Recognizing and Intercepting Users of Fake Number Plates

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Abstract - Law enforcement and public safety are seriously threatened by the widespread use of fake and modified license plates. Using state-of-the-art technology, this project, "Recognizing and Intercepting Users of Fake Number Plates," aims to create a complete system that will identify and reveal fraudulent actions connected to vehicle identification. The suggested system analyzes and compares real-time photographs of vehicle number plates against a carefully maintained database of authentic plates by integrating deep neural networks, machine learning algorithms, and powerful computer vision techniques. The technology uses artificial intelligence to detect even minute differences, abnormalities, or tampering with the visual features of license plates. These tamperings could involve changes to the typeface, color, size, or general design of the plate. The principal aim of this research is to equip security systems and law enforcement organizations with a powerful instrument for quickly and precisely identifying vehicles with forged or altered license plates.

Keywords: Fake Number Plate Recognition. Deep Learning, Machine Learning, Neural Networks, Computer Vision.

1. INTRODUCTION

Modern civilization has never had greater mobility thanks to the widespread use of motor vehicles, but it has also created a covert problem with the spread of fake license plates. The usage of fake license plates is on the rise along with the number of vehicles, posing a complex threat to law enforcement, public safety, and the foundation of social order. This study aims to investigate the intricacies of the "Recognizing and Intercepting Users of Fake Number Plates" dilemma, delving into the background, incentives, strategies, and technological defenses linked to this clandestine activity.

From the busy city streets to the vast freeways that link different regions, the cover provided by fictitious license plates has encouraged people and criminal organizations to partake in actions that are contrary to the laws and social mores. There are many different reasons why people use fake license plates, from avoiding traffic tickets to more nefarious activities like terrorism,organized crime, and illegal trading. A thorough grasp of the underlying causes is essential as we work through the complexities of this phenomenon in order to create measures for enforcement and prevention that work.

The main goal of this project is to immediately apprehend individuals using fictitious license plates in order to reduce the risks and illegal activity connected to vehicles that drive under false pretenses. The research seeks to identify key information about a vehicle, such as its make, model, color, and number plate, by merging many deep learning and machine learning techniques. This comprehensive method not only improves detection accuracy but also allows for a more in-depth comprehension of the traits connected to cars that use fictitious license plates.

Following the extraction and processing of pertinent data by the algorithms, the specifics are cross-referenced with an extensive database. This database acts as a repository for accurate vehicle data, making it possible to conduct a thorough validation procedure to ascertain the veracity of the recognized vehicles. This stage maintains a balance between identification process efficiency and precision by preventing the system from unintentionally flagging real vehicles. When the system detects that a vehicle is using a fake [1] license plate, a quick and automatic reaction mechanism is initiated. On the path of the vehicle, an alert message is immediately sent to the closest law enforcement agencies. By examining the vehicle's path, this alert's accuracy is increased even further and it becomes possible to determine which law enforcement forces are closest to the developing situation. This dynamic method increases the likelihood of intercepting the vehicle before it can participate in illegal activity or elude law enforcement, while also speeding up the apprehension procedure.

This study tries to dissect the many layers of the fake number plate phenomena, offering insights into the reasons behind its spread, the changing strategies used by offenders, and the technology advancements that might be used to effectively discourage. By bringing attention to this hidden problem, we add to the larger conversation about law enforcement, public safety, and the relationship between technology and crime in the twenty-first century. Exposing the fake [4] license plates is not just a research project; it's an essential step in strengthening the fundamentals of a safe and stable community in a time of increased mobility and advanced technology.

2. Methodology

Using deep learning neural networks like CNN and RNN [9] [10] as well as state-of-the-art deep learning algorithms, this study suggests a method for the detection and recognition of vehicle number plates. The number of the identified vehicle will be compared to the database to determine its kind, color, model, brand, and other details. The alert message and the picture of the car will be sent via a mobile application to the closest police station along the vehicle's journey if the number is found to be fraudulent. A different database will hold the information about the automobiles with fictitious license plates, their location, time, and, if applicable, facial recognition.

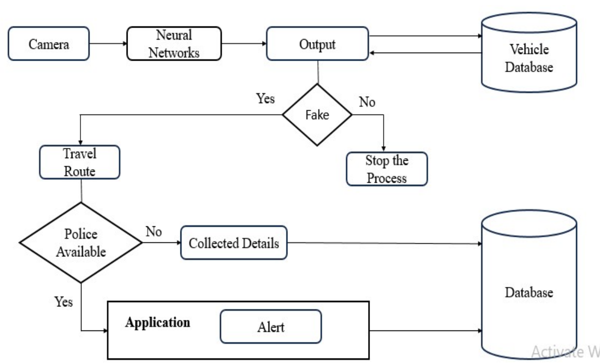

Figure 2.1: Overall working

2.1 System of Unified Networks

The procedure in this extensive neural network arch itecture starts with camera feed photos, which are first processed using YOLO (You Only Look Once) and DeepSORT algorithms for effective object detection. Each discovered object is then given a unique identity. The output is then smoothly routed into five different networks, each designed for a particular task. For accurate classification, Vehicle Type Identification uses Single Shot Multibox Detector (SSD) and Recurrent Neural Networks (RNN). Vehicle Model Identification makes use of Inception and MobileNet to accurately categorize models, while Vehicle Brand Identification makes use of the capabilities of ResNet and VGG architectures. DenseNet and EfficientNet are used simultaneously in Vehicle Color Identification to determine the color characteristics of the identified automobiles.

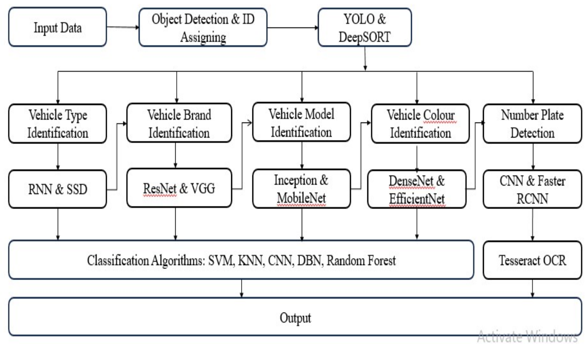

Figure 2.2: Work Flow of Neural Networks

Furthermore, license plate information extraction is the main function of a specialized Number Plate Detection network that is aided by Convolutional Neural Networks (CNN) and Faster RCNN. In order to improve and refine the classification accuracy, the outputs from the first four networks are then fed into classification algorithms such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), CNN, Deep Belief Networks (DBN), and Random Forest. Simultaneously, Tesseract OCR [15] [16] processes the output of the fifth network, which contains information on number plates, in order to accurately extract vehicle identification numbers. Ultimately, all of the refined outputs are combined and sent to the controller, providing a thorough and well-organized solution for reliable and accurate item identification, categorization, and detection in a changing visual environment.

3. Detection and Fine-grained Classification Models

Modern detection models that take into account all item labels as independent of one another include Yolov5 and Faster-RCNN. Therefore, the hierarchical link between the fine-grained labels of the item is not modeled by them. Thus, since more visual clues are present and fewer samples per class are available, the challenge of detecting fine-grained objects grows with deeper class definition. Label Relation Graphs Enhanced Hierarchical Residual Network (HRN), provides state-of-the-art performance on fine-grained classification datasets. Their design does not use object detection; instead, it transfers the hierarchical information through residual connections between feature levels, taking use of the parent-child correlation between labels. As a result, we merged the models for object recognition [7] and classification to achieve better results with fine-grained vehicle detection.

3.1 Annotation Process

Based on factors such as traffic density, vehicle box size, and occlusion, we choose 5502 out of 16311 high-quality photos from the IDD Detection dataset. Four incredibly talented annotators and two knowledgeable reviewers for quality assurance make up the annotation team. First, we provide fine-grained labels for a small number of FGVD samples in order to train the annotators for the task. Second, we offer the template, a list of items that need to be annotated, and the recommendations. The popular vehicles in the scene can be identified by the annotators with the right training. On the other hand, they can utilize Google Lens or picture search on the internet if the car is still unrecognizable. Take into consideration, for instance, the situation in which the annotator may identify the manufacturer simply by observing the brand emblem. Despite this, the model name is obscured by truncation, occlusion, or other complications. In these kinds of situations, the annotator would browse the manufacturer's website for comparable vehicles.

The primary focus of the [7] image categorization process is the general appearance of the vehicle, as well as the design of its components (e.g., the rear of certain scooters are equipped with petrol pumps), the brand emblem, and the model name. Images have a temporal relationship since numerous images from the continuous video frames are used to create the IDD-Detection dataset. Due to truncation, the Tata Sumo cannot be identified with certainty in the first frame. However, in the second frame, the brand label is visible, giving the annotator the confidence to label even if they are unable to identify the vehicle's design. Similar to this, the annotators propagate the label in the subsequent frame, when a great deal of occlusion from other vehicles occurs. If they do not make the connection between the knowledge from several frames, annotating becomes quite difficult.

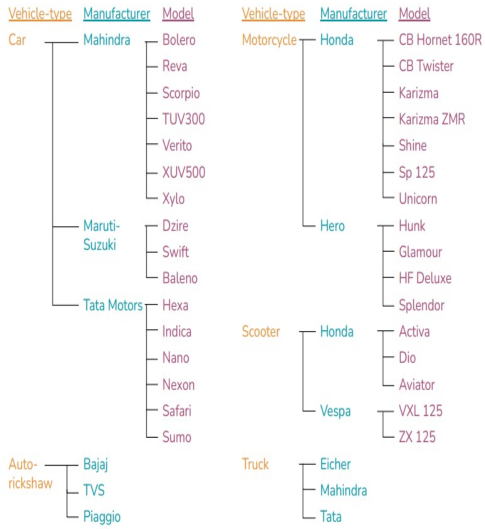

Figure 3.1 : Hierarchy Tree of the FGVD dataset

3.2 Vehicle Localization

Using the FGVD dataset3, we train the YOLO & DeepSORT model to locate the vehicles. The YOLOv5 model was selected for vehicle localization for a number of reasons. First, the Cross Stage Partial Network (CSPNet) is integrated into the neck and backbone of YOLOv5. Richer gradient combinations may be achieved with less computation thanks to CSPNet, which also guarantees good inference speed and accuracy while minimizing model size. Furthermore, maintaining high accuracy for vehicle localization is crucial because the HRN's classification accuracy is dependent on the performance of the localization model.

Subsequently, the YOLOv5 head produces feature maps in three distinct sizes (18×18, 36×36, and 72×72) in order to accomplish multi-scale prediction, which allows the model to handle objects of varying sizes.

To enhance the detection outcomes, YOLOv5 additionally auto-learns unique anchor boxes so that the anchors are tailored to our FGVD dataset. Additionally, it uses several augmentations during training, including mosaic, which greatly aids in generalization. Additionally, we test Faster-RCNN; nonetheless, YOLOv5 yields the greatest results and requires the least amount of training time.

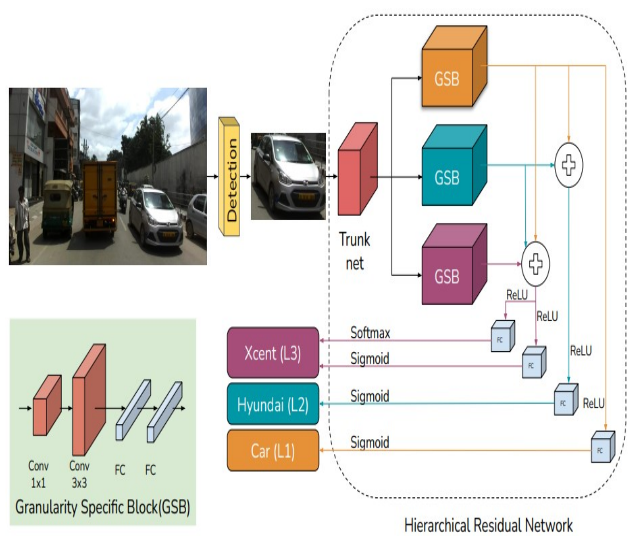

Figure 3.2 : Architecture for fine-grained Vehicle detection

For every one of our fine-grained classes, we additionally construct a hierarchical tree structure of labels in the format demanded by the HRN design. It is significant to note that, at inference time, we use the softmax output for the fine-grained class rather than the sigmoid output from the HRN model. According to Chenetal, the softmax output channel calculates independent cross-entropy loss to give the fine-grained classes that are mutually exclusive greater weight during training.

3.3 Non-Standard Number Plates.

It is critical to understand the dynamic environment of number plate designs in order to build a strong model. Our system tackles the problem of non-standard representations with sophistication, going beyond traditional recognition methods. Our dataset is a tribute to inclusion, with variances in font styles, elaborate designs, a range of sizes, symbolic features, and even the use of other languages. Our training data captures the variety of ways that number plates might differ from the norm, with 1080 unique design images for each numeric digit (0-9) and 1070 different typeface and design style images for each alphabet (a-z). This large dataset makes sure that our model is not only trained but also well-versed in the nuances of non-standard representations, enabling it to recognize and understand a variety of unusual number plate patterns with accuracy.

Figure 3.3 : Non Standard Alphanumeric types

Our model's flexibility in responding to the dynamic field of number plate aesthetics is its main asset. The large dataset is used in the training phase [22], exposing the model to 1080 distinct design images for every numeric digit and 1070 images with different fonts and design styles for every alphabet. This extensive training program gives our model the adaptability required to deal with the wide range of non-standard representations found in real-world situations. [1] From unique font designs to complex patterns, our system is ready to identify the subtleties that set each license plate apart. We guarantee that the model not only recognizes but also performs exceptionally well in interpreting the intricacies of non-standard number plates by submerging it in this varied dataset. This establishes the groundwork for precise and dependable recognition in a variety of settings.

4. App to Action: Intercepting the Fake Number Plate Vehicles.

The creation of a cutting-edge technology is at the forefront of identifying and combating the threat posed by fake license plates in a time when traffic safety [6] is of the utmost importance. Police units may be mobilized in real-time to stop vehicles with fake license plates because to this cutting-edge solution's seamless integration with law enforcement protocols. The central hub is a dedicated mobile application that transmits critical information to the closest police station along the vehicle's journey very quickly. When there are no police present, the system updates a large database in a timely manner, offering copious amounts of data for post-analysis and strategic planning. Proactive tactics also include [8] traffic control, which involves deliberately managing signals to ensure that users of fictitious license plates are intercepted even in situations with high traffic.

Figure 4.1: Traffic controlling.

In addition to providing law enforcement with fast decision-making tools, the intuitive interface also supports a predictive approach to possible hotspot identification through periodic notifications and diagnostic assessments. The system's ability to adapt and develop over time demonstrates its dedication to staying at the forefront of technical innovations and provides a comprehensive and effective way to combat the widespread use of fake number plates on our roadways.

4.1 Notification of Real-Time Fake Detection.

Our sophisticated technology guarantees that, should a vehicle with a fictitious number plate be spotted, the closest police station along the vehicle's route will be notified immediately, allowing for timely action. This smooth communication is made possible by a specific smartphone application made with law enforcement in mind. The tool makes it possible to respond and intervene right away, which helps law enforcement fight fraud on the roadways more effectively. When law enforcement is unavailable, the system uses intelligence to update the database with pertinent vehicle data and photos so that further investigation and action can be taken.

Our technology keeps a thorough database that acts as a repository for all detected occurrences of fraudulent number plates in the event that real-time police access is not available. Images of vehicles and other pertinent information are being added to this strategic database. This resource can be used by law enforcement organizations for post-analysis, investigations, and strategic planning. The methodical gathering of data facilitates an intelligence-based strategy to tackle the issue of counterfeit license plates, providing law enforcement with significant knowledge to improve their future reactions.

4.2 Enhanced Signal Control for Traffic.

Our system goes above and beyond simple detection in high-traffic scenarios, taking aggressive steps to bring the vehicle with the fake license plate to a stop. Law enforcement can intercept the counterfeit vehicle at a tactical advantage by manipulating signals along the vehicle's path. An "initiate" button in the program lets alert users or law enforcement personnel call for help from the next police unit if the circumstance calls for it. This dynamic element adds to the overall security framework's efficacy by guaranteeing a prompt response even under difficult traffic conditions.

The law enforcement mobile application has an intuitive interface that facilitates easy system interaction. The application's user-friendly interface guarantees that police can quickly retrieve important data, react to notifications, and take appropriate action as needed.[6] The application of a user-centric strategy improves the efficacy of law enforcement operations by facilitating prompt and well-informed decision-making with the aim of upholding road safety and averting criminal activities associated with counterfeit number plates.

4.3 Diagnostic Analysis and Data-Driven Insights.

Our system runs on a proactive basis, sending weekly or monthly notifications when no police presence is identified on a vehicle's driving path, addressing any gaps in law enforcement coverage. Concurrently, the software performs diagnostic evaluations to pinpoint regions where instances of fraudulent license plates are most likely to occur. By recommending different locations where these kinds of cars are common, law enforcement organizations can better focus their resources and improve their monitoring activities. In order to combat fraudulent activities on the roads, a more proactive and planned approach is encouraged by this predictive strategy.

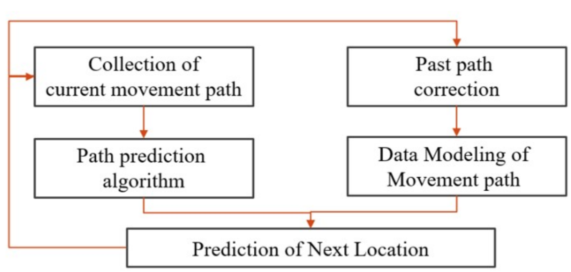

Figure 4.2: Structure of Path prediction.

Continuous improvement and adaptation are the cornerstones of our system. Software is at the forefront of technical breakthroughs thanks to regular upgrades and improvements. In the continuous development process, user comments, practical experiences, and developing trends are actively taken into account. This dedication to development guarantees that law enforcement organizations can depend on a state-of-the-art system that successfully handles the ever-changing issues related to fake license plates.

5. Experimental Results

The use of an advanced neural network architecture to the task the "Recognizing and Intercepting Users of Fake Number Plates" produced remarkable outcomes and completely changed the field of automated vehicle identification. The system successfully identified cars with fake license plates and detected objects in real time by integrating the YOLO and DeepSORT algorithms. The outputs were then routed into specific neural networks, each designed for a different task, and the results showed impressive accuracy. Specifically, Vehicle Model Identification, which used Inception and MobileNet, proved adept at classifying complex model details, while Vehicle Type Identification, which used Single Shot Multibox Detector (SSD) and Recurrent Neural Networks (RNN), effectively classified a variety of vehicle types. Vehicle Color Identification made use of DenseNet and EfficientNet at the same time to provide a sophisticated understanding of the color attributes associated with identified vehicles, while Vehicle Brand Identification added ResNet and VGG architectures to further improve the system's ability to distinguish different vehicle brands.

Object Localization Loss:

SmoothL1(x):
If $|x| < 1$: $0.5x^2$
Otherwise : $|x| - 0.5$

Evaluating the accuracy of object detection:

IoU=Area of Intersection / Area of Union

Figure 5.1: Accuracy score for 2 cars.

Confidence Score = Object Probability X Class Confidence

Where,

Object Probability: Probability that the bounding box contains object.

Class Confidence: Confidence of the predicted class for the object within the bounding box.

```
1/1 [==============================] - 1s 834ms/step
Class:  XL6
Confidence Score: 0.79686344
```

Figure 5.2: Vehicle class and Confidence score

Precision & Recall:

Precision = True positives/ (True positives + False positives)

Recall = True positives/ (True positives + False negatives)

Where,

- True Positive - The anticipated name is break even with to the lesson and the ground truth name is rise to to the class.
- True Negative - The anticipated name is the lesson whereas the ground truth label isn't the class.
- False Positive - The anticipated name is the class and the ground truth isn't the course (Type I Error).
- False Negative - The anticipated name isn't the lesson and the ground truth name is the classType II Error).

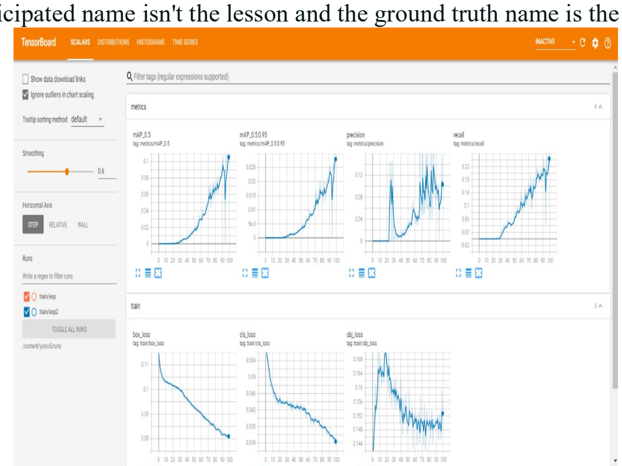

Figure 5.3: TensorBoard with mAP, Precision, Recall and F1 Score.

Accuracy Per Class		
Class	Accuracy	Samples
Alto	0.83	30
Baleno	0.8	25
Breezza	0.94	33
Celerio	0.81	31
Ciaz	0.83	46
Cultus Crese	0.8	5

Eeco	0.95	42
Ertiga	0.8	25
Fronx	0.79	19
Grand Vitara	0.79	14
Ignis	0.79	29
Invicto	0.86	7
Ginmy	0.99	24
S-Presso	0.82	28
Swift	0.83	29
WagonR	0.89	36
XL6	0.9	29

Table 5.1: Accuracy per class for the Maruthi Susuki Car Brand.

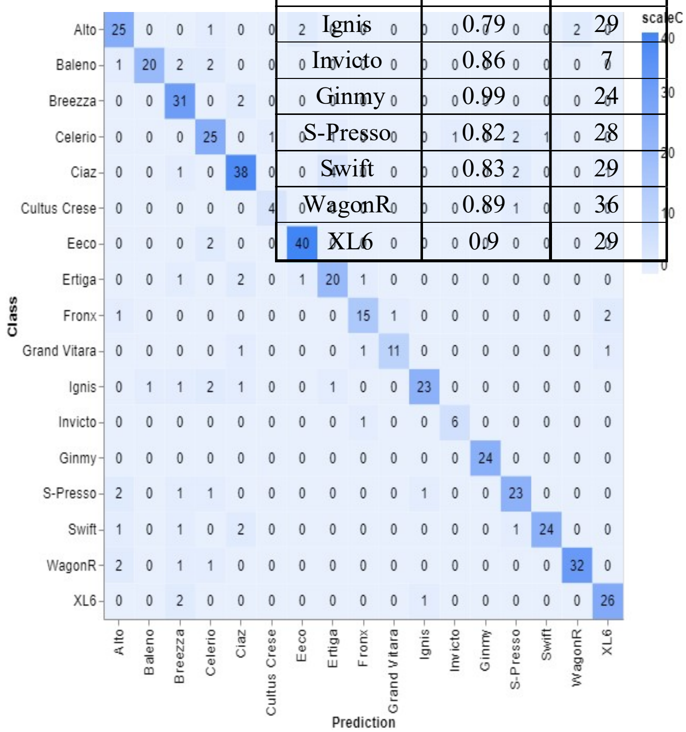

Figure 5.4: Confusion Matrix for the Maruthi Susuki Car Brand.

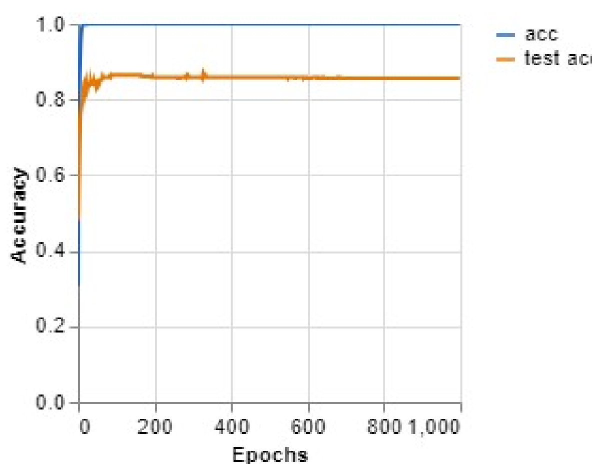

Figure 5.5: Accuracy curve over the epochs- Maruthi Susuki Car Brand.

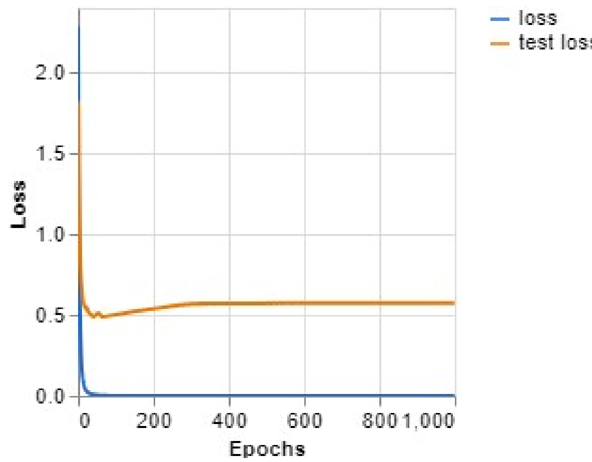

Figure 5.5: Loss curve over the epochs- Maruthi Susuki Car Brand

It is clear from these results that the designed system is resilient in practical situations. Combining various neural networks improved the identification accuracy of cars with fictitious license plates and demonstrated the flexibility and adaptability needed in changing circumstances. Moreover, the overall effectiveness of the system was enhanced by the successful integration of Tesseract OCR for number plate extraction and classification algorithms. These results represent a significant breakthrough in the field of automated vehicle identification and provide a firm basis for the creation of intelligent surveillance systems that will be useful to law enforcement organizations throughout the world.

6 Conclusion

To sum up, the "Recognizing and Intercepting Users of Fake Number Plates" offers a ground-breaking investigation into the field of automatic car identification, focusing on the problem of fake license plates. The neural network architecture that was designed, which incorporates YOLO, DeepSORT, and many deep learning algorithms, has demonstrated exceptional effectiveness in real-time object recognition and identification of automobiles that use fake number plates. Specialized networks' subtleties in terms of car type, model, brand, color recognition, and number plate extraction highlight how flexible and adaptive the system is in changing conditions.

The thorough integration of Tesseract OCR with categorization algorithms improves the system's accuracy and increases its usefulness for law enforcement. The effective use of this technology in the real world holds the potential to completely transform monitoring operations by offering a clever and effective way to quickly identify and apprehend cars engaged in illegal activity. Consequently, this study makes a substantial contribution to the development of automated surveillance systems and provides a strong framework for tackling the enduring problem of fraudulent license plates in our progressively mobile and networked world. The information provided here represents a significant advancement in maintaining the integrity of vehicle identification systems and enhancing public safety in the face of changing technological threats.

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