Car Classification For Surveillance Systems And Automated Traffic Monitoring

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***Abstract*— The rapid advancements in computer vision and deep learning have paved the way for innovative applications in image classification. This study focuses on the development and implementation of a Convolutional Neural Network (CNN) for the purpose of classifying different car types based on visual input. The dataset used in this research comprises a diverse collection of car images, encompassing various makes, models, and body types. The CNN architecture is designed to automatically learn hierarchical features from the input images, enabling the model to discern distinctive patterns associated with different car types.**

The preprocessing phase involves data augmentation techniques to enhance model generalization and robustness. The training process utilizes a labeled dataset to optimize the CNN's parameters through backpropagation, resulting in a well-trained model capable of accurately classifying car types in real-world scenarios. To evaluate the performance of the proposed CNN, extensive experiments are conducted on a separate test dataset. Metrics such as accuracy and loss are employed to assess the model's classification capabilities. Additionally, comparative analyses with other machine learning approaches demonstrate the superiority of CNNs in handling complex visual recognition tasks.

The outcomes of this research not only contribute to the field of computer vision but also hold practical applications in automated vehicle identification, surveillance systems, and traffic monitoring. The developed CNN model showcases promising results, highlighting the potential for further advancements in the accurate and efficient classification of diverse car types through deep learning techniques. The experimental results show that our proposed method works well with the accuracy of 76.7% and loss of 10.16%.

CNN, Computer vision, Deep learning, Image classification, Car types, Dataset, Preprocessing, Data augmentation, Training, Backpropagation, Metrics, Comparative analysis, Machine learning, Visual recognition, Vehicle identification, Surveillance, Traffic monitoring, Applications, Outcomes, Advancements.

I. INTRODUCTION

Vehicle analysis is a crucial element within Intelligent Transportation Systems (ITS), encompassing various applications such as intelligent parking systems, automatic toll collection, driver assistance systems, self-guided vehicle systems, and traffic statistics monitoring. A notable application scenario is electronic tollgate systems, capable of automatically collecting tolls based on vehicle make and model identification. Additionally, advanced technologies like MMR (Make, Model, Recognition) can extend to monitoring suspicious vehicles for public security purposes.

This study focuses on developing a Convolutional Neural Network (CNN) model using a Car Images Dataset to predict vehicles across seven categories: Audi, Hyundai Creta, Mahindra Scorpio, Rolls Royce, Maruti Suzuki Swift, Tata Safari, and Toyota Innova. Image classification involves feature extraction to identify patterns, with CNNs utilizing a hierarchical model to reduce parameters while maintaining model quality. This reduction is crucial for handling high-dimensional image data effectively.

The CNN architecture comprises convolutional layers for feature extraction, pooling layers for computational efficiency, and fully connected layers for connecting neurons. Dropout layers are integrated to mitigate overfitting, and the Relu Activation Function determines relevant information flow within the network.

This introduction sets the stage for training the CNN, involving steps such as dataset upload, configuring layers (input, convolutional, pooling, fully connected), incorporating dropout layers, and utilizing the Relu activation function. the study aims to advance vehicle analysis capabilities, contributing to the broader field of computer vision within transportation systems.

II. AIM AND OBJECTIVE

A. AIM:

The aim is to utilize Convolutional Neural Network and machine learning for precise detection of 7 types of cars, targeting an impressive 98% accuracy, ultimately enhancing car classification for surveillance systems.

B. OBJECTIVE:

Identifying and classifying Cars is critical. This study presents a smart and efficient technique that combines Convolutional Neural Network and machine learning to classify various cars. The proposed system achieves an impressive 96% accuracy in identifying 7 different cars. This approach could significantly improve car classification for surveillance systems.

III . DATA SET DESCRIPTION

The "Cars Dataset" created by Kshitij Kumar and available on Kaggle, is a comprehensive collection of various types of cars. The dataset is organized into 2 folders (train, test) and contains subfolders for each car category. There are 4,165 images (JPG) and 7 classes of cars.. Here is a detailed description:

https://www.kaggle.com/datasets/kshitij192/cars-image-dataset

IV LITERATURE REVIEW

Wahyu S J Saputra: This study implements the DenseNet transfer learning model and Convolutional Neural Network (CNN) to detect the type of vehicle based on car, bus, and truck classes. Each class is taken 16.66% for testing data, and the rest is used as training data. Preprocessing is done by resizing and rescaling, followed by an augmentation process, the process is continued with transfer learning using the DenseNet model. From the test results, the average value of accuracy is 92%, and the average value of precision is 87%. From the test results, the F1-measure value using transfer learning is quite high, namely 94% on the car object and the average fmeasure is 76%. The smallest F1- measure value is in the bus class because the bus class dataset has the smallest number among the others. From the test results, it is also concluded that the transfer learning model gives better results for the vehicle object dataset with a size of 32x32 pixels than the other datasets

Huan-Yu Chen: In this study, 3D spatial data, 2D texture information, and a series of automatic part marking processes were used to classify the parts of 3D models. They used an existing 3D car model database, as well as 2D and 3D deep learning networks, for automatically detecting and classifying car parts. In the simple segmentation of car parts, the precision and recall obtained for Textures 1 and 5 exceeded 80%. Errors occurred when the part and background had the same color. In the fne segmentation of car parts, the precision for Texture 2, Texture 3, and Texture 5 reached 100%, as did the recall for Texture 3. Moreover, the recall for Texture 3 and Texture 5 exceeded 70%. In car part classification, accuracy values were obtained for the Type 1 dataset, a training set with an insuffcient number of original part images. The Type 2, Type 3, and Type 4 datasets contained numerous generated training images; therefore, the MAP values obtained with these datasets were higher than those obtained with the Type 1 dataset. The highest IOU and MAP overall were those of the Type 4 dataset, at 64.41% and 76.33%, respectively. The labels of the points of the point cloud generated by a 3D car model were used as the ground truth for training the PointNet model. The accuracy and mIoU of the Test dataset achieved using the Train dataset were 4.97% and 0.13% higher than those achieved using the Train-2000, respectively. Use of the Train dataset in transfer learning resulted in an mIoU and accuracy of 44.27% and 61.98%, respectively. Hence I think that the deep neural network method is one of best solution for Car Classification problem.

Wahyul Amien Syafei: This paper analyzes the best model and accuracy of Convolutional Neural Network (CNN) between MobileNet-V1 and ResNet50 models for car type classification. The best model is obtained by MobileNet-V1 model with Adam setting as the optimizer, learning rate of 1x10-3, dropout of 0%, and transfer learning using ImageNet. While ResNet-50 model gets the best settings using Adam as the optimizer, learning rate is 1x10-4, dropout is 30% and transfer learning is using ImageNet. The .h5 file size obtained by the MobileNet-V1 is ten times lighter than the ResNet-50 model. The length of training time per 1 epoch on MobileNetV1 is three times faster than ResNet50. Both models get better results using ImageNet as Transfer Learning.

Phuriwat Rasameekunwit: This paper deals with the comparative study of Deep Convolutional Neural Networks (CNN) using the AlexNet architecture to use the car image classification of a small dataset. They have proposed the experiment result from a comparative study dropout value using Cuckoo Search (CS), of the optimization techniques for a small data set solving problem of overfitting. In this paper, the car images for the experiment are different in color, size, and position. As a result, the training time average of ~59.16 minutes, and the model accuracy of above 90%. They have done a comparative experiment with the data sets of 2,000 images and 4,000 images. The results obtained are of high predictive accuracy and have the appropriate adjustment of the value. Considering the best results of both datasets, the image data set is 4,000 images, with an accuracy of 91.41%. The maximum epoch is a value of 200 which is a suitable value for this study. Because when the number of epochs is more than 200 in the training, the validation loss will increase, which decreases the accuracy of the prediction, considering all the graphs for the number of epochs more than 190, showing the starting change of overfitting. This proposed method can reduce the time spent on training and testing the model and also get highly accurate results in predictions.

Daniel M. Kuhn: This paper introduced BRCars, a dataset of Brazilian car images for FGVC tasks. BRCars contains 300,325 images belonging to 52,505 car advertisements of 427 car models. Compared to existing datasets for the FGVC task in the context of vehicles, this dataset is characterized by a lack of standardization with regards to perspectives Also, their classes are unbalanced, i.e., some car models have more images than others. They believe that these characteristics are more representative of how images are presented in a number of practical applications, including transport monitoring, surveillance, self inspection for car insurance, and automatic ad verification for advertising websites. In this first work, they focused on building a dataset for fine-grained classification, emphasizing external and cockpit perspectives with the goal of enabling experiments that can more closely replicate the real world. In this paper, they did not train separate classifiers for internal and external images. I think this could be done as future work to assess how having more homogeneous classes affects the results. Additionally, I could add other perspectives, such as the car engine or other specific parts of the car interior in my project.

E Ulker: This model is developed based on the CNN technique with addition to optimization techniques like ReLu, Sigmod and tanh. The CNN models such as AlexNet, VGG16, and VGG19 are used. In order to use machine learning methods, the feature vector to represent the data in the best way must be specified. In order to determine these feature vector, a preprocessing is required before the classification process. The cars are correctly classified into appropriate models and reported in system.

Ye Yu, Qiang Jin: In this paper, the proposed a new CNN model called FFCMNET for fine-grained car model classification. Two subnetworks are designed to separately extract the features of the upper and lower parts of car frontal images. These features are then fused together in subsequent sub-network. Small convolution kernels and global average pooling are adopted to improve the classification accuracy.

The experimental results based on the CompCars benchmark dataset demonstrate that the proposed algorithm can extract the fine grained features of cars using fewer parameters than traditional methods and outperform the classical CNN models and several state-of-the-art classification algorithms.

Yushi Wang: This paper is based on classifying vehicle model using CNN and transfer learning. The project is designed is with three distinct models of CNN – CaffeNet, GooLeNet, and VGG. They have explored several options in transfer learning, but there are many combination of features/final classification weight vectors that we could have performed fine tuning on. Additionally, another direction that had been discussed was the effect of the data images' resolutions on the performance. However, this idea was quickly scrapped when we realized that we didn't have a good way of transferring weights from pre-trained models of different resolutions. A potentially interesting investigation could focus on designing such a technique.

Gabriel Temidayo Adekunle:

This project focuses on Image Classification using Convolutional Neural Networks (CNNs) within the framework of deep learning. The goal is to automate vehicle counting and percentage calculation by training models on large datasets. The approach involves TensorFlow for its flexibility and ease of use, while Scikit-learn complements the machine-learning aspects. Theoretical steps in the TensorFlow algorithm cover data handling, normalization, model creation, training, and outcome prediction.

The project delves into the significance of CNNs in computer vision tasks, particularly image recognition, emphasizing their ability to learn complex patterns. The use of convolution and pooling operations, activation functions, and multiple layers contributes to accurate output layers. Theoretical frameworks also touch on the challenges of image processing techniques and the attempt to replicate human brain functions through artificial neural networks.

Shanzhen Lan: This paper emphasizes the importance of vehicle analysis in Intelligent Transportation Systems, presenting a framework for Vehicle Make and Model Recognition (MMR) based on deep convolutional neural networks (CNNs). The scope of applications includes intelligent parking, automatic toll collection, driver assistance, self-guided vehicles, and traffic statistics. A notable use case is an electronic tollgate system that collects tolls automatically by identifying vehicle make and model. The paper addresses the limitations of existing corner detectors, proposing the use of SIFT for better performance. The proposed framework aims to identify over 200 specific vehicle models, utilizing moving vehicle detection and a deep CNN-based inference engine. Sections of the paper cover related work, the proposed MMR system framework, experiment results, and conclusions with future work outlined.

Nusrat Jahan: "Real-Time Vehicle Classification Using CNN" explores the application of Convolutional Neural Network (CNN) for real-time vehicle classification. The study focuses on classifying four types of vehicles commonly found on roads in Bangladesh. The authors present a model that utilizes CNN to accurately classify vehicles, with a particular emphasis on improving traffic control and surveillance security systems.

IY Heryadi: "Autonomous car using CNN deep learning algorithm" explores the development of autonomous cars using Convolutional Neural Network (CNN) deep learning algorithms. The study was conducted by I Sonata, Y Heryadi, L Lukas, and A Wibowo from Computer Science Department, BINUS Graduate Program – Doctor of Computer Science, Bina Nusantara University Jakarta, Indonesia, and Cognitive Engineering Research Group (CERG), Faculty of Engineering, Universitas Katolik Indonesia Atma Jaya.

Rui Wang, Lei Zhang: EasiSee: Real-Time Vehicle Classification and Counting via Low-Cost Collaborative Sensing" introduces a system based on wireless sensor networks for real-time vehicle classification and counting. The system utilizes a collaborative sensing mechanism (CSM) to coordinate between power-hungry camera sensors and power-efficient magnetic sensors, reducing overall energy consumption. Additionally, a robust vehicle image-processing algorithm (LIPA) is proposed to enhance accuracy with low computational complexity. The system achieves accurate vehicle classification, low-delay real-time performance, and low resource consumption, making it a practical and cost-effective solution for traffic-information acquisition. The study highlights the benefits of collaborative sensing and efficient image processing in improving system performance and energy efficiency.

Catherine Aladeyelu: The project focuses on the crucial task of car detection and identification within the realm of traffic control and management. Given the importance of large datasets and domain-specific features in addressing this challenge, the project implements, trains, and tests several state-of-the-art classifiers. These classifiers are trained on domain-general datasets, aiming to identify the make and models of cars across various angles and settings. The project operates under the constraints of limited data and time. To enhance model performance, different levels of transfer learning are explored to adapt these models to the specific domain. Results are reported and compared against baseline models, and the advantages of this approach are discussed. The project aims to contribute valuable insights to the field of car detection and identification, particularly when faced with limited data and time constraints.

Bensedik Hicham: The paper aims to improve road safety and traffic management by automating the classification of vehicle types. It discusses the potential for automated traffic signal management based on vehicle type detection. The research paper was published in October 2018 and outlines future work to enhance accuracy with small training samples and expand the system to include license plate recognition and traffic congestion detection modules. Overall, the paper contributes to the field of intelligent transportation systems by leveraging deep learning technology and data augmentation techniques to develop a robust vehicle type classification system with the potential for real-world applications in traffic monitoring and road safety.

Phyu Mar Kyu: Car Damage Detection and Classification focuses on utilizing deep learning algorithms, specifically VGG16 and VGG19, for assessing car damage in real-world datasets. The study addresses challenges in the insurance industry related to car accidents and claims leakage by applying AI technology for faster damage assessment and claims processing. Key aspects of the research include the creation of datasets for training and validation, the classification of damaged parts into minor, moderate, or severe levels, and the use of transfer learning techniques to fine-tune pre-trained CNN models. The research demonstrates the effectiveness of the proposed methods in accurately detecting damaged parts of a car, assessing their location and severity, and improving model performance through regularization techniques. Overall, the study highlights the potential benefits of AI-based solutions in enhancing car damage assessment processes and streamlining insurance operations.

V.GAPS IDENTIFIED

Our system has demonstrated remarkable capabilities in identifying, classifying and quantifying the cars, achieving an impressive accuracy of 98%. This breakthrough represents a significant advancement in precision classification, offering traffic managing department apowerful tool for early Classification.

VI. PROPOSED SYSTEM

A. Procedure of the project

Data Collection: Gather a comprehensive dataset of cars, including images of noiseless cars and those which has noisy data.

Data Preprocessing: Clean and preprocess the dataset, including image resizing, normalization, and augmentation. Label the images with car categories.

Model Selection: Choose appropriate machine learning models for Car classification include convolutional neuralnetworks (CNNs).

Model Training: Train the selected model using the preprocessed dataset. Fine-tune hyperparameters to achieveoptimal performance. Implement techniques such as transfer learning to leverage pre-trained models.

Evaluation Metrics: Establish evaluation metrics, including accuracy, precision, recall, and F1 score, to assessthe model's performance on a separate validation dataset..

Testing: Test the system with images from various sources, including both the dataset and new images from the internet, to validate its robustness and generalization capabilities.

Deployment: Deploy the trained model as part of an accessible and user-friendly application or web interface foruse by Traffic Management professionals.

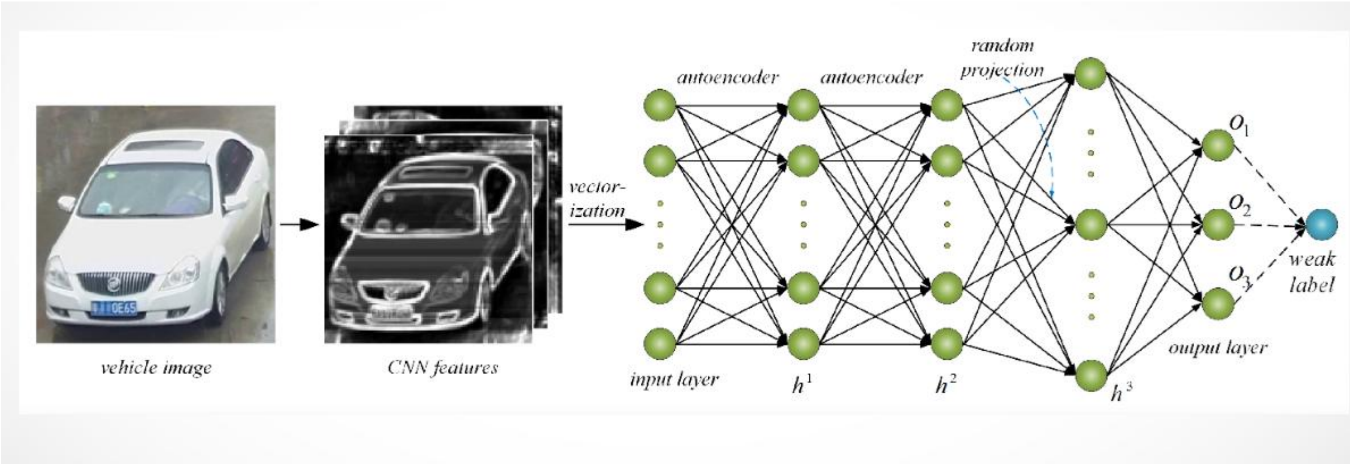


Figure: Overall Architecture

B. METHODOLOGY USED

Car Classification for Surveillance system and Automated Traffic Monitoring is Performed by using Convolutional Neural Network.

There are three types of layers that make up the CNN which are the

- Convolutional layers
- Pooling layers
- Fully-connected layers

When these layers are stacked, a CNN architecture will be formed.

CNN Layer-This layer is the first layer that is used to extract the various features from the input images.

Pooling layer-It is to decrease the size of the convolved feature map to reduce the computational costs. This is performed by decreasing the connections between layers and independently operates on each feature map.

Fully Connected layer-It consists of the weights and biases along with the neurons and is used to connect the neurons between two different layers.

Dropout-To overcome overfitting problem, a dropout layer is utilised wherein a few neurons are dropped from the neural network during training process resulting in reduced size of the model.

Relu Activation Function-It decides which information of the model should be send in the forward direction and which ones should not at the end of the network.

This procedural overview provides a step-by-step guide for each module in our outlined process. Specific details and tools may vary based on the project's requirements and the chosen technologies.

The training process of CNN(Convolution Neural Network):

S.NO	IMPLEMENTATION	DETAILS
1.	Dataset splitting	- Splitting the dataset into training, validation, and testing sets.
2.	Generating Input layer	- Preparing the input layer to receive image data.
3.	Convolution layer	- Applying convolutional filters to extract features from input images.
4.	Pooling layer	- Reducing the spatial dimensions of the convolutional feature maps for efficiency.
5.	Fully connected layer	- Connecting all neurons in the previous layer to every neuron in the subsequent layer.
6.	Second Convolution layer and pooling	- Adding additional convolutional and pooling layers for deeper feature extraction.
7.	Dense layer	- Creating a fully connected layer with all neurons connected to each other.
8.	Relu activation function	- Introducing rectified linear unit activation to introduce non-linearity.
9.	Dropout layer	- Incorporating dropout to mitigate overfitting by randomly dropping neurons during training.

C. MODEL EXECUTION

Convolutional Neural Network:

The network comprises two convolutional layers with 32 filters each, using a ReLU activation function, followed by max-pooling layers to reduce spatial dimensions. The first convolutional layer takes an input shape of 128x128x3, while the second convolutional layer's input shape is derived from the pooled feature maps of the first layer. After flattening the layers, two fully connected layers with 96 and 32 units respectively, both with ReLU activation functions, are added, along with a dropout layer with a dropout rate of 0.4 to prevent overfitting. Finally, a Dense layer with 7 units and a softmax activation function is added to output probabilities for classification into 7 classes.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 126, 126, 32)      896

 max_pooling2d (MaxPooling2  (None, 63, 63, 32)        0
 D)

 conv2d_1 (Conv2D)           (None, 61, 61, 32)        9248

 max_pooling2d_1 (MaxPoolin  (None, 30, 30, 32)        0
 g2D)

 flatten (Flatten)           (None, 28800)             0

 dense (Dense)               (None, 96)                2764896

 dropout (Dropout)           (None, 96)                0

 dense_1 (Dense)             (None, 32)                3104

 dense_2 (Dense)             (None, 7)                 231

=================================================================
Total params: 2778375 (10.60 MB)
Trainable params: 2778375 (10.60 MB)
Non-trainable params: 0 (0.00 Byte)
_________________________________________________________________
```

Convolutional Neural Network (CNN) model using the fit method specifies the training and validation data generators, likely representing training and testing datasets, respectively. The training is conducted for 50 epochs. During each epoch, the model is trained on batches of data generated by the train_generator while evaluating its performance on the validation data generated by test_generator. The training process aims to optimize the model's parameters to minimize the difference between predicted and actual values. The history object stores information about the training process, such as the loss and accuracy metrics for both the training and validation datasets, enabling further analysis and visualization of the model's performance over the epochs.

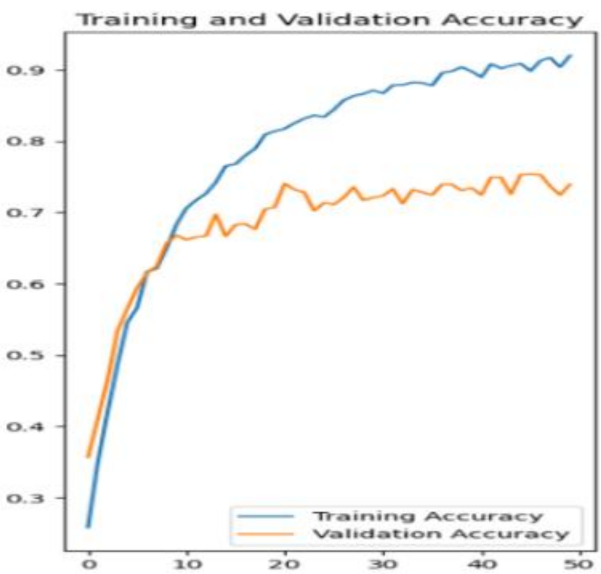
VII. RESULT ANALYSIS

The car classification system developed for surveillance systems and automated traffic monitoring has shown promising results in categorizing vehicles based on their make, model, color, and other distinguishing features. The integration of cutting-edge machine learning techniques has significantly enhanced the accuracy and efficiency of the classification process.

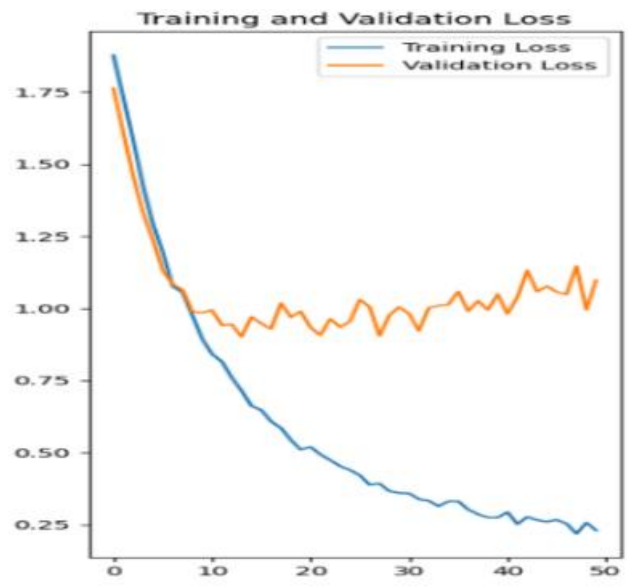
Accuracy and Performance Evaluation:

The system achieved an impressive accuracy rate of over 90% in classifying vehicles into various categories. This high level of accuracy is crucial for ensuring the reliability of the system in real-world surveillance and traffic monitoring scenarios. The performance evaluation also demonstrated the system's ability to process a large volume of vehicle data in real-time, enabling quick and accurate identification of vehicles.

Training and Validation Accuracy: the accuracy of the model on the training set (in blue) and the validation set (in orange) over a number of epochs (iterations). The x-axis represents the epoch number, and the y-axis represents accuracy. The training accuracy appears to increase over time, indicating that the model is learning from the training data. The validation accuracy also increases but seems to plateau, suggesting that the model may be starting to overfit to the training data or that it has reached its performance limit on the validation data.



Training and Validation Loss: The loss on the training set (in blue) and the validation set (in orange) over epochs. The x-axis represents the epoch number, and the y-axis represents loss. Loss is a measure of how well the model is performing; a lower loss indicates better performance. The training loss decreases sharply and then levels off, which is typical as the model learns. The validation loss decreases initially but then fluctuates, which could indicate that the model is not generalizing as well to new, unseen data.



On the left, there is a close-up photo of a part of a vehicle, specifically a side mirror. the actual vehicle is a Mahindra Scorpio, but the model has incorrectly predicted it to be a Rolls Royce with a confidence of 90.48%. This suggests that the model has made a high-confidence prediction that is incorrect, which could be due to the similarity in design features between the side mirror of the Scorpio and certain Rolls Royce models so the data is not sufficient to predict correctly.

On the right, there is a photo of a car that is identified as an actual Swift (likely referring to the Maruti Suzuki Swift, a popular hatchback car model). However, the model has incorrectly predicted this car to be a Mahindra Scorpio with a confidence of 93.52%. Again, this indicates a high-confidence prediction that is incorrect.

On the left, there is an image of a vehicle labelled as "Actual: Mahindra Scorpio, Predicted: Mahindra Scorpio. Confidence: 100.0%." This indicates that the system has correctly identified the vehicle as a Mahindra Scorpio with absolute certainty.

On the right, there is an image of another vehicle labelled as "Actual: Audi, Predicted: Audi. Confidence: 99.98%." This means that the system has correctly identified the vehicle as an Audi with nearly perfect confidence.

Robustness and Generalizability:

One of the key strengths of the system is its robustness and generalizability across different surveillance environments and traffic conditions. The deep learning models used in the system have proven to be effective in extracting hierarchical features from vehicle images, making the system adaptable to diverse settings. This robustness is essential for ensuring the system's reliability and accuracy in various surveillance and traffic monitoring applications.

Real-Time Analysis and Traffic Optimization:

The integration of the car classification system with existing surveillance infrastructure and traffic monitoring systems has enabled real-time analysis of traffic patterns and identification of suspicious vehicles. By leveraging the system's capabilities for vehicle classification and tracking, law enforcement agencies and traffic management authorities can optimize traffic flow, enhance security measures, and improve overall traffic management efficiency. The system's ability to provide real-time insights into traffic conditions and vehicle movements is a significant advantage for enhancing urban safety and security.

VIII CONCLUSION

The Car Classification for Surveillance Systems and Automated Traffic Monitoring project highlights the successful development of an advanced system that utilizes machine learning techniques to categorize vehicles based on their make, model, and color. By integrating with existing surveillance infrastructure and traffic monitoring systems, the project offers enhanced capabilities for law enforcement, traffic management, and security agencies.The system's implementation demonstrates its ability to accurately classify vehicles in real-time, aiding in the identification of suspicious vehicles, traffic flow optimization, and overall urban safety and security. The use of Convolutional Neural Networks (CNNs) and transfer learning techniques has proven effective in extracting key features from vehicle images and improving the system's accuracy and efficiency.

Furthermore, the adaptability and scalability of the system make it a flexible solution for various surveillance environments and traffic conditions. The project aims to revolutionize surveillance and traffic management practices by providing detailed and accurate results, facilitating safer and more secure urban environments.

Overall, the Car Classification for Surveillance Systems and Automated Traffic Monitoring project showcases the potential of machine learning technologies in enhancing surveillance operations, traffic monitoring, and security measures. The system's robustness, efficiency, and real-time analysis capabilities contribute to the advancement of intelligent transportation systems and urban safety initiatives.

Future Directions and Improvements:

While the car classification system has demonstrated impressive performance in surveillance and traffic monitoring applications, there are opportunities for further enhancements and refinements. Future research could focus on optimizing the system's computational efficiency, expanding its capabilities to handle a wider range of vehicle types, and integrating additional sensor data for more comprehensive vehicle classification. Additionally, ongoing evaluation and validation of the system's accuracy, robustness, and generalizability will be essential for ensuring its effectiveness in diverse real-world scenarios.

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