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ORIGINAL ARTICLE

Handcrafted and Transfer Learned Feature Techniques for Vehicle Make and Model Recognition on Nigerian Road

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Abstract

The vehicle makes and model recognition (VMMR) is a challenging task due to the wide range of vehicle categories and similarities between different classes. Studies have shown that works have recognized vehicles of different countries' make and models. Popular vehicles on Nigerian roads may include products like; Toyota, Honda, Peugeot, Benz, Innoson Vehicle Manufacturing (IVM), etc. The VMMR is important in the intelligent transport system hence, this paper presents a handcrafted and transfer learning model to detect stationary vehicles and classify them based on brand, make, and model. A new dataset was introduced consisting of selected images of popular brands of vehicles driven on Nigerian roads. Framework for a vehicle make and model recognition was developed by extracting features using EfficientNet and HOG models and evaluated on the locally gathered datasets. For classification, a linear Support Machine Vector (SVM) was used. Experimental results showed 94.5% on HOG, 97% with EfficientNet, and 98.1% accuracy when HOG and EfficientNet features were concatenation. The proposed concatenated model outperformed HOG and EfficientNet extracted features by providing higher accuracy and confusion matrix with the highest number of classified images. The study shows the advantages of the proposed model in terms of its accuracy in terms of identifying the vehicle make and model.

Keywords: Vehicle Make and Model, Recognition, EfficientNet, Histogram of Oriented Gradient, Innoson Vehicle Manufacturing (IVM), Nigeria Vehicle

Introduction

Analysis of vehicles by automation has become a necessary task in several applications due to the increase in the number of vehicles, the traditional vehicle recognition is the License Plate Recognition (LPR) system (Manzoor et al., 2019). This system can lead to incorrect identification due to the forgery of plate numbers and other ambiguities. The challenges of the LPR led to the need for computer vision-based Intelligent systems to replicate human visual capabilities i.e., being able to recognize things with the help of the brain. Gaussian Mixture Model (GMM) algorithm has been used traditionally in vehicle detection systems but is limited due to illumination changes and other occlusions (Chen et al., 2018), (Irhebhude, Odion, et al., 2016). There are several datasets used on vehicle recognition which have been highlighted by Ni and Huttunen (2021), these datasets consist of different variations.

Vehicle Make and Model Recognition (VMMR) is beneficial in different systems over the traditional ways of recognizing vehicles. A vehicle can be identified by its make (e.g. Toyota, Ford, Honda) model (e.g. Toyota Camry, Ford Explorer, Honda Civic), colour (e.g. red, black, white) (*"Vehicle make model recognition with color [updated 2022]: PLATE RECOGNIZER ALPR"*, 2021) and several other prominent features. Humans use their physical eyes to achieve this task but recognizing and remembering vehicles based on their features such as; make, model and colour can be complex, time-consuming, and demanding.

The VMMR can be applied in various ways most especially in intelligent transport systems (Jamil et al., 2020) to monitor vehicles without fatigue. Intelligent Transport Systems (ITS) provides new services related to modes of transportation and traffic control as well as enabling various users to be more informed and make safer and well-coordinated smart use of road transportation networks (Yang & Pun-Cheng, 2018). Coordinated movement of goods and people is an important activity globally that involves transportation and has an impact on economic resources and the quality of life globally. It has an impact on traffic congestion, pollution, fatigue as a result of driving, and risks encountered due to accidents (Manzoor et al., 2019). As the number of vehicles increases, it is necessary to automate the vehicle analysis process. Vehicle identification analysis can assist in classification depending on its use in different applications. A vehicle detection system should be intelligent enough to recognize changes in illumination, occlusion, varying weather, and environmental condition.

Detection of vehicles can be based on appearance as they come in various sizes, shapes, and colors as well as different features (Irhebhude et al, 2016). According to Yang and Pun-Cheng (2018), appearance-based vehicle detection has two basic steps; hypothesis generation (HG) and hypothesis verification (HV). The HG has to do with hypothesizing the possible locations of vehicles in images while HV performs tests to verify the presence of vehicles in images. The appearance-based approach for vehicle detection uses prior knowledge to separate the object of interest from the background containing complementary sets (Barnich & Droogenbroeck, 2011).

Feature descriptor algorithms are used in recognition systems for extracting features from images and used to make decisions about different classes of objects, they allow quick and efficient ways to search for objects in images. Feature descriptors have been used effectively in vehicle detection, they can be used individually or in a combination. The region, Local Binary pattern (LBP), and HOG have been combined by Irhebhude, Nawahda, et al. (2016), these approaches have low feature representation but with CNN-based approach rich representation, faster, more reliable, and promising results have been achieved in terms of accuracy (Chen et al., 2018).

The Innoson Vehicle Manufacturing (IVM), a Nigeria vehicle manufacturing company has different (e.g. IVM) models (e.g. IVM Caris, IVM G20 Smart, IVM Ikenga, etc), varied colours (e.g. red, black, white, etc) and several other prominent features. As reported by Ni and Huttunen (2021) authors surveyed different algorithms for vehicle make and model recognition. The authors pointed out the need for future research, especially as a result of an increase in new car models from time to time which poses a challenge in real-world recognition as there are only a few samples available for classifiers to identify new models of cars. From the works of literature, no known study has recognized IVM vehicles. This study seeks to propose a model that will recognize selected contemporary vehicles and selected IVM vehicles on Nigerian roads.

EfficientNet

According to Tan and Le (2019), EfficientNet is a convolutional neural network architecture and scaling method that uses a compound coefficient to uniform scale network depth, width, and resolution dimensions (see Fig. 1).

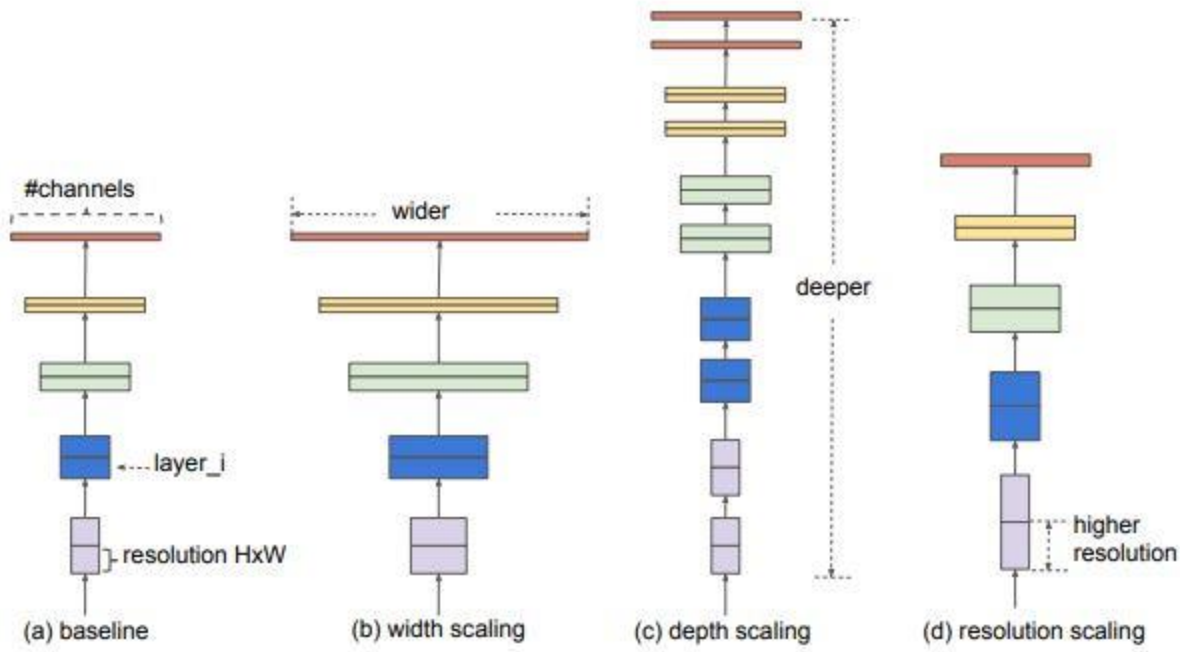


Figure 1: Model Scaling (Tan & Le, 2019)

The EfficientNet-b0 (see Fig. 2) convolutional neural network has been trained on millions of images from the ImageNet database (*ImageNet*), and the network can classify thousands of images into various object categories. As a result, the network has learned detailed feature representation from different kinds of images.

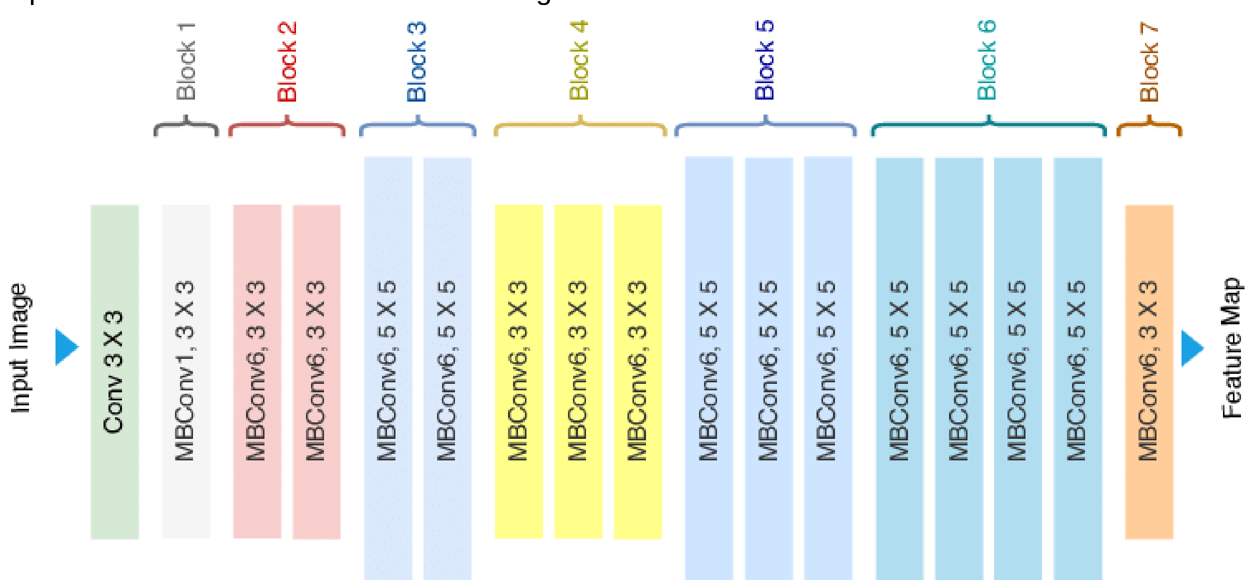


Figure 2: EfficientNet Model (Imane, 2023)

Tan and Le (2019) proposed the use of the EfficientNet model to train different widely used datasets to achieve better efficiency and accuracy compound scaling method for convolutional neural networks to achieve better efficiency and accuracy. Features were extracted using

EfficientNet-b0 from MATLAB and used as features presented to SVM for classification in vehicle make and models.

Histogram Oriented Gradient

Histogram-oriented gradient (HOG) as reported in (Dalal & Triggs, 2005) and presented in (Irhebhude, Nawahda, et al., 2016) is a feature is a local descriptor that extracts appearance and shape information based on intensity and edge transformation. HOG is calculated by computing the image gradient in *i* and *j* directions on the image window divided into regions named cells. The accumulated cells are contrast normalized to ensure invariance in illumination to achieve a robust representation of an image. Different normalization factors can be utilized: L1-norm and L2-norm. Further details can be found in (Dalal & Triggs, 2005). HOG in MATLAB with blocksize [32 32] was utilized for the experiment.

Literature Review

CENsus Transformed histogRam Oriented Gradient (CENTROG) features were used by Irhebhude et al. (2015) to propose a feature-based technique to detect pedestrians and vehicles captured at night time. SVM classifier was applied to CENTROG features, and the performance of their technique was compared with CENsus TRansformed hISTogram (CENTRIST). Experimental results showed the CENTROG approach had better accuracy. Similarly, CENTROG was applied by Irhebhude, Odion, et al. (2016) to recognize vehicles at both night and day time recording 97.2% and 100% accuracy for day and night time respectively. The authors further suggested identifying more categories of vehicles. Vehicles were classified into four categories by Irhebhude, Nawahda, et al. (2016) using a combination of features consisting; of the region, HOG, and Local Binary Pattern (LBP) to achieve 95% average classification accuracy on vehicle video datasets. Using a similar approach, vehicles were classified into cars and vans by Nguyen et al. (2016) the dataset consists of 60 vehicles captured from CCTV video footage, and a combination of HOG-LBP, region descriptor, and SVM classifier were used for experimental analysis to achieve accuracy of 93%. The authors suggested further increases in size of dataset and addition of other vehicle classes.

Fine-grained image classification was used by Krause et al. (2013) to represent 2D objects in 3D considering the appearance and location of local features. According to Amirkhani and Barshooi (2022), features used for vehicle classification are mostly extracted from the headlight, grill, scoop, and bumper sections, with the combination of these features the authors developed a model to classify vehicles using a dataset consisting of images of a front view and front three-quarters of vehicles achieving an accuracy of 92.14% and 96.72% respectively in automated and manual scenarios.

Lyu et al. (2022) introduced a new dataset for VMMR called Diverse Large scale VMM (DVMM) consisting of samples with the most popular 23 makes and 326 vehicle models used in Europe. A deep learning-based approach was applied to perform vehicle make and model recognition in two stages, experimental result shows the model was able to reduce inter-make ambiguity, providing 93.95% accuracy on the DVMM dataset and 95.85% on the traditional VMMR dataset.

Wang et al. (2021) proposed a feature extraction framework called the weighted mask hierarchical bilinear pooling (WMHBP) based on hierarchical bilinear pooling (HBP) for VMMR, which was evaluated on the Stanford cars public datasets. An accuracy of 95.1% was achieved which showed the superior power of the method used.

Hu et al. (2017) focused on car model classification using a spatially weighted pooling strategy (SWP) to improve the robustness of most DCNNs. The SWP is a novel pooling layer consisting of a predefined number of specially weighted masks. 93.1% was achieved on the Stanford cars-196 dataset and 97.6% on the CompCars dataset.

Hassan et al. (2018) conducted an empirical survey on VMMR, evaluation was done on the performance of several recent deep neural network models in recognizing and identifying vehicles based on their make and model. The aim was to classify 196 different types of vehicles based on their make, model, and year using several models trained by transfer learning. The Ensemble model learning gave the highest accuracy of 93.96% when compared to other models. The authors concluded that VMMR is challenging due to the high intra-class and inter-class variation. More data and the use of other image processing techniques were recommended to increase the classification rate of VMMR.

Images of trucks based on their body type using transfer learning were identified by Nezafat et al. (2018), SVM, MLP, and KNN classifiers were used to achieve accuracy results of 88%, 96.5%, and 84.7% respectively. The intra-class variation challenge was addressed by Xiang et al. (2020), the focus was on fine-grained vehicle classification using datasets of mixed viewpoints. Interactions between parts of vehicles were integrated into CNN to identify relationships between parts and classify each correctly to a particular vehicle type. The experiment showed greater performance compared to other CNN methods, however, the proposed model could not recognize new vehicle types.

VMMR has different challenges such as occlusion, image acquisition, and inter and intra-class similarities. Manzoor et al. (2019) presented a real-time robust approach to tackling some of the challenges and accurately recognizing vehicles based on the make and model. Histogram of Gradient (HOG) features on Random Forest (RF) and Support Vector Machine (SVM) algorithms were used for classification. The National Taiwan Ocean University-Make and Model Recognition (NTOU-MMR) dataset was used and modified to include the generation of vehicles. The results showed an accuracy of 94.53% for RF and 97.89% for SVM in identifying vehicles based on their make, model, and generation This result reflects a better performance compared to other existing systems that have used the same dataset. A further recommendation was made for future enhancement of the system and the inclusion of a larger dataset with more vehicle types.

Naseer et al. (2020) proposed a VMMR system based on deep features extracted from the region of interest with the VGG16 convolutional neural network model, using an SVM classifier to distinguish different makes and models of vehicle images, achieved an accuracy of 96.86% on the selected region of interest from NTOU-MMR dataset (Chen et al., 2015). The author's approach was compared to several techniques and recommended feature optimization and selection methods to yield more promising results.

Front-view images captured at night time were used by Balci et al. (2019) to identify the make and models of cars using a deep learning-based approach. To overcome the challenges of low light conditions, like a cloudy or rainy day; the authors used a shot multi-box detector. To address challenges in real-time vehicle automation, Lee et al. (2019) used frontal views of vehicle images with Residual SqueezeNet architecture to identify VMMR achieving an accuracy of 96.33%. The dataset used were Korean manufactured vehicles and other commonly used imported vehicles.

Abbas et al. (2020) proposed the use of an image enhancement technique for the vehicle make and model recognition and achieved an accuracy of 97.31% which was a significant improvement over the 91.5% achieved on the dataset used without the use of image enhancement.

Jamil et al. (2020) proposed a bag of expressions (BOE) for VMMR application, extracting features with a combination of HOG and different keypoint detectors. The approach was tested on the NTOU-MMR dataset, the feature-based approach was considered to be computationally fast when compared to Scale Invariant Feature Transform (SIFT) descriptor (Lowe, 2004) which is computationally expensive.

Ni and Huttunen (2021) surveyed different algorithms for a vehicle make and model recognition which have reported significant recognition accuracies that have almost exceeded human performance. The authors pointed out the need for future research, especially as a result of an increase in new car models from time to time which poses a challenge in real-world recognition as there are only a few samples available for classifiers to identify new models of cars. The use of Few shot learning algorithm by Wang et al. (2019) will help models recognize new classes having few samples with supervised learning.

Ali et al. (2022) presented a vehicle dataset consisting of 3847 images for make and model recognition having various lighting conditions and angles that demonstrate real-world scenarios.

Deep learning has become the preferable approach to vehicle recognition systems as against the traditional way. From the work done by Nezafat et al. (2018), when a new vehicle makes class is added, algorithm performance drops leading to the formulation of a new classification model. IVM vehicles are vehicles that have never been categorized hence the need for this study. Popular vehicles on Nigeria roads and selected IVM vehicle make will be used for the experiment.

Materials and Method

The proposed methodology in Figure 3 is based on hybridized deep-learned and handcrafted features extracted from the rear, frontal and side views images of stationary vehicles captured in digital form and used as a dataset for the experiment. These images were read as input on a region of interest cropped, and features were extracted using EfficientNet pre-trained network and HOG models. The extracted features are concatenated and used for training and testing by the SVM classifier.

The proposed framework for the VMMR as shown in Fig. 3, is discussed briefly in the following subsections:

Input Image

The dataset used as input image consists of eighteen different selected vehicle make and models as described in Table 1 showing several captured images. A total of 3452 images with 18 different make and models of vehicles were captured locally using a smartphone camera, they were taken from the front, angular side, and back views. The input images were resized and the region of interest was cropped as shown in Fig. 4, this was done for the effective extraction of features in the next stage.

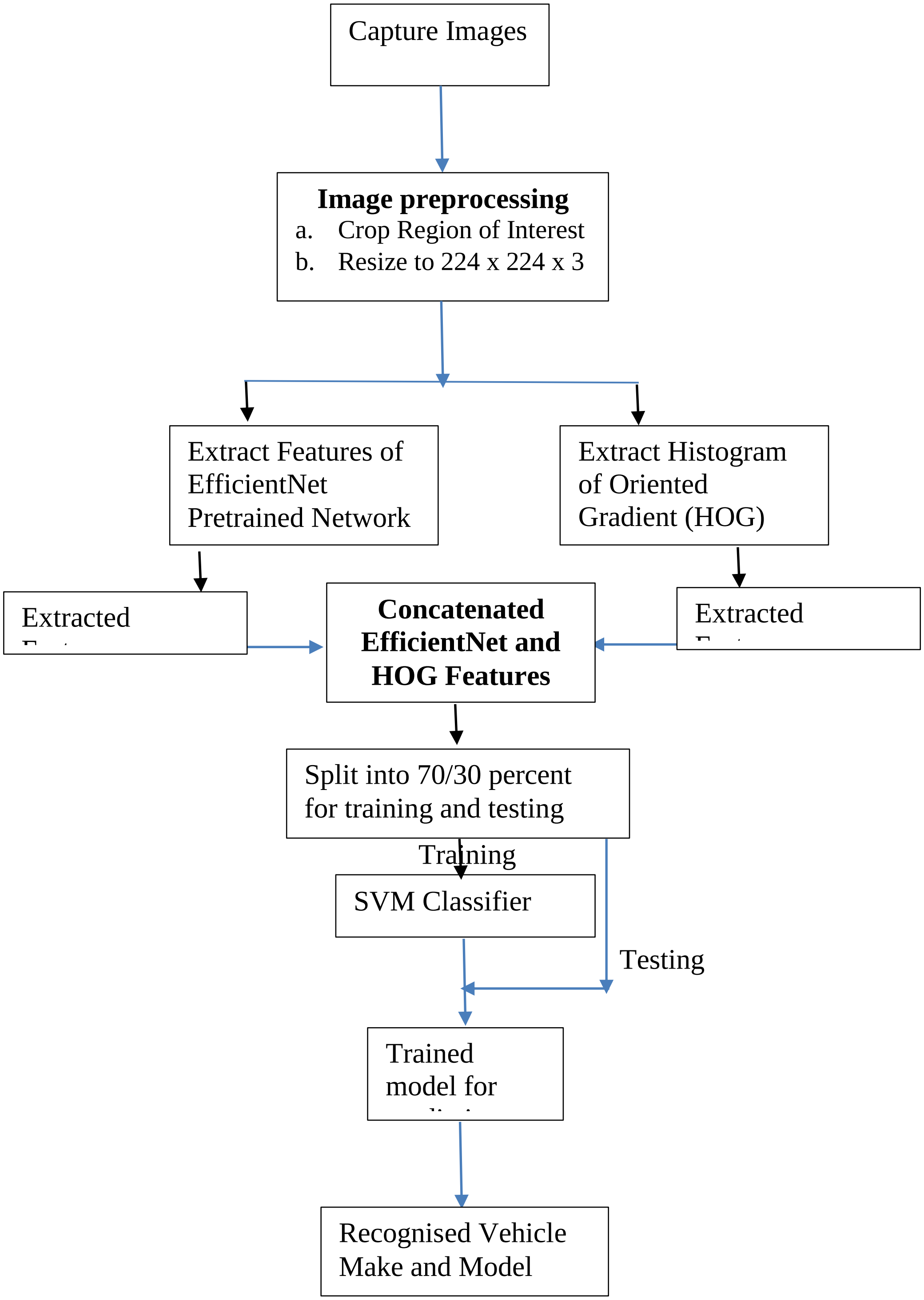


Figure 3: Proposed Methodology

Table 1: Dataset for VMMR model

Class	Vehicle Type	Number of images captured
1.	Benz C-class	150
2.	Benz E-class	157
3.	Honda Accord	197
4.	Honda Civic	180
5.	Honda CRV	169
6.	IVM 6125	207
7.	IVM 6499 (seriki)	200
8.	IVM 6800 (Coaster Bus)	200
9.	IVM G6T	200
10.	IVM G20 Smart	200
11.	IVM Granite	200
12.	IVM Granite A	200
13.	IVM Shuttle Bus	200
14.	Peugeot 206	172
15.	Peugeot	180
16.	Toyota Corolla	250
17.	Toyota Camry	222
18.	Toyota Highlander	168

Feature Extraction

Feature extraction is the process of dimensionality reduction that selects or combines variables into features where raw data is effectively reduced to manageable groups for processing while still accurately describing the original data set (*"Feature Extraction"*, 2019) and (Navamani, 2019), it reduces the number of resources required to describe a dataset. Features were extracted from the layer before the Fully Connected Layers of the EfficientNet model. The process of feature extraction is shown in Figure 2.

The feature extraction network process consists of the convolutional layer, pooling layer, and classification network. The input dataset is read to the convolutional layer which consists of filters to perform operations on the input images. The pooling layer is used for dimensionality reduction, average pooling, and maximum pooling are two functions used in the pooling operation. For the proposed methodology, features were extracted using two models namely; EfficientNet and HOG models. The extracted features from each of the two models were concatenated and used for the experiment.

Classification

At this stage features selected are used to train and test on SVM classifiers in other to differentiate the various make and models of the vehicles yielding different performance metrics. In this paper, the performance of the model is evaluated using accuracy, confusion matrix, and ROC curves.

Analysis and Discussion of Result

A dataset of vehicle makes and models was created which includes brands of commonly used vehicles in Nigeria, including 8 of the IVM made in Nigeria vehicles. Fig. 4 shows sample images dataset collected.

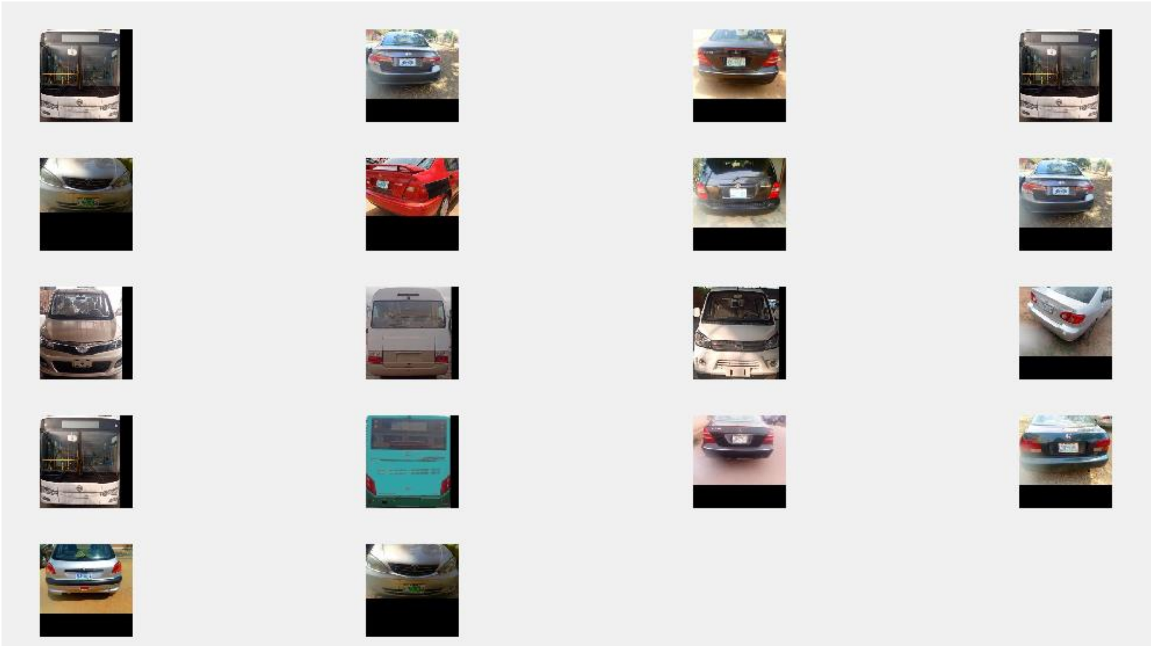


Figure 4: Sample of Captured Vehicle Make and Models

The purpose of the experiment conducted is to identify and classify vehicle images based on their make and model. To achieve these, three different experiments were performed using three different techniques namely; extracted HOG features with SVM linear classifier, extracted EfficientNet transfer learning features with SVM linear classifier, and combination of HOG and extracted EfficientNet features with SVM classifier. Accuracy, confusion matrix, and ROC curve were used for evaluating the proposed model. The dataset consists of 3452 vehicles with 18 classes. For the experiments, the data was split into 70:30 for training and testing. Table 2 gives a summary of accuracy results for each model, time taken for training, and other parameters used.

Table 2: Performance Evaluation Results

Methods	HOG	EfficientNet	EfficientNet and HOG
Accuracy (%)	94.5	97	98.1
Training time(sec)	185.84	33.43	21.494
Selected features	144/144	1280/1280	1424/1424
Model size (MB)	4	28	31
No correctly classified	978	1004	1015
Incorrectly classified images	57	31	20

HOG, EfficientNet, and a combination of HOG with EfficientNet with an SVM classifier are used in all three instances. The confusion matrix in Figs. 5, 6, and 7 shows the number of observations for the vehicle classification model when different features were used to classify vehicles, the classes were labeled from 1 to 18 with each number representing a vehicle type depicted in Table 1.

It is generally observed that classes 16, 17, and 18 had high numbers of misclassified vehicles, it is also observed that the three classes belong to the same vehicle brand; Toyota. It is also noted that the IVM vehicle types were all accurately classified to their corresponding classes as there were no misclassified values.

Training the datasets with no applicable optimizer, the HOG, EfficientNet, and a combination of the two models resulted in 94.5%, 97%, and 98.1% accuracy respectively (see Table 2).

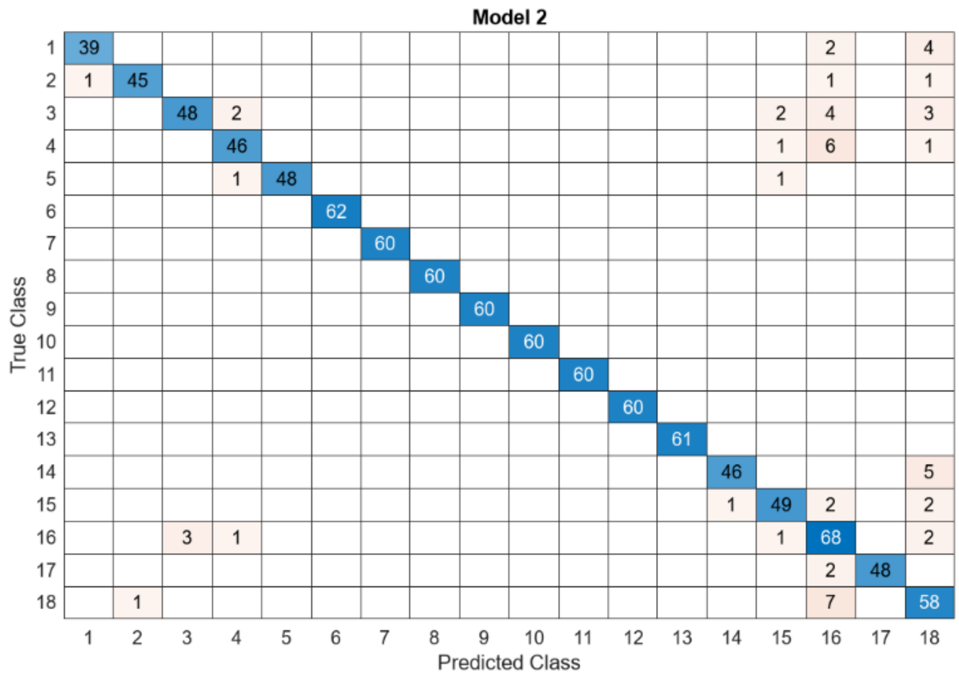


Figure 5: Confusion Matrix Showing Number of Observations with HOG Features

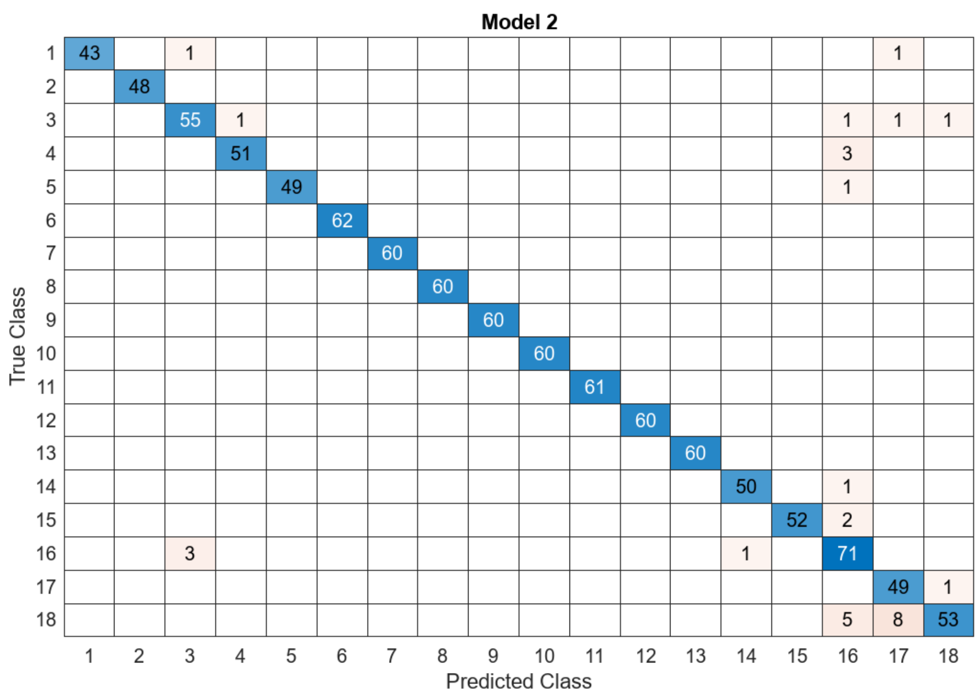
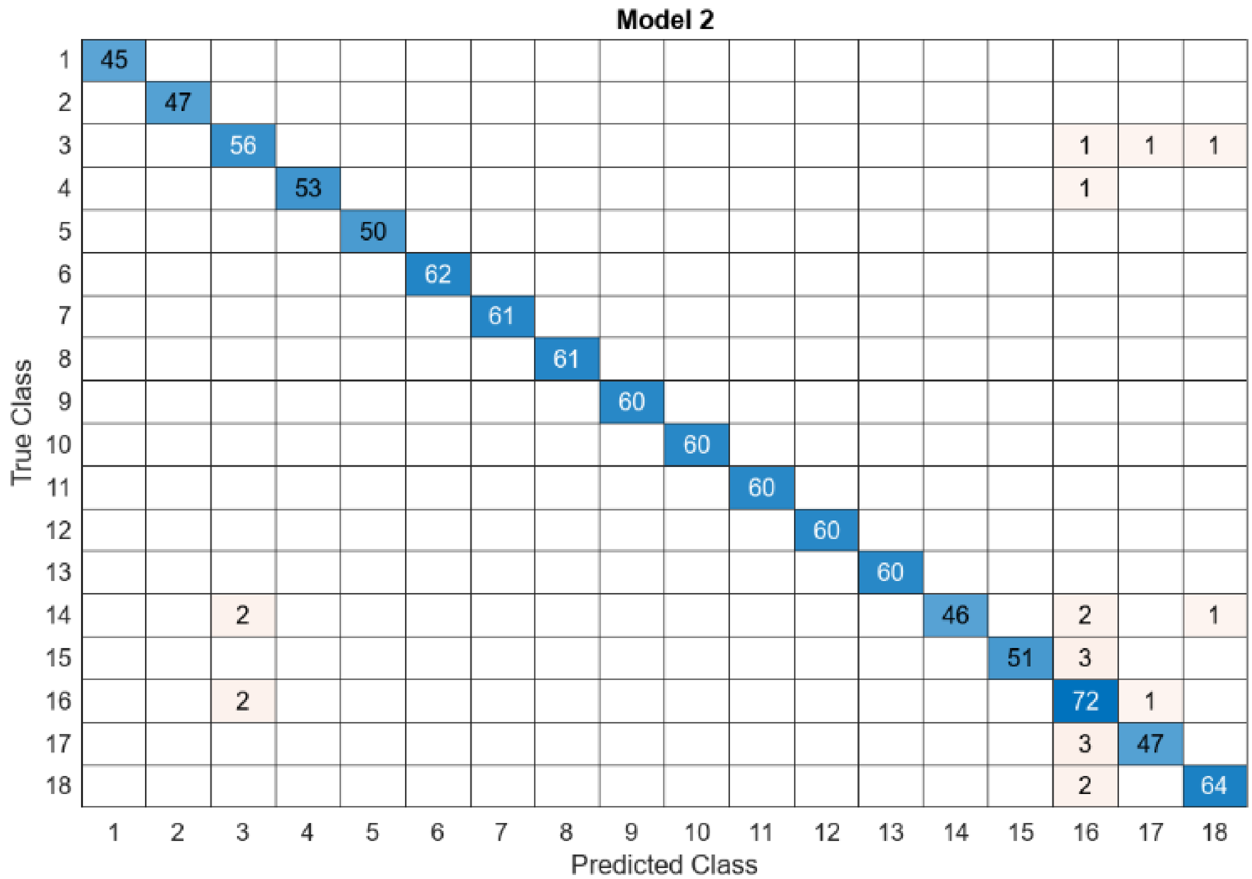


Figure 6: Confusion Matrix Showing Number of Observations with EfficientNet Features



(c)

Figure 7: Confusion Matrix Showing Number of Observations with Combination of HOG and EfficientNet Features

The plots in Figs. 8, 9, and 10 show the ROC curve for the performance of the three models used with Area under the curve (AUC) values of 0.9963, 0.9999, and 1. This shows that the HOG has a 99.63% ability to correctly distinguish more numbers of the true positive class than the false positive while the EfficientNet and combination of the two models have 99.99% and 100% respectively. Compared to other models, a combination of EfficientNet and HOG gave an AUC value of 1, this suggests a 100% chance of the model to correctly classify the vehicle images between all the positive and negative which reflects a perfect accurate test for the vehicle classification model.

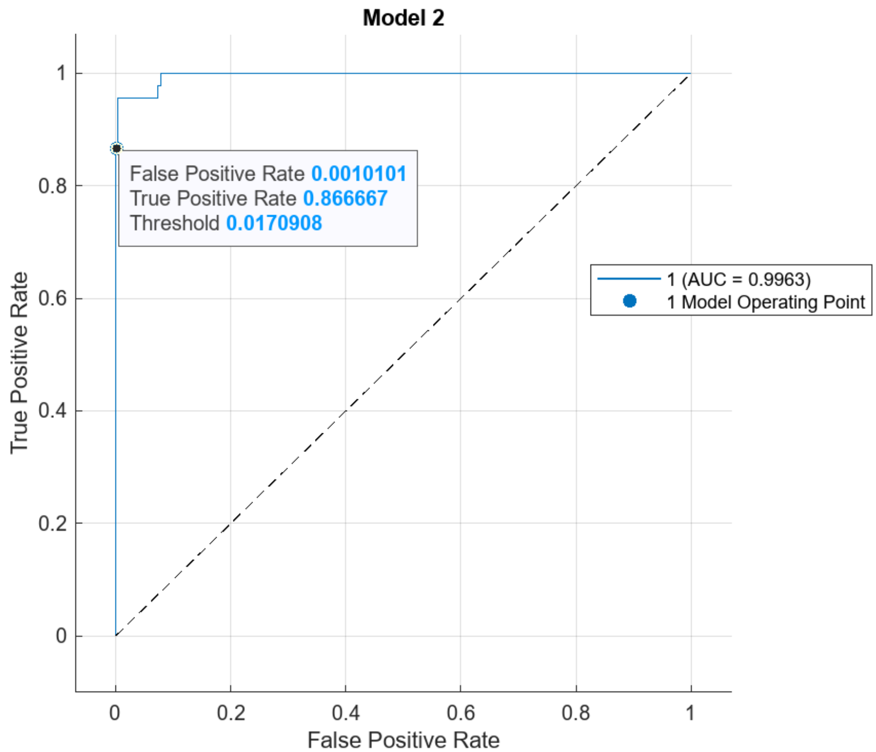


Figure 8: ROC Curve Showing AUC with HOG Features

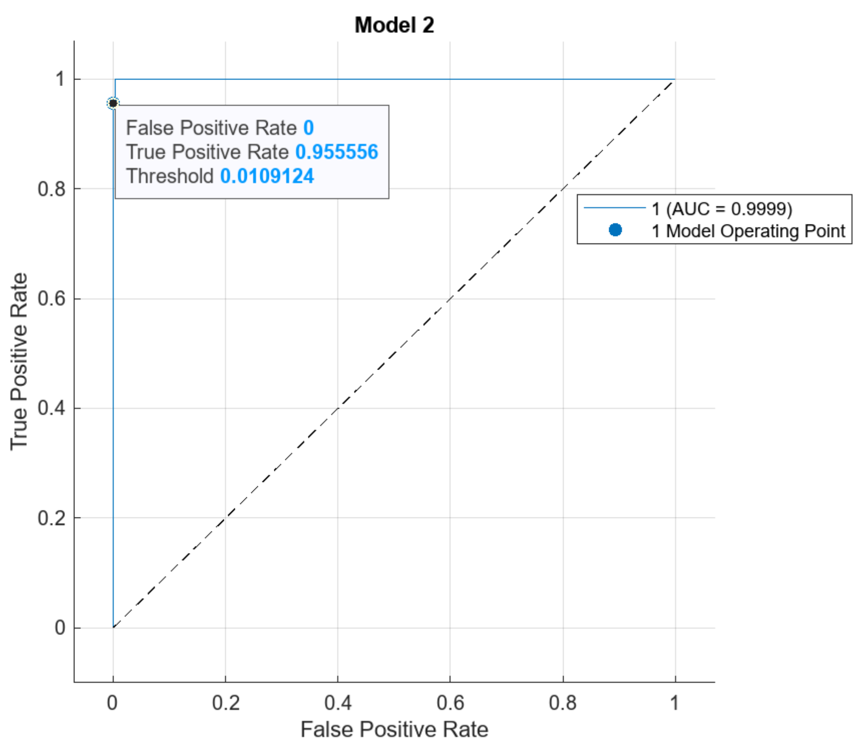


Figure 9: ROC Curve Showing AUC with EffecientNet Features

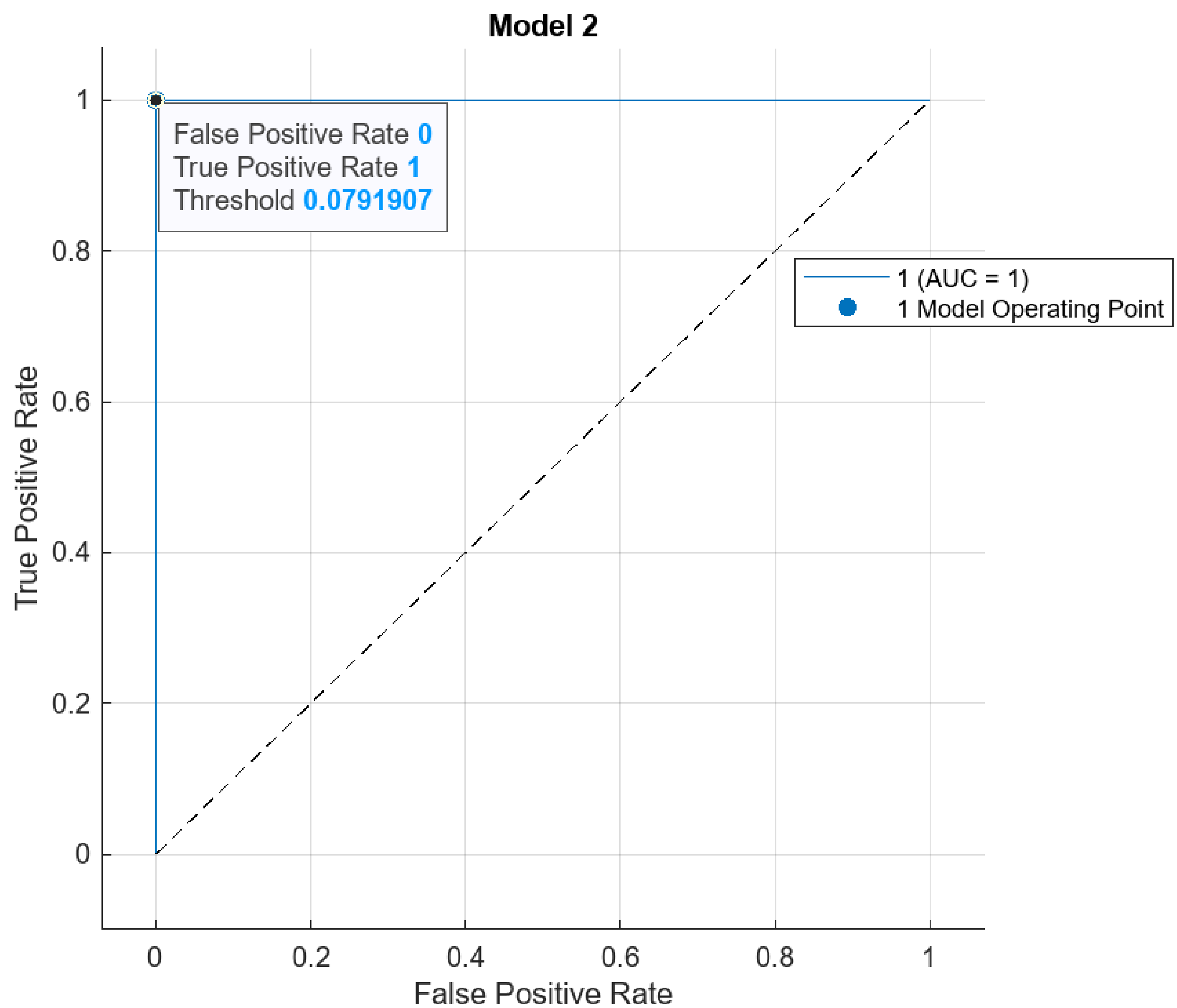


Figure 10: ROC Curve Showing AUC with a Combination of HOG and EfficientNet Features

Results from experiments show that HOG can adequately categorize vehicle makes and models (Manzoor et al., 2019). The study also shows that deep learning features reported better performance results when compared to handcrafted features. The combination of features gave more accurate and stable results as confirmed by Jamil et al. (2020). The proposed technique which is a combination of deep-learned EfficientNet and HOG features gave better performance results when compared to techniques used in (Manzoor et al., 2019) and Jamil et al. (2020).

Conclusion

In this study, a vehicle makes and model recognition model that identifies and recognizes the make and models of selected popular vehicles and locally manufactured vehicles in Nigeria using handcrafted and transferred learned extracted features with an SVM classifier. The dataset contained vehicle images of IVM and another popular brand of vehicles in Nigeria with different colours. Experimental results have shown the superiority of our proposed model; concatenation of the HOG and EfficientNet over single feature technique.

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