them suitable for detecting different types of number plates across various environments. The combination of cascade classifiers can help reduce false positives. Cascade classifiers quickly narrow down potential regions of interest, improving overall detection accuracy. Combining OpenCV, and cascade classifiers allows for a hybrid approach that harnesses the strengths of each technique. This results in improved overall performance and reliability.

Masking parameters: The region of Interest of the license plate is derived by character recognition by making use of the Haar Cascade Classifier. Once it identifies the RoI using coordinates (x, y, w, h) , a black rectangle is drawn and filled over this region to obscure the image and hide it.

V. IMPLEMENTATION

Importing Libraries and Modules:

First, we import all the necessary libraries and modules required for image processing, machine learning, and deep learning. We import OpenCV as `cv2`, numpy as well as Tensorflow and Keras

License Plate Detection (Cascade Classifier):

In this implementation, we utilize a specific model known as the Haar Cascade Classifier for license plate detection, with a focus on recognizing Indian License Plates. This classifier has been trained using a predefined set of features and rules

encoded in the './indian_license_plate.xml' file. The Haar Cascade Classifier operates by contouring characters and identifying groups that potentially form a license plate, guided by the criteria defined within the Cascade Classifier.

To achieve license plate recognition, we employ the 'detect_plate' function, which leverages the Haar Cascade Classifier. This function's purpose is to identify license plates within an image and draw rectangles around the detected plates. To illustrate the effectiveness of this algorithm, we load a sample input image and pass it through the 'detect_plate' function, thereby showcasing the license plate detection process.

Character Recognition and License Plate Composition:

For using the Cascade Classifier, we make use of the './indian_license_plate.xml' file, which is an XML file that contains rules that define features that are commonly found in Indian License Plates, and by using this information, the characters are first contoured and then the ones that may constitute a license plate are joined to form a license plate number that the algorithm identifies based on the information provided by the Cascade Classifier. Then the predicted license plate number is displayed.

Displaying Results:

Matplotlib is used to show the detected character contours. Then once the correct characters are identified, a rectangular black bounding box is inserted around all the identified license plates in the image and a final output image is generated which is the input image but with all the detected license plates covered by a black bounding box.

VI. RESULTS AND CONCLUSION

When the code is executed, it processes a sample image and produces an output image that is masked.in Fig.2

In essence, this implementation offers a holistic solution for license plate detection and masking, employing cascade classifiers and image processing techniques. The system showcases the power of computer vision in automating license plate identification, analysis, and visualization. In contrast to deep learning-based approaches, which have gained prominence in recent years for license plate detection and masking, this implementation relies on OpenCV and cascade classifiers, offering a distinct set of advantages.

While deep learning methods often require large labeled datasets, and significant computational resources, and may raise concerns about privacy and interpretability, the proposed system excels in simplicity, efficiency, and transparency. It showcases the power of computer vision in automating license plate identification and analysis without the need for extensive training data.

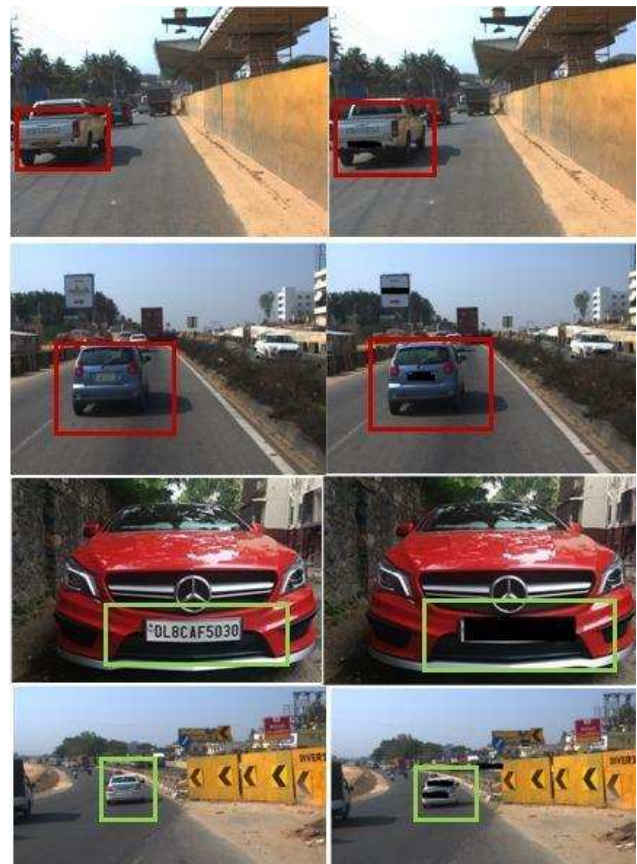
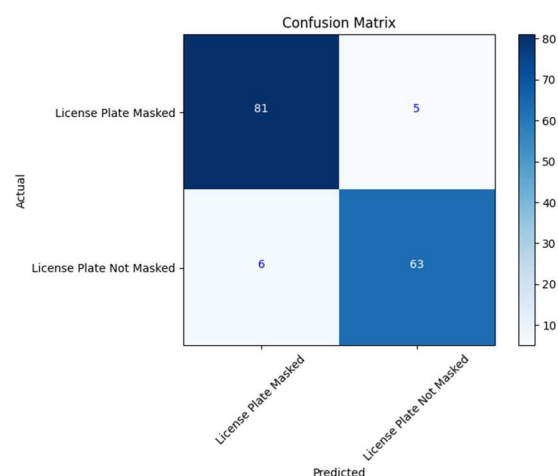


Fig.2: Before and After Processing



The confusion matrix for the masking model is shown in Fig.3. Fig.3 Confusion Matrix

For the sake of classification, we have manually divided our dataset into two classes - text in images that contain License plates, and text not containing license plates. Based on this binary classification, we have generated a confusion matrix where TP(True Positives) represent the license plates which are actually present and have been masked, FN(False Negatives) represent license plates that are present but have not been masked, FP(False Positives) represent license plates that are not present but have been masked and TN(True Negatives) represent license plates that are not present and

have not been masked. Based on this, we have calculated the accuracy, precision and recall values for our model -

Accuracy measures how often the model makes correct predictions overall and is represented by $(TP+TN)/(TP+FP+FN+TN)$. On calculation, our model is found to have an accuracy of **92.90%**

Precision measures how many of the predicted "License Plate Masked" instances are actually "License Plate Masked." It focuses on minimizing false positives. It is represented by $TP/(TP+FP)$. On calculation, our model is found to have a precision of **0.93**.

Recall measures how many of the actual "License Plate Masked" instances are correctly predicted as "License Plate Masked." It focuses on minimizing false negatives. It is represented by $TP/(TP+FN)$. On calculation, our model is found to have a recall of **0.94**.

F1-score is a metric that combines both precision and recall into a single value to provide a balanced measure of a model's performance. The F1-score is the harmonic mean of precision and recall and is represented by $2*Precision*Recall/(Precision + Recall)$. On calculation, our model is found to have an F1-score of **0.935**.

EVALUATION METRICS	CALCULATED VALUE
ACCURACY	92.9%
PRECISION	0.93
RECALL	0.94
F1-SCORE	0.935

These metrics have been calculated based on the performance of the model on a real-time dataset provided by a laboratory of the **WIRIN**. This dataset is a comprehensive dataset that tests all the edge cases as well as exceptions to the predictive and masking ability of the model, and based on the thorough evaluation metrics used, it can be inferred that the model has a high degree of deployability for real-world use cases.

VII. INFERENCE

To enhance the model's resilience, a range of data augmentation techniques are used during the training process of images. This will help the model generalize better to different lighting conditions, orientations, and angles and

help the model become more invariant to changes in object positions. In preprocessing steps, adaptive thresholding techniques are introduced to better segment the license plate from the background, especially when dealing with images of varying lighting conditions. The confusion matrix evaluates the performance of a model for detecting and masking number plates. A confusion matrix is a tabular representation that shows how a classification model's predictions match up against the actual labels. It provides a comprehensive view of how well a model is performing by breaking down the predictions it has made into different categories and comparing them to the actual ground truth labels.

VIII. FUTURE WORK

Future work for this multifaceted implementation holds promising avenues for advancement. Refining the privacy-focused masking feature using advanced methods like generative adversarial networks (GANs) could bolster identity protection. Real-world testing and optimization under diverse conditions, such as varying lighting and vehicle types, could enhance system reliability. Extending the system's applicability to different license plate formats from various regions could broaden its impact. Adapting the system for deployment on mobile and edge devices could bring real-time license plate detection to traffic management. The development of a user-friendly interface would enhance accessibility. These steps represent a future where the system integrates deep learning, improves privacy, and ensures real-world robustness, solidifying its position as a transformative force.

IX. ACKNOWLEDGEMENT

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