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Automatic Detection of Toll Tax-exempted Vehicles Using Machine Learning Techniques

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Abstract: Roads are essential for connecting cities and easing the movement of people, goods, and services throughout Pakistan. To manage these roads, toll plazas are set up to acquire funds for the construction and maintenance. However, many toll plazas in Pakistan are operated manually. In particular, verification for toll tax-exempted vehicles usually relies on the identification of authorized stickers applied to their windshields. In this research, we first develop a custom dataset of vehicles that contains images of vehicles with stickers and without stickers. In our custom dataset, the vehicles contain two types of stickers; one that makes them exempt from paying the toll tax and other ones, such as stickers of McDonald etc. The dataset is preprocessed to standardized formats, dimensions, and resolution. We perform extensive experiments on the dataset by implementing state-of-the-art machine learning techniques. Experimental results show that YOLOv8 for object detection and ResNet for image classification achieve better results than the existing approaches. YOLOv8 with an accuracy of 91.17% outperformed Faster R-CNN, and RT DETR with 87.37% and 85.00% accuracy, respectively. ResNet with an accuracy of 90.8% outperformed Decision Tree Classifier, and Support Vector Machines with 77.41% and 69.0% accuracy, respectively.

Keywords: Sticker Detection; Toll Tax Exemption; Vehicle Detection; Machine Learning; YOLOV8; ResNet Classification; Computer Vision

1. Introduction

Roads are the most used source of traveling in Pakistan, enabling the movement of people, goods, and services from one place to another. To maintain these roads, toll plazas are established for collecting toll tax from passing vehicles. These Toll plazas ensure the upkeep, maintenance, and further development of the country's road infrastructure. Toll plazas also play a vital role in maintaining the traffic congestion on busy routes. A toll plaza is a specified area on a road or highway where vehicles must stop to pay a tax to continue using the road. The National Highway Authority (NHA) of Pakistan operates over 100 toll plazas nationwide. From January 2019 to June 2023, a total of 135.488 billion PKR was generated through toll revenue [1].

As a vehicle reaches a toll plaza, a barrier is in place to halt its progress. The vehicle must pay the assigned toll before continuing. Upon successful payment of the correct toll, the barrier lifts, allowing the vehicle to pass through the toll plaza. Due to the lack of technology, the tax collection process is manual in the early stages. However, technological advancements introduced various automated tax collection systems, such as Radio Frequency Identification (RFID) tags. These tags are attached to the vehicle's windshield. As the vehicle crosses the toll plaza, the RFID reader at the toll plaza reads the data on the tag to recognize the vehicle along with its account, automatically withdrawing the toll amount [2]. The RFID signal can be disrupted by environmental variables, such as climate conditions. The Automated Number Plate Recognition (ANPR) system is another method for toll collection. It utilizes an ANPR camera to take an image of the vehicle's number plate. It applies an optical character recognition method to read the details of the number plate to charge the correct amount of toll [3]. At certain times, an ANPR system can misread the details on the number plate, leading to an inappropriate toll amount. MTAG is a prepaid RFID chip that automatically deducts toll as the vehicle passes through the scanner [4]. Both the RFID and ANPR systems are sensitive to misuse. RFID transfer may result in illegal control of personal data. While ANPR may not recognize fake number plates.

While most vehicles are asked to pay a toll tax, some of them are exempt from paying it, such as ambulances, official government vehicles, and the vehicles of nearby government institutes, such as universities. For example, employees and students at Mehran University of Engineering & Technology (MUET), Jamshoro, are given official stickers, which are stuck to the windscreen of their vehicles; the vehicles having the stickers of the above university are exempted from paying the toll tax at Jamshoro Toll plaza only. The detection of tax-exempt vehicles is currently manual in almost all the toll plazas of Pakistan. The manual checking of tax-exempted vehicles is a time-consuming process and often results in traffic jams at toll plazas. Most of the existing research work [2-4, 7-9] focuses on collecting the toll tax automatically at toll plazas; the detection of tax-exempted vehicles is often ignored. The detection of tax-exempted vehicles is a challenging task due to the non-availability of a publicly available dataset that contains the images of the both tax-exempted and tax paying vehicles.

In this research work, we propose an effective and efficient solution for the detection of tax-exempted vehicles. First, we build a custom dataset that contains images of both tax-exempted and tax paying vehicles. We use an existing dataset of Pakistani vehicles and apply various stickers, such as McDonalds' and MUET, Jamshoro's authorized stickers, on the windscreen of the vehicles. We perform extensive experiments on our custom-built dataset by employing the state-of-the-art machine learning techniques. The experimental results show that machine learning techniques successfully detect the stickers applied to vehicles and classify them as either tax-paying or tax-exempted vehicles.

The rest of the paper is organized as follows: the related work section provides the overview of research work that focuses on Toll plazas and the latest object detection techniques. In the third section, we explain the process of creating the custom-built dataset. In the fourth section, we present the settings of our experiments and their results in detail. Finally, we conclude the paper in the last section.

2. Related Work

Recently, there have been many developments on machine learning techniques that has changed the scenario in vehicle detection/classification/counting mainly focusing on traffic management/surveillance. A very few research papers focus on the detection of vehicles for the collection of toll tax. The demand for efficient vehicle analysis methods is rising, with smart traffic management systems using more temporary and comprehensive real-time data. The literature encompasses various types of methodologies and algorithms used to tackle these tasks, from classical approaches to modern sophisticated techniques.

The paper [3] proposes a solution for the collection of toll tax by using number plate recognition. Authors in paper [3] stress that use of RF tags and bard codes is not an efficient solution to address the problem but have some disadvantages. A new solution via automatic toll deduction using ANPR (Automatic Number Plate Recognition) claims to bridge these gaps during collection at various places.

In Malaysia, once the tax is paid, the government then issues a sticker that contains information including the license plate number of the vehicle and its expiry date to apply it on the vehicle's windscreen. Before the formation of the automatic system, the Malaysian police manually executed the verification of stickers. Alharaki and Zeki [5] propose a vehicle Road Tax Recognition system (RTR) that inspects vehicles to capture Road Tax sticker images. Neural networks and image processing methods such as edge detection, image filtering, and binarization are used. The RTR system initiate working by sensing the presence of the vehicle and tells the system's camera through signals to take an image of the vehicle. The RTR system software reads the number of license plates and the details of Road Tax stickers from the captured image. The system then stores important information in the database. Whereas our research focuses on toll tax exempted vehicles using stickers, and this work does not address the detection of stickers.

Zhong Zhao et al. [6] proposed a method for Defect Detection for Cigarette Packet Seal Stickers. This automatic system checks whether the sealed sticker is skewed, folded, or missing on a cigarette packet. The working of the system includes that when a cigarette packet passes by a displacement sensor, a trigger signal is sent to the acquisition controller, which then signals the image acquisition card. This prompts the Charge Coupled Device (CCD) camera to capture an image of the cigarette packet. The captured grayscale image in BMP format is sent to a computer where the image recognition techniques are applied to check whether the seal on the cigarette packet is properly applied. On the other hand, our system uses deep learning to identify both authorized and unauthorized stickers on the windscreen of vehicles. We employ YOLOV8, an advanced object detection method, in place of conventional image processing to reliably detect exemptions at the toll plaza by identifying stickers.

The current tax payment method at toll plazas is manual in Indonesia. When the vehicle arrives at the toll gate, the barrier stops it, and they provide a driver with a receipt. The driver then pays the tax manually before allowing the vehicle to proceed. This procedure usually results in long lines and delays at toll plazas, as each vehicle needs to stop and complete the toll payment separately. To solve this problem, Okugata Fahmi Nurul Yudho Fauzan et al. [7] introduced an automatic toll collection process named the Multi-Lane Free Flow (MLFF). In the MLFF system, the vehicles can cross the toll plaza without pausing. The researchers evaluate three different types of object detection algorithms involving the Faster Region-based Convolutional Neural Network (Faster R-CNN), You Only Look Once version 4 (YOLOv4), and the Single Shot Multi-Box Detector (SSD). The results demonstrated that YOLOv4 outperformed other algorithms with an accuracy of 89%. Whereas our system detects authorized stickers on the windscreen of the vehicle using YOLOV8, a sophisticated object detection algorithm that provides faster and more accurate detection than earlier versions.

Zhegum Abbas. [8] Proposed an automated toll-collection system using Radio Frequency Identification (RFID) techniques. When a vehicle reaches the toll gate, an RFID reader reads the tag, and the system verifies that the vehicle's data matches the data saved in the database, which includes the preloaded account balance of the vehicle owner. The system automatically identifies the tag, and deducts the toll charges from the account, so that vehicles can easily pass the toll plaza without stopping. In case of poor account balance and invalid tag, the image of the vehicle is further verified from the system. To ensure the smooth working of the system, it also allows users to register new RFID tags and refill their account balance. The system is built using a Raspberry Pi 4, along with programming languages such as Python, CSS, SQL, and HTML. Unlike this toll payment system, our method uses YOLOV8 to identify toll tax permitted stickers on a vehicle's windscreen, automating toll exemption without the need for manual verification or RFID tags.

Segun I. Popoola et al. [9] introduced an Electronic Toll collection (ETC) system developed for smart and connected communities based on the cloud. It utilizes the Zigbee technology to digitize the detection, classification, and toll collection of vehicles. The system comprises two main Zigbee devices: one placed at the toll booth (Controller Unit) and the other placed at each vehicle (In-vehicle Unit). These devices use wireless communication, creating a network that detects and classifies vehicles as they reach the toll booth. The vehicle's battery powers the In-Vehicle unit, and a unique Media Access Control (MAC) address identifies it, allowing only registered vehicles to connect for data transmission. The cloud hosts the central database and web server, which manages transactions, monitoring, and notifications. Vehicle owners use a mobile app for tax payments, subscriptions, and notifications, while administrators use a web dashboard to monitor activities and track payments. Our approach automates the detection of toll tax-exempted vehicles by detecting authorized stickers using YOLOV8, which eliminates the need for specialized in-vehicle hardware or user intervention.

Md Nahid Sadik et al. [14] evaluate two object detection models, YOLO V8 and Real Time Detection Transformer (RT-DETR-L), on a dataset of complex urban environments. The YOLO V8 large model shows the best performance, with high precision. RT-DETR, a transformer-based model, efficiently handles multi-scale features and reduces computational demand while maintaining real-time detection without the need for post-processing. The study demonstrates how these models improve traffic monitoring by offering reliable, real-time detection, making urban traffic management more efficient. Our system employs YOLOV8 to identify authorized stickers for automatic toll exemption, in contrast to their emphasis on urban traffic surveillance.

Bahzad Taha Jijo et al. [15] explore a decision tree classifier, a widely used method for data classification in fields like medical analysis, tax classification, and image recognition. A decision tree splits data into two branches based on decision rules, forming a tree-like structure that leads to classification. Researchers focus on extending the decision tree using available data. The paper provides an overview of decision tree algorithms, their applications, datasets, and outcomes, analyzing various approaches to identify the most accurate classifier.

Ali Sentas et al. [16] present a system for classifying vehicles using real-time traffic video data. It employs two methods, Tiny YOLO and Support Vector Machines (SVM) classifier with Histogram of Oriented Gradients (HOG) features. The SVM classifier aims to find the best separation line between classes using HOG to extract useful image features. YOLO performs both object detection and classification simultaneously. The study also highlights the role of convolutional neural networks, widely used in object detection and classification. CNNs consist of convolutional, pooling, and fully connected layers. While [15] concentrates on generic decision tree applications and [16] employs Tiny YOLO and SVM for vehicle classification, our approach uses YOLOV8 for object detection and ResNet for vehicle classification.

Most existing systems rely on traditional image processing techniques like edge extraction and the Radon transform, which have become outdated compared to more advanced machine learning methods. They focus only on certain features, like the position and angle of the straight lines on the sticker. As a result, they can struggle in different situations, such as when the stickers are applied at various angles. These systems are limited to the tax collection part of the process. RFID and Road Tax Recognition technology are used for tax collection. They lack functionality for automatically identifying and exempting vehicles that qualify for tax exemption, such as public service vehicles, police mobiles, ambulances, and other vehicles containing authorized stickers. As a result, these systems do not accommodate vehicles that are legally exempt from paying the toll tax.

3. Methodology

In this research work, we focus on proposing a solution that effectively detects tax-exempt vehicles at toll plazas in Pakistan. Generally, there are two types of tax-exempted vehicles: (i) official vehicles such as ambulances, police cars, army jeeps, and (ii) vehicles of an institute or locality that are located very near the toll plaza. For example, in Jamshoro, Sindh, official vehicles of MUET, Jamshoro, as well as the vehicles of the university's students and employees, are exempt from paying the toll tax. However, university students and employees are obliged to pay toll tax at all other toll plazas of Pakistan. The first type of tax-exempted vehicles is easy to identify because of their color and look of the vehicles. However, the identification of the second type of tax-exempted vehicles is challenging since these vehicles are allowed to pass the toll plaza without paying tax only when they show either some official card or sticker applied to the windscreen of vehicle.

So far at the most toll plazas of Pakistan, identification process of tax-exempted vehicles is manual and time-consuming process that often results in traffic jam at the toll plazas. The automatic detection of tax-exempted vehicles is even more challenging because the windscreen of a vehicle may contain several stickers and effective detection of only one sticker, that makes the vehicle to be tax-exempted, is difficult. Therefore, we mainly focus on the detection of second type of tax-exempted vehicles in this research work. Another major reason that makes the automatic detection of tax-exempted vehicles challenging is the unavailability of the dataset that contains the images of both types of vehicles, i.e., tax paying and tax-exempted vehicles. Although, there are several datasets publicly available, which contain images of various vehicles; however, to the best of our knowledge, there is no any image dataset that contains stickers applied to windscreen of vehicles.

As we know that, any machine learning algorithm must be trained on a dataset for detection or classification of objects, so we develop a custom dataset that contains images of vehicles which have authorized stickers (such as MUET Jamshoro) and un-authorized stickers (such as MC & KFC) applied to their windscreens. For this purpose, we use an existing dataset Pakistani Vehicle-Dataset-SAZ [10] that contains images of only cars, buses, trucks, and other vehicles, which mainly run on roads of Pakistan.

However, the collected dataset lacks images of official vehicles like ambulances and police cars, which are essential for our research work. To address this, we collect images of these vehicles from various sources. By appending these additional images to the existing dataset, we create a more comprehensive and diverse collection of vehicle types. However, the dataset still does not fully suit the research problem, as it is used to detect stickers applied to the windscreens of vehicles, but it does not contain a single image where the windscreen of a vehicle contains stickers.

Figure 1. Images of a vehicle before and after applying stickers on windscreen

To deal with this problem, we use Adobe Photoshop to apply three different types of stickers on the vehicles' windscreens: a McDonald's sticker, a KFC sticker, and the MUET Jamshoro's authorized sticker.

These stickers are selected based on their relevance, visibility, and practicality for training the model. The McDonald's and KFC stickers are commonly seen on vehicle windscreens in real-world scenarios. The reason behind applying the McDonald's and KFC stickers is to ensure that the model differentiates between authorized and unauthorized stickers for exemption detection. Including a variety of stickers trains the model to recognize the unique features of the authorized Mehran University's sticker while ignoring other irrelevant stickers. This targeted variety permits strong training without overloading the model with too many variations, making sure that it learns the important visual features necessary for accurate exemption detection. This approach may help to train a more accurate model that effectively distinguishes between authorized and unauthorized stickers for the exemption of toll tax at toll plazas. Figure 1 shows the image of a vehicle before and after applying stickers to its windscreen. As one can see, we have applied stickers in a realistic way such they are neither clearly visible nor very small. Moreover, we have applied stickers to vehicles randomly, i.e., some vehicles may contain only one sticker, and others may contain all three stickers. Although these stickers were artificially applied, it is essential to notice that the model's performance may vary in real-world scenarios. Furthermore, training with real-world sticker data will be necessary to justify the system's efficiency under real situations.

The images in the collected dataset display varying formats, dimensions, and resolutions. To ensure consistency, a function standardizes all the images to a uniform format, dimension, and resolution. Converting these images into a common format, dimension, and resolution is essential for maintaining data consistency, which plays a crucial role in efficient machine learning model training. A size of 640 x 640 pixels is chosen to balance detail and performance, capturing essential features of the vehicles, including authorized stickers, while remaining small enough for fast processing in machine leaning algorithms. Images in our custom dataset are set at a resolution of 96 dots per inch (dpi), to ensure clarity and visual quality on digital screens, while keeping file sizes manageable. The data annotation is crucial before applying the object detection algorithms. Annotation includes pointing out the objects of interest in the image, which is an important step for training models to accurately detect and classify objects. In this research work we use Roboflow, an end-to-end computer vision platform, facilitates this annotation with a user-friendly interface that enables drawing bounding boxes around target objects and assign appropriate labels to them.

Our research work aims to upgrade the existing toll plaza operations by employing modern machine learning techniques that effectively detect the vehicles which must pay the tax, and the tax-exempted ones. Once the toll plazas are equipped with this solution then they can easily track the record of the vehicles, which have paid the tax or not. This will allow the system to be faster by saving individuals from the manual checks and speeding up the process at toll booths. Note that our research work focuses on toll plazas, but it can easily be applied to any office building or shopping center where the parking fee of vehicles depends on stickers.

4. Results and Discussions

In this section, we present and analyze the results obtained from the experiments conducted on our synthetic dataset.

The dataset Pakistani Vehicle-Dataset-SAZ [10] contains 4868 images of 53 various vehicles. However, as discussed in Section 3, this dataset does not contain images of official vehicles such as ambulances, police cars, and vehicles containing stickers. Therefore, we added the images of official vehicles and also the vehicles containing stickers; as a result, the number of images in the dataset increases to 5068. For experiments, the dataset is divided into three subsets: 70% for training, 15% for validation, and 15% for testing. The largest part is the training data, which allows the model to learn patterns and features in the images. The validation set assists with hyperparameter fine-tuning during training, provides an estimate of the model's performance on unseen data, and helps to minimize overfitting. Finally, the test set is reserved for evaluating the model's performance on completely new data.

Automatic detection of authorized vehicles primarily involves two key tasks: object detection and image classification. We find several prominent algorithms for each task in the literature; however, for experiments, we select the most commonly used algorithms. For object detection, the most used algorithms are Real-Time Detection Transformer (RT DETR), Faster R-CNN, and You Only Look Once (YOLO). For image classification, the most used algorithms are Decision Tree, Support Vector Machines (SVM), and Residual Network (RESNET), a type of convolutional neural network. We evaluate the algorithms by using accuracy measures: precision, recall, and F1-score.

Accuracy: The number of correct predictions is divided by the total number of predictions.

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

Precision: It is the percentage of all the positive predictions are positive.

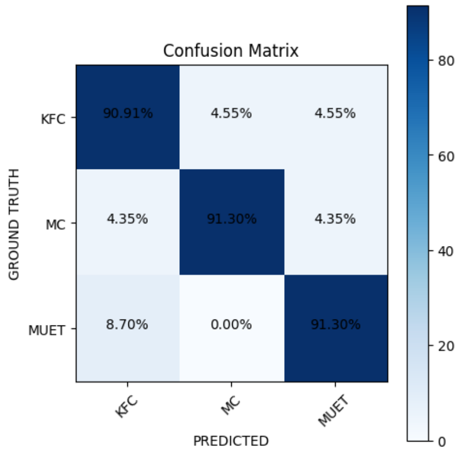
$$\text{Precision} = \frac{TP}{TP+FP}$$

Recall: the percentage of predicted positives out of all positives.

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

F1-score: It is the average (harmonic mean) of the precision and recall. It combines both the false positive and the false negative. Hence, it works well with imbalanced data.

$$\text{F1-score} = \frac{2*precision*recall}{precision+recall}$$



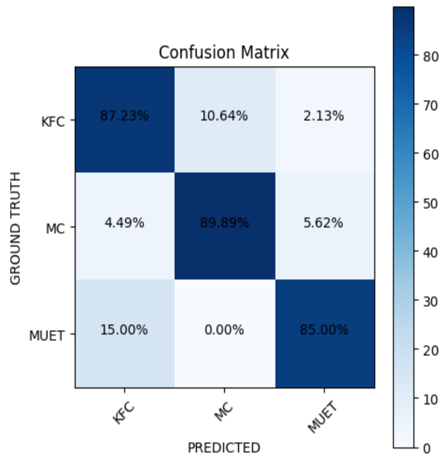


Figure 2. Confusion matrix of YOLO V8 **Figure 3.** Confusion matrix of Faster R-CNN

Figures 2, 3, and 4 show the performance of YOLOv8, Faster R-CNN, and RT DETR in the form of confusion matrices. The confusion matrix in Figure 2 shows the YOLOv8 model performed in a 3-way object detection task of KFC, MC, and MUET stickers; The diagonal elements are those that are predicted correctly whereas the off-diagonal element shows missed predictions. The performance based on the testing data indicated that KFC, MC and MUET have been detected with 90.91 %, 91.30%, and 91.30%; precision, recall, and accuracy, respectively. Clearly, the confusion matrix shows that separating three classes by using YOLOv8 model is working well overall. Figure 3 shows the performance of Faster R-CNN model for detection of KFC, MC and MUET stickers. The results presented show that the model performs well for KFC and MC, with accuracy rates of 87.23% and 89.89%. Despite this, it provides meager accuracy for the MUET class at an 85.00% classification rate correctly classified. Overall, the confusion matrix portrays that Faster R-CNN model work to distinguish among those 3 classes and it is little bit needed to done enhancement in detection of MUET instances.

Figure 4 shows the performance of the RT DETR. It is evident from the results that the model performs well in KFC, MC, and MUET, with an accuracy of 83.67%, 85.86%, and 85.58%, respectively. Generally, the confusion matrix indicates that the RT DETR model can effectively distinguish the three classes, and there is slight underperformance in detection of KFC stickers.

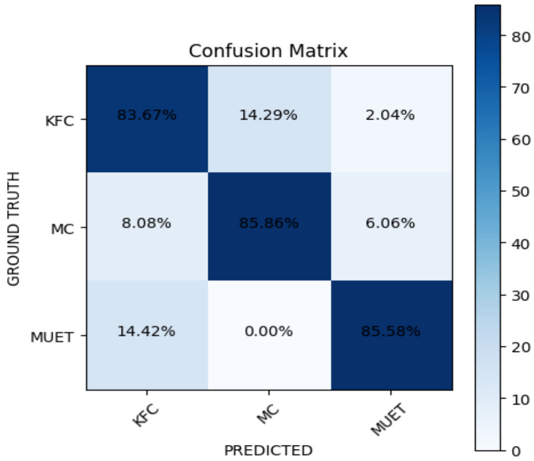


Figure 4. Confusion matrix of RT-DETR

Table 1. Accuracy comparison of object detection algorithms

Algorithm	Accuracy	Precision	Recall	F1-Score
YOLO-V8	91.17%	92.65%	91.17%	91.87%
FASTER R-CNN	87.37%	89.57%	87.37%	88.30%
RT DETR	85.0%	85.0%	85.0%	85.0%

Table 1 compares the accuracy of all three models: YOLO V8, Faster R-CNN, and RT DETR. The YOLO-V8 achieved the highest accuracy of 91.17 % given that it could detect and classify objects present on dataset properly. Below that, Faster R-CNN demonstrated slightly lower accuracy at 87.37%, with RT-DETR coming next as the lowest-performing model achieving only 85.0% of test set performance It goes to show that in a general sense, YOLO-V8 provide better classification but other models are still providing robust results. This system had the best precision rate of 92.65%. With an average precision of 85.0%, RT-DETR consistently maintained higher than Faster R-CNN which had a precision of 89.57%. YOLO-V8 performance seeing lower false alarms, which means it was more reliable in object detection followed by Faster R-CNN. YOLO-V8 model also achieved the highest recall with 91.17% which means it detects most objects successfully in this entire test set, Faster R-CNN was very close behind with the recall of 87.37% while RT-DETR had the lowest recall at 85.0%. This implies that overall, YOLO-V8 is more suitable for many objects per scene where it could end up missing fewer objects in particularly difficult scenes compared to Faster R-CNN and RT-DETR. An F1-score of 91.87% conveyed a well balance between precision and recall in YOLO-V8 which is mentioned the table wide for operator. RT-DETR attained an average F1-score of 85.0% while Faster R-CNN achieved a high-quality F1 score – 88.30%. This shows that YOLO-V8 is best suited when both precision and recall are weighed equally.

By comparing the results, it is obvious from this comparison that YOLO-V8 is superior in accuracy to Faster R-CNN and RT-DETR models with an accuracy of 91.17%, precision of 92.65%, recall of 91.17%, and F1score of 91.87%. Due to the YOLO-V8 architecture, it is more likely that the performance of our pipeline seems improved only in this dataset with faster and more accurate object detection. Although slower than other models, Faster R-CNN is still able to accurately detect objects in all metrics. RT-DETR on the other hand scores slightly lower, but it is perfectly fine if you need high-quality detection so that comparison with some older models we have already covered.

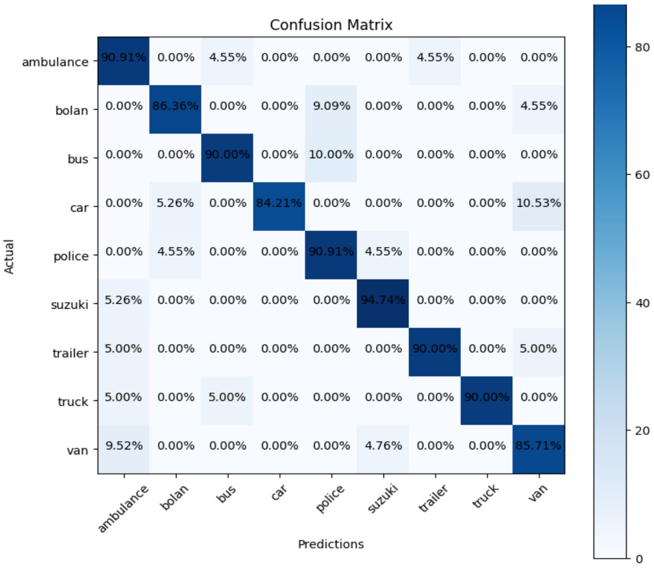


Figure 5. Confusion matrix of CNN

It is important to note that one of those tasks of our research work is to identify the vehicles which are officially exempted from paying toll tax such as Police car and ambulances. Although dataset contains more than 55 various types of the vehicles but just for the sake of brevity we show here the confusion matrix of algorithms for 10 vehicle classes. Figure 5 shows the performance of CNN (ResNet) model. The results show the model performs well for different class ambulances, Bolan, bus, car, police, Suzuki and van as accuracy is higher than 80 %. But for trailer and truck, it shows a good accuracy of 90 %, 85.71% respectively. Collectively, a confusion matrix tells us the CNN (ResNet) model is efficient in identifying all ten vehicles but there are still some areas where it could improve like classification of trailers and truck. Figure 6 shows the confusion matrix of Decision tree algorithm and as we can see it gives great performance for Car, with accuracy of 91.83%, but very modestly good result of Trailer and Truck connected correctly (for both it is 78.26%). In general, the confusion matrix indicates that our Decision tree model is good for vehicle class ten, but it may struggle with truck and trailer classification.

The confusion matrix shown in Figure 7 shows the performance of the SVM model for the multi-class classification task with ten different vehicle classes. Considering the results of the confusion matrix, the model correctly classifies several classes, such as ambulance, Bolan, bus, car, police, Suzuki, and van, with more than 60% accuracy. However, the model has corrected classification rates between 69.23% for trailer and 69.23% for truck. Overall, the confusion matrix illustrates that the SVM model is good at differentiating between the ten vehicle classes. However, there is still scope for improvement in accurately predicting the instances of class trailer and truck.

Table 2. Accuracy Comparison of Classification Algorithms

Algorithm	Accuracy	Precision	Recall	F1-Score
CNN (RESNET-18)	90.8%	89.7%	89.2%	89.3%
DECISION TREE	77.41%	79.6%	77.4%	77.9%
SVM	69.0%	72.2%	69.1%	69.8%

The Table 2 shows the comparison of accuracy between three models i.e. CNN (ResNet-18), Decision Tree Classifier, and Support Vector Machine (SVM). CNN achieves 90.8% accuracy which reveals that CNN is able to correctly classify around 91 % of all instances and has a good general performance. While it achieves 89.7% and 89.2, precision and recall, respectively. Overall, The CNN (ResNet-18) has the best performance among all other models in terms of each metric type making it a great candidate to use for any task requiring high accuracy as well-balanced precision-recalls trade-offs. The decision tree classifier is doing fine but it lags behind CNN in precision, recall, and average accuracy. As can be seen from the results, SVM turns out to perform worst with minimum scores in all area, particularly accuracy and recall. This may not be the best choice for this classification task.

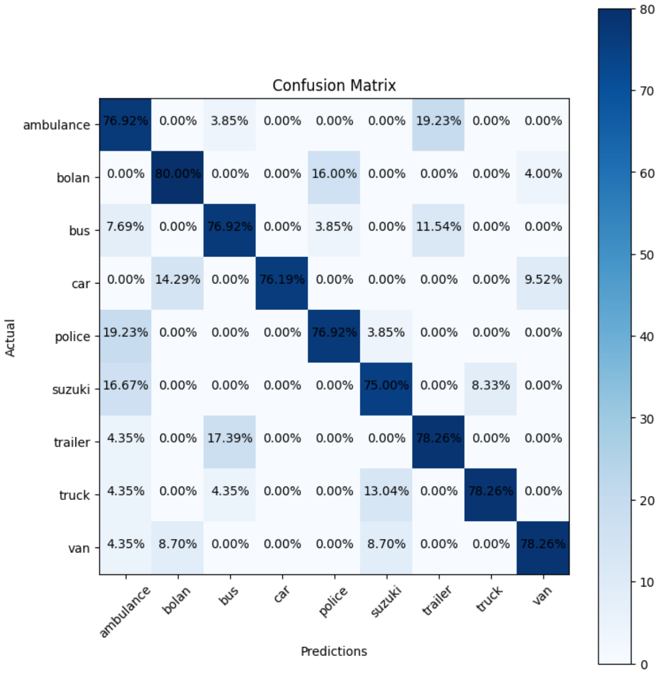


Figure 6. Confusion matrix of Decision Tree

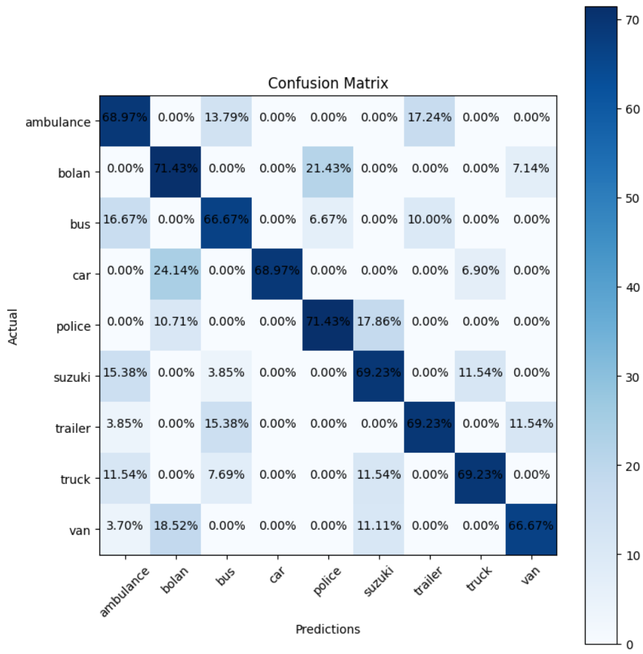


Figure 7. Confusion matrix of SVM

Overall, CNN (ResNet-18) outperforms the other models by a large margin, having very high accuracy and balanced precision-recall-f1 score. It shows that CNN model is more capable of this kind problem. While SVM has performed the worst in this comparison, along with low accuracy; it is also a bit unbalanced precision and recall.

In real-world scenarios, elements like dim illumination, dust, rain, or partial sticker occlusion (by wipers or reflectors) may decrease the accuracy of detection. These problems may make it difficult for models to recognize the stickers accurately. To improve resilience, future research will concentrate on adding a wide variety of training data and employing preprocessing or picture enhancement methods to lessen these impacts.

5. Conclusions

In this research work, we have proposed a solution to the toll plaza management that automatically detects the vehicles that are exempted from paying the toll tax, such as Police cars, ambulances, and vehicles containing authorized stickers. The existing system manually checks tax-exempted vehicles, which is timing time-consuming process and often results in traffic jams at toll plazas. The main contribution of our project includes the development of a custom dataset of vehicles and performing experiments on that dataset by implementing state-of-the-art algorithms. The experimental results show that YOLOv8 detects the stickers applied to the windscreens of vehicles more accurately than other algorithms. Similarly, another deep learning algorithm, CNN (Resnet) achieves the best accuracy for identifying the vehicles, while SVM performs the worst.

References

1. Staff, P. (2023) *NHA has collected rs. 135 billion as toll tax since January 2019*, *ProPakistani*. Available at: https://propakistani.pk/2023/08/01/nha-has-collected-rs-135-billion-as-toll-tax-since-january-2019/ (Accessed: 23 October 2024).
2. Kumawat, A. and Chandramore, K., 2014. Automatic toll collection system using RFID. *International Journal of Electrical and Electronics Research*, *2*(2), pp.67-72.
3. VeerasekharReddy, B., Thatha, V.N., Maanasa, A., Gadupudi, S.S., Japala, S.K. and Goud, L.H., 2023, June. An ANPR-Based Automatic Toll Tax Collection System Using Camera. In *2023 3rd International Conference on Pervasive Computing and Social Networking (ICPCSN)* (pp. 133-140). IEEE.
4. Zoy, K.H., Shahrier, M. and Huq, A.S., 2020. A systematic review of electronic toll collection systems. In *International Conference on Transportation Research*.
5. Alharaki, *O.O. and Zeki, A.M., 2012, November. Image recognition technique of road tax sticker in Malaysia. In 2012 International Conference on Advanced Computer Science Applications and Technologies (ACSAT) (pp. 397-401). IEEE.*
6. Zhao, Z., Dong, Y. and Chang, C., 2015, November. Cigarette packet seal defect detection based on image recognition technology of support vector data description. In *2015 Chinese Automation Congress (CAC)* (pp. 552-558). IEEE.
7. Fauzan, O.F.N.Y., Perdana, R.S. and Adiono, T., 2022, November. Machine Learning for Real-Time Vehicle Detection in All-Electronic Tolling System. In *2022 International Conference on Data and Software Engineering (ICoDSE)* (pp. 42-46). IEEE.
8. Abbas, Z., 2022. Toll automation system using RFID and web portal. *Engineering Proceedings*, *20*(1), p.44.
9. *Popoola, S.I., Popoola, O.A., Oluwaranti, A.I., Badejo, J.A. and Atayero, A.A., 2017. A framework for electronic toll collection in smart and connected communities. In Proceedings of The World Congress on Engineering and Computer Science (pp. 723-726).*
10. Baig, A. (2020) *Pakistani_Vehicle_Dataset_SAZ*, *Kaggle*. Available at: https://www.kaggle.com/datasets /abdulazizbaig/pakistani-vehicle-dataset-saz-vrs (Accessed: 23 October 2024).
11. Powers, D.M., 2020. Evaluation: from precision, recall and F-measure to ROC, informedness, markedness and correlation. *arXiv preprint arXiv:2010.16061*.
12. Comprehensive Vehicle Dataset with Stickers (kaggle.com)
13. Souza, B.J., da Costa, G.K., Szejka, A.L., Freire, R.Z. and Gonzalez, G.V., 2024. A deep learning-based approach for axle counter in free-flow tolling systems. *Scientific Reports*, *14*(1), p.3400.
14. Sadik, M.N., Hossain, T. and Sayeed, F., 2024. Real-Time Detection and Analysis of Vehicles and Pedestrians using Deep Learning. *arXiv preprint arXiv:2404.08081*.
15. Charbuty, B. and Abdulazeez, A., *2021. Classification based on decision tree algorithm for machine learning. Journal of Applied Science and Technology Trends, 2(01), pp.20-28.*
16. Şentaş, A., Tashiev, İ., Küçükayvaz, F., Kul, S., Eken, S., Sayar, A. and Becerikli, Y., 2020. Performance evaluation of support vector machine and convolutional neural network algorithms in real-time vehicle type and color classification. *Evolutionary Intelligence*, *13*, pp.83-91.