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A Hybrid Deep Learning VGG-16 Based SVM Model for Vehicle Type Classification

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Abstract - Car classification is important in daily life because there are many distinct types of automobiles made by various manufacturers. Although there are numerous methods for classifying autos, machine learning technologies have not been widely utilized, resulting in low accuracy levels. The goal of this paper is to create a machine learning system that is especially made to categories models of two Pakistan's top automakers, Toyota, and Honda. Ten Toyota models such as Avalon, Land Cruiser, Camry, Corolla, C-HR, Highlander, Prius, Tundra, RAV4, and Yaris and a dataset of Honda automobiles, which also includes 10 models (Accord, Civic, CR-V, Fit, HR-V, Insight, Odyssey, Passport, Pilot, and Ridgeline), are used to evaluate the model's performance. A deep learning-based VGG integrated with support vector machine (SVM) is proposed, utilizing a dataset from Kaggle.com, providing high-definition images for multiple classes. Comparisons with other models such as VGG16, AlexNet, and Convolutional Neural Network (CNN) reveal that the suggested model (VGG16 + SVM) achieves superior accuracy. For the Toyota dataset, the proposed model achieves 99% accuracy, outperforming VGG16 (66%), AlexNet (52%), and CNN (65%). Similarly, for the Honda dataset, the suggested model achieves 98% accuracy, surpassing VGG16 (96%), AlexNet (71%), and CNN (82%). In conclusion, the proposed deep learning-based model demonstrates enhanced accuracy in classifying Toyota and Honda cars, highlighting its effectiveness for image-based classification tasks in the automotive domain.

Keywords— AlexNet, Convolutional Neural Network, Long Short-Term Memory, ResNet, Random Forest, Support Vector Machine, Very Deep Convolutional Networks.

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1. INTRODUCTION

Cars are a major form of transportation for people all over the world due to their convenience and mobility. The vehicle business has expanded dramatically over time, resulting in improvements in safety features, technology, and fuel economy. Modern automobiles are more adaptable and ecologically friendly because of advanced technologies including electric drivetrains, infotainment systems, and autonomous driving. Sedans, SUVs, pickups, and hybrids are just a few of the car types that serve a range of consumer needs and tastes. Vehicle classification is becoming more complicated because of the growing diversity of models and rising manufacturer competition. Both consumers and businesses must comprehend these categories to make better decisions and conduct more effective market research.

An automatic classification system is required for cars to quickly determine their location to identify the best car type in terms of more adaptable and ecologically friendly because of advanced technologies. Otherwise, several factors will be used to determine its location [1],[2]. Numerous studies use a variety of terminologies and techniques to classify automobiles. A quick, very effective, multi-feature, real-time detection technique is required [3],[4],[5]. Different classification and detection models like SVM, random forest, and other data classification algorithms make this procedure possible and accurate. These algorithms showed best results in field of objects classification and detection[3]. Machine learning and automated data detection are fields that are seeing rapid growth in the realm of car categorization and detection. However, a very small number of researchers have employed machine learning techniques with poor accuracy rate for automobile categorization [6],[7],[8],[9]. Recent advancements in image processing & machine learning have enhanced vehicle monitoring in transportation systems, but vehicle classification (VC) remains challenging. This paper introduces a dual-phase approach combining XGBoost & Multi-Objective Optimization Genetic Algorithm (Mob-GA) for optimal VC. Tested on 10 datasets, the hybrid model demonstrated superior performance, achieving faster execution times (0.16 ns) and improved accuracy compared to standalone methods [10].

The paper in [11] presents a real-time traffic monitoring system that uses CNN-based machine learning and image processing techniques to detect, track, and classify vehicles. A video camera captures road footage, calibrated for accurate projections, with techniques like background modeling and edge detection enhancing object tracking. Leveraging transfer learning improves efficiency and accuracy, enabling the system to classify multiple vehicles, calculate speed, and monitor traffic across multiple lanes simultaneously. Similarly a paper in [12] implements the XGBoost algorithm for vehicle classification, aiming to enhance accuracy by considering shapes and features. Vehicle classification challenges, such as feature extraction, image segmentation, and semantic classification, are addressed using XGBoost to improve performance on large surveillance datasets. This work presents a cutting-edge machine learning model that combines SVM and VGG16, providing greater accuracy and precision along with faster and more efficient performance than earlier models. The goal of the project is to create a machine learning system specifically designed for categorizing different car models from Toyota and Honda, which are the two biggest automakers in Pakistan. Ten different Toyota models the Avalon, Camry, C-HR, Corolla, Highlander, Land Cruiser, Prius, RAV4, Tundra, and Yaris will be the subject of the study. Ten Honda vehicles, including the Accord, Civic, CR-V, Fit, HR-V, Insight, Odyssey, Passport, Pilot, and Ridgeline, will also be categorized by it. In the context of these well-known OEMs, this method aims to improve the accuracy of car models. The main contribution of this study is given as below:

1. This study presents a machine learning model that combines SVM and VGG16, which offers improved accuracy and precision in categorizing automobile models from two of the top automakers, Honda and Toyota.
2. The study aims to address the distinct features of Toyota and Honda automobiles by developing a customized algorithm that closes a gap in the current classification techniques.
3. The study's analysis of ten different models from both Toyota and Honda expands the area of vehicle classification, making it relevant to a greater range of automobile types and supporting more precise market analysis.
4. To evaluate the model's correctness and guarantee superior outcomes when compared to current state-of-the-art models, such as CNN, VGG16, and AlexNet.

There are still four sections in the book. Section 2 explains the associated tasks. While Section 3 provides an explanation of the training model and suggested approach. Section 4 presents the findings and analysis, while Section 5 presents the conclusions and suggestions.

2. LITERATURE REVIEW

Various researchers have presented different techniques for the car classification problem. Research on the categorization of automobiles and non-cash commodities was proposed by [4]. Similarly another paper in [13] suggested a method for classifying cars using drone footage. They utilized a data collection that included photos from various angles for better outcome prediction. For drone-based detection, they used G-ORF. The gradient of two far-off picture patches is represented by G-ORF. To achieve better results, they applied the CNN model for categorization. They employed python libraries for simulation purposes. The analysis demonstrates that the model attained an efficiency rating of 89%. Further a study in [14] proposed a real-time car brand classification in his research. The dataset was manually gathered from security cameras. Nearly 30000 high-definition photos make up the data set. Images go through pre-processing. Following that, several classes are classified using the SVM machine learning model. As a result, the experiment's findings demonstrate excellent efficacy.

In [15] this study uses deep learning (DL) architectures to investigate a wide range of vehicle detection & classification techniques, with an emphasis on their applications in real-time monitoring, toll management, traffic density estimation, and other fields. It offers a thorough examination of core ideas, benchmark datasets, and DL methodologies. Along with a detailed analysis of the related difficulties, the study also reviews important applications, such as vehicle identification, classification, and performance evaluation. Notable technological developments in the field within the past few years have also been highlighted.

Another paper in [16] proposed several categorization and prediction techniques in this process. The author employed a variety of techniques, including Bayesian classifiers, slow learners, functions classifiers, neural networks, and rules classifiers. Among the many techniques with a wide variety of applications is classification. With this dataset, 66 distinct classifiers are used. This study's goal is to use the WEKA tool to compare and assess several classification algorithms to identify the one that works best with the car dataset. The total procedure demonstrates that Bayesian classifiers function best, with a high accuracy of 94%.

Similarly in [17] the author develop a simple precise CNN-based model for vehicle classification in low resolution surveillance photographs (96 dpi) utilizing a modest security camera remote from the ROI. This is accomplished by first creating a dataset consisting of 4800 low quality vehicle images taken from security video frames. To categorize automobiles in low resolution surveillance images taken by a conventional security camera placed far from a traffic scene. The proposed model is evaluated on a new dataset of small (100 100 pixels) and low resolution (96 dpi) car pictures. The suggested model's precision and complexity are then compared to well-known CNN models built on the VGG16 dataset. The results show that, despite the well-known models' superior accuracy, the suggested method provides a simple and portable solution for vehicle classification in low quality photographs with sufficient accuracy (92.9%).

In [18] this research, proposed a real-time system for identifying automobiles on roadways that is both resilient and extremely accurate is presented. It uses an embedded feature selection technique, edge and region-based segmentation for feature extraction, a random wavelet transforms for pre-processing, and the XGBoost algorithm for vehicle classification (VC). The system outperformed the previous model with best accuracy of 98% and 98.81% after testing on 10 datasets, including a new SRM2KTR dataset with 75,436 vehicle pictures. Utilizing an FPGA platform, it exhibits high speed, accuracy, and durability in a variety of weather, lighting, color, and occlusion circumstances, processing images in 0.16 nanoseconds with an average accuracy of 97.79%.

In [19] this paper focusses on categorizing emergency vehicles from CCTV footage. The research offers comprehensive information on emergency vehicle classification, an essential duty for setting these vehicles' priority on the road, which may ultimately save lives. Eight CNN architectures' performances are compared by the authors using the Analytics Vidhya Emergency Vehicle dataset. The best classification performance is provided by DenseNet121, which is the optimal architecture for this task, according to the results. The minimal memory requirements of DenseNet121 further make it perfect for real-time applications. Another paper in [20] sued a framework which was tested on nine predefined passenger car models, demonstrating the ability of non-visual sensors to classify vehicle type, model, and fuel type. This innovative approach could greatly improve how transport and infrastructure agencies collect and share data for intelligent traffic monitoring systems (ITMS), offering more accurate insights for better roadway usage, transportation forecasting, safety enhancements, and environmental impact reduction. The paper presents a system framework, experimental design, and evaluation compared to automatic number plate recognition. Similarly in [21] this paper introduces an application that uses a neural network, powered by YOLOv5, to classify vehicular traffic in video footage, achieving 89% accuracy. By analyzing video data from a dataset of 750 images captured by surveillance cameras, it provides valuable insights to address traffic congestion and accident prevention. The dataset is also available for use in further research. Further in [22] this study utilized datasets like MB7500, KITTI, and FLIR, applying data augmentation and sharpening techniques, and trained a hybrid model integrating Faster R-CNN and YOLO. The proposed model achieved 98% detection accuracy, outperforming YOLO (95.8%) and Faster R-CNN (97.5%), demonstrating its effectiveness in improving traffic management.

Further another study in [23] leverages seismic surface waves to classify vehicle types (Bus/Truck, Car, Motorcycle) using artificial intelligence methods on vertical component seismic data. Support Vector Machine, Logistic Regression, and Naïve Bayes (NB) classifiers were trained on 4185 samples & tested on 1395, with NB showing high accuracy. A convolutional neural network was used as a baseline, highlighting the effectiveness of ML-based approaches for secure, cost-efficient traffic analysis without compromising privacy.

The evaluation involved collaboration between academia, public road administration, and private companies, ensuring diverse interests were considered during development. The literature review demonstrates the previous study being done by many scientists in automatically classifying cars. Various researchers have demonstrated diverse approaches to the problem. Various tools and locations, such as parking lots and busy roads, are offered for classification approaches. However, relatively few researchers have made use of low-accuracy and low-learning-rate machine learning models. To solve that issue, it is advised to combine the cutting-edge machine learning model SVM with the deep learning model VGG to provide improved results with a low loss rate and high accuracy.

The proposed model titled "A Novel SVM-Based VGG Model for Car Classification" combines the strengths of the VGG convolutional neural network (CNN) & Support Vector Machine (SVM) to achieve efficient vehicle classification. The VGG model, pretrained on large datasets like ImageNet, is used as a feature extractor by retaining its convolutional and pooling layers. These extracted features are then flattened and passed to an SVM classifier, replacing the traditional fully connected layers for classification. The model is trained by first optimizing the VGG network for feature extraction and then freezing the layers to train the SVM on the extracted features. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the hybrid model's performance. This approach leverages VGG's ability to capture detailed visual features and SVM's effectiveness in handling complex decision boundaries, particularly for smaller datasets. The novelty of the model lies in this hybrid design, balancing deep learning feature extraction with robust SVM classification for improved car classification accuracy and efficiency. Table 1 shows the summary of the works done.

Table 1. Comparative Study Literature Review

Ref	Methodology	Dataset	Results	Remarks
[8]	Car classification using drone footage with G-ORF for feature extraction and CNN for categorization	Dataset includes photos from various angles	Efficiency rating of 89%	Uses drone-based detection and Python libraries for simulation
[9]	Real-time car brand classification using SVM	Manually gathered dataset of ~30,000 high-definition images	Excellent efficacy achieved	Pre-processing and SVM are utilized for classification
[10]	Deep learning architecture for vehicle detection and classification with an emphasis on real-time applications	Benchmark datasets	Comprehensive analysis provided	Highlights technological advancements and challenges in real-time vehicle classification
[11]	Comparison of 66 classification algorithms using the WEKA tool	Car dataset	Bayesian classifiers achieve 94% accuracy	Bayesian classifiers are identified as the best-performing algorithm
[12]	vehicle classification using CNN-based model in surveillance images of low-resolution	Dataset of 4800 low-resolution images (96 dpi, 100x100 pixels)	Accuracy of 92.9%	Offers a simple, portable solution for vehicle classification in low-quality images
[13]	Real-time system with edge and region-based segmentation, random wavelet transforms, and XGBoost for classification	10 datasets including a new SRM2KTR dataset with 75,436 vehicle images	Best accuracy of 98.81%; processing in 0.16 nanoseconds with average	High speed, accuracy, and robustness across various conditions;

			accuracy of 97.79%	
[14]	Emergency vehicle classification using 8 CNN architectures, with DenseNet121 yielding the best performance	Analytics Vidhya Emergency Vehicle dataset	DenseNet121 delivers optimal classification performance	Minimal memory requirements make DenseNet121 suitable for real-time applications
[15]	Framework for vehicle classification using non-visual sensors tested on nine predefined car models	Not explicitly mentioned	Highlights improvements for intelligent traffic monitoring systems (ITMS)	Focuses on non-visual sensor classification to enhance roadway usage, forecasting, and safety insights.
[21]	Use neural network, powered by YOLOv5,	classify vehicular traffic in video footage	achieving 89% accuracy	analyzing video data
[22]	Integration of Faster R-CNN & YOLO.	MB7500, KITTI, and FLIR,	YOLO (95.8%) and Faster R-CNN (97.5%),	demonstrating its effectiveness in improving traffic management.
[23]	Support Vector Machine, Logistic Regression, & Naïve Bayes (NB)	vehicle types (Bus/Truck, Car, Motorcycle) dataset	NB showing high accuracy.	Uses seismic signals for vehicle classification,

3. Proposed Methodology

A detailed review of the methodology used in the proposed research work is given below in Figure 1.

3.1 Data Collection

One of among the most crucial and challenging jobs in every research project is data collection. Due to the availability of our required dataset on Google at the time of our procedure, the proposed study gathered dataset obtained via the internet at https://www.kaggle.com/datasets/prondeau/the-car-connection-picture-dataset named "The cars connection". This collection includes more than 60,000 300x200 pixel high resolution photos representing 32 distinct car brands. Toyota and Honda car photos will be suggested for classification in this study. Toyota Avalon, Toyota Land Cruiser, Toyota Prius, Toyota Camry, Toyota C-HR, Toyota Corolla, Toyota Tundra, Toyota RAV4, Toyota Highlander, and Toyota Yaris are just a few of the TOYOTA vehicle models that are covered in the ten classes. Further to the proposed model, the model is further deployed on Honda cars dataset including 10 classes, including accord, civic, CR-V, Fit, HR-V, insight, odyssey, Passport, Pilot and Honda Ridgeline.

3.2 Data Preprocessing

The fundamental step in the field of machine learning is data preprocessing. We had to evaluate the data for relevancy and other issues before feeding it to the machine. Data in the real world is changing / upgrading daily. Therefore, several pretreatment operations like data scaling, data cleaning, image cropping, data transformation, & image segmentation are done to generate the best & optimal outcomes from the data processing. In this study, several techniques, including data cleaning, data resizing, image enhancement, & data partitioning, are used to preserve data preprocessing.

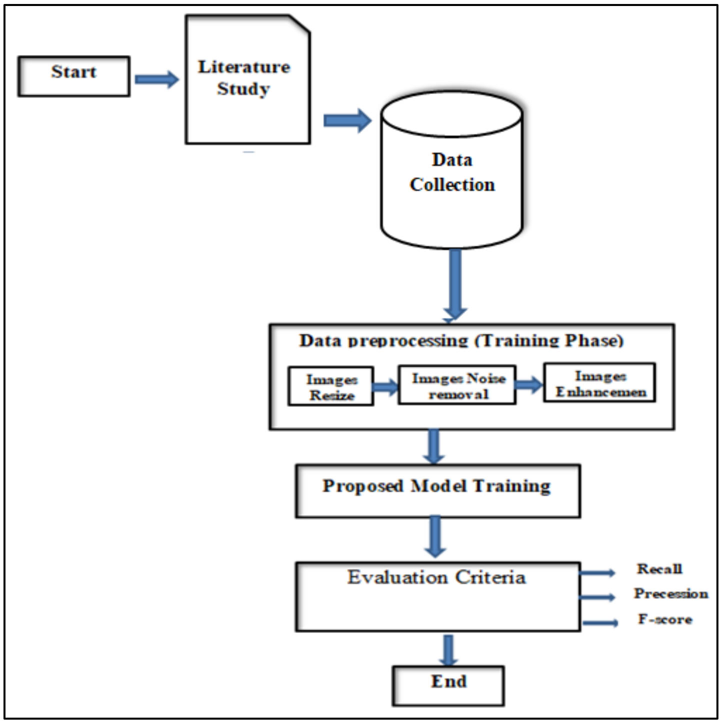


Figure 1. Proposed Research Flow Diagram

a. Resize Image

Image resizing is done after data cleansing. To guarantee that the size ratio of both the input & the output images is equal. This is finished to correctly recover dataset data. The photos must be resized to 224x224 pixels, because it is input shape for the proposed model. Even though there were more pictures in the data gathering.

b. Image Enhancement

The process of altering an image's colors is known as image enhancement. At this point, the image's color or intensity values are changed to saturate the high and low intensities. The transformation of one image into its best version is known as image enhancement.

c. Data Partitioning

Data partitioning is the process of dividing the input dataset into two classes test and train. The proposed study used random partitioning, and the dataset is divided to 80:20. Means the dataset is divided to 80% of training and 20% of testing data.

3.3 Proposed Model

The proposed study has suggested various CNN models in the research methodology. However, we'll employ one model as a suggested model, called VGG, together with the machine learning model SVM. In terms of picture categorization and detection, VGG [24] is the most often used model. There are two versions of it [25], [26]. There are 16 layers in the initial version. While the second edition receives more updates and has 19 more levels [27], [28]. SVM is a machine learning model that produces highly advanced classification results. Results from the combination of the two models will have a high precision, recall, and accuracy rate. The proposed study would classify cars using an SVM-based VGG model. Thus, the suggested model combines the VGG16 variant and the SVM machine learning model. The proposed model's output layer in this case will be an SVM. Prior to producing any output, the data will first be categorized using the deep learning model VGG. The output of the VGG is then sent into the SVM machine learning model. The proposed model's output layer in this case will be an SVM. Prior to producing any output, the data will first be categorized using the deep learning model VGG. The output of the VGG is then sent into the SVM machine learning model as input to do further classification among various classes. The outcome of the SVM will be the outcome, and the SVM model's forecast will be the desired prediction of the proposed work. The proposed model's flow diagram is shown in Figure 2. The pseudocode of the proposed algorithm is given in Algorithm 1.

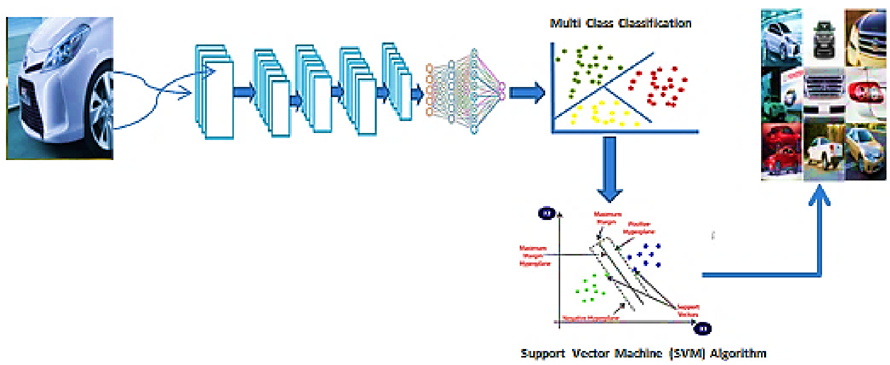


Figure 2. Proposed Model Architecture

Algorithm 1: Proposed Method

1. Load and preprocess dataset
   1.1. Define image size = (224, 224)
   1.2. Load images from the dataset directory
   1.3. Apply preprocessing: resize images to (224, 224) and normalize pixel values
   1.4. divide the dataset into training & testing sets

2. Load VGG-16 model (pre-trained on ImageNet)
   2.1. Import VGG-16 model from the deep learning library
   2.2. Set the model's `include_top` parameter to False to exclude fully connected layers
   2.3. Define input shape as (224, 224, 3) for RGB images

3. Extract features using VGG-16
   3.1. Pass each image from the dataset through the VGG-16 model
   3.2. Obtain the output from the last convolutional layer (before fully connected layers)
   3.3. Save the extracted features for each image

4. Flatten the features
   4.1. Convert the output from 3D convolutional features (height, width, depth) to 1D (flatten the array)
   4.2. Store the flattened features as the input data for the SVM classifier

5. Prepare the labels:
   5.1. Convert the categorical car type labels into numerical labels (e.g., sedan = 0, SUV = 1, etc.)

6. Train the SVM classifier
   6.1. Define an SVM model with a linear kernel (or experiment with other kernels like RBF)
   6.2. Feed the flattened features (from step 4) and the corresponding labels (from step 5) into the SVM model
   6.3. Train the SVM model

7. Evaluate the model on the test data
   7.1. Use the trained SVM model to predict car types for the test data
   7.2. Compare the predicted labels to the true labels
   7.3. Calculate the classification accuracy

8. Output the results:
   8.1. Print the accuracy of the classifier

3.4 Evaluation Results

After the Model has been assessed using Python 3.6, the classification results are calculated and performance for a specific data set taken from the Kaggle. To check the performance of the proposed model various performance parameters are used such as given as below.

a. Confusion Matrix

The number of output classes determines the dimension of the confusion matrix M (n*n). Therefore, it is thought that the total collection of all returned positive values, combination of both true positives (TP) as well as false positives (FP), provides the most accurate identification. (False positives are claims that an element is not linked to a class when it does belong to that class. On the other hand, true positives are claims that an element is connected to a class and belongs to that class). Because they comprise false positives and false negatives (FP + FN), all of which are inaccurate, all other cases are regarded as rejected. The confusion matrix's details are listed in Table 2.

Table 2. The Confusion Matrix

	Predicted Class	
Actual Class	TP	FN
	FP	TN

b. Recall

The True Positive Rate (TPR) was another name for the recall rate. The true positive ratio (TPR) is calculated by dividing the total number of true positive values by the sum of true both positive and false negative values. Recall is a measurable indicator of how comprehensive the outcome was. The percentage of correctly identified instances is known as the true positive rate. A high recall indicates that the data was correctly and successfully recovered. The recall formula can be found in Equation (1).

$$Recall = \frac{TP}{TP+FN} \tag{1}$$

c. False Positive Rates

Divide the total number of mistakenly identified positive values by the sum of the true negative as well as false positive values to obtain the false positive rate (FPR). Measures of the False Positive Rate returned positive data that had been incorrectly identified as positive. A high False Positive Rate (FPR) suggests that the results were flawed and ineffective. The definition of false positive rates is given in Equation (2).

$$FP\ Rate = \frac{FP}{FP+TN} \tag{2}$$

d. Precision

Count the exact number of successfully recovered positive entries. Specifically, the total number of values that are obtained as being members of a particular class yet are not. Precision can be calculated by dividing the actual Positive score by the sum of all values and classes that were successfully recognized. Equation (3) provides an explanation of a model's precision.

$$Precision = \frac{TP}{TP+FP} \tag{3}$$

e. F-Measure

When comparing two models, it can be difficult to compare a model having outstanding precision and high recall to one with low precision and high recall. Instead of using mathematical tools, F-measure uses harmonic ones. The formula for the F-Measure is explained in Equation (4).

$$F - Measure = \frac{2 * Recall * Precision}{Recall + Precision} \tag{4}$$

f. Accuracy

Our model's usefulness depends on how accurate it is. The fact that our technology can distinguish between positive and negative numbers is evidence of both how secure and flexible it is as well as how closely the results correspond to the actual values that our model is creating. Equation (5) represents the accuracy formula in mathematical terms.

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Where TP denotes True positive, TN presents true negative, FP presents false positive, and FN presents false negative numbers.

4. RESULT AND DISCUSSION

The proposed VGG + SVM performance is compared to that of the AlexNet, ResNet and CNN models. Additional assessments and validations of the recommended model's performance are carried out in terms of recall, precision, f-measure, and accuracy. The efficacy of the suggested VGG + SVM model is assessed in this work using two datasets pertaining to TOYOTA and HONDA cars. The f-measure, recall, accuracy, loss, and precision were used to assess the model's performance. Both testing and training sets of data were used with the models. The data was divided into two sets, one for testing and the other for training with an 80:20 ratio.

4.1 Preliminaries

An Intel Core i5 CPU running at 2.0 GHz with 8 GB of RAM was used for the studies. The operating system is Microsoft Windows 10. The Keras Python module is used to test and train the model across all datasets. The recall, precision, f-measure, accuracy of AlexNet, VGG16 and CNN have been compared to investigating the proposed VGG + SVM model. Four models are subjected to many tests using different measures, such as accuracy, recall, precision, as well as f-measure. A list of models that are utilized in simulation is as follows: such as proposed VGG + SVM, AlexNet, VGG16 and CNN.

4.2 Performance Evaluation of TOYOTA Dataset

Table 3 and Figure 3 demonstrate the performance achieved by AlexNet, VGG16, CNN and proposed VGG+SVM. From the table below, it can be achieved that our proposed model achieved 99% of accuracy, while VGG16 achieved 66% of accuracy, AlexNet achieved 52% and CNN model achieved accuracy of 65% for TOYOTA cars dataset.

Table 3. Performance Evaluation of Used Models for TOYOTA Dataset

Model	Precision	Accuracy	F1 Score	Recall
Alex Net	57	52	51	52
VGG 16	73	66	65	66
CNN	69	65	64	65
VGG + SVM	99	99	99	99

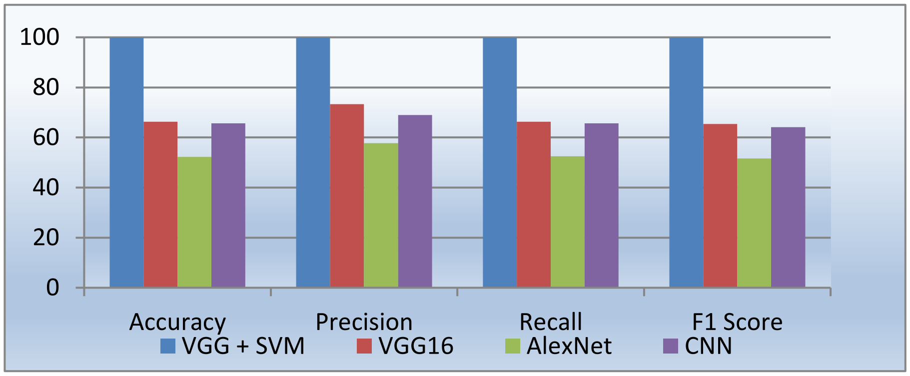
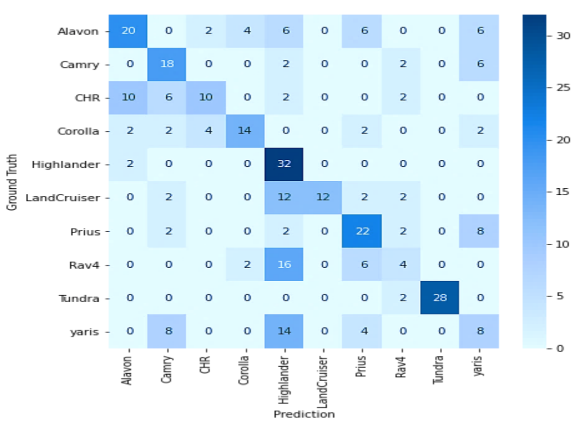
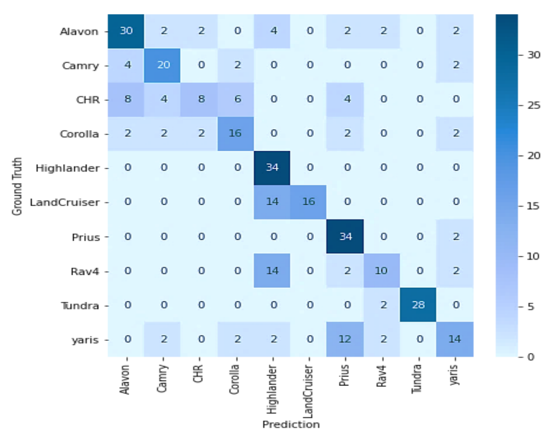


Figure 3. Graphical Representation of Performance Achieved by Various Model for TOYOTA Dataset

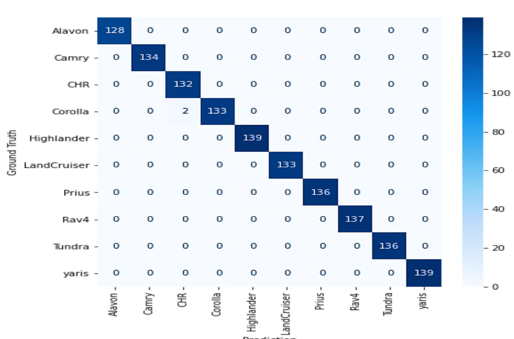
Table 3 shows the overall performance of various models like VGG16, Alex Net, CNN and proposed model for TOYOTA dataset. The table demonstrates that the proposed (VGG+SVM) achieved an impressive result, as it achieved the accuracy of 99%, precision, recall and F-Measures also of 99%. Furthermore, Table 3 demonstrates that VGG16 achieved fine results as it achieved accuracy of 66%, precision pf 73%, recall of 66%, while F-measure as 65%. Further AlexNet achieved very poor results as it achieved accuracy of 52%, precision of 57%, recall of 52% and F-measure as 51%. While the performance of CNN model was 65% of accuracy, 69% of precision, 65% of recall and the F-Measure of CNN was 64%. The performance of various models for TOYOTA dataset is described in Figure 3 in graphical presentation, while the confusion matrix achieved by different models for TOYOTA is displayed in Figure 4.



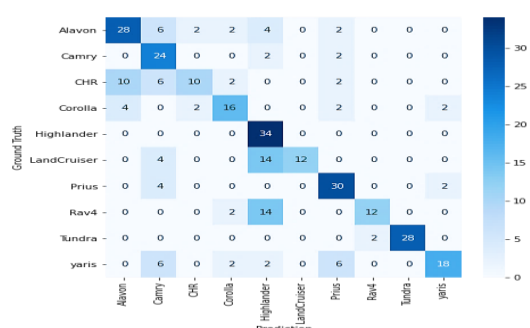
AlexNet Model



CNN Model



Proposed (VGG + SVM) Model



VGG Model

Figure 4. Confusion Matrix of Various Models for TOYOTA Dataset

4.3 Performance Evaluation on HONDA Dataset

Table 4 and Figure 5 demonstrate the variations of results between the AlexNet, VGG16, CNN and proposed VGG+SVM for Honda dataset. From the table below, it can be achieved that our proposed model achieved 98% of accuracy, while VGG16 achieved 96% of accuracy, AlexNet achieved 71% and CNN model achieved accuracy of 82% for Honda cars dataset. Table 4 shows the overall performance of various models like VGG16, Alex Net, CNN and proposed model for Honda dataset. Table 4 demonstrates that the proposed (VGG+SVM) achieved an impressive result, as it achieved accuracy of 98%, precision, recall and F-Measures also of 98%. Furthermore, the table demonstrates that the VGG16 achieved fine results as it achieved accuracy of 96%, precision, recall and F-measure as 96%. Further AlexNet still shows poor results as it achieved accuracy of 71%, precision of 73%, recall of 71% and F-measure as 71%. While the performance of CNN model was 82% of accuracy, 85% of precision, 82% of recall and the F-Measure of CNN was 82%. The performance of various models for Honda dataset is described in Figure 5 in graphical presentation, while the confusion matrix achieved by different models for Honda is displayed in Figure 6.

Table 4. Performance Evaluation of The Used Models for Honda Dataset

Model	Accuracy	Precision	Recall	F1 Score
VGG + SVM	99	99	99	99
VGG 16	96	96	96	96
Alex Net	71	73	71	71
CNN	82	85	82	82

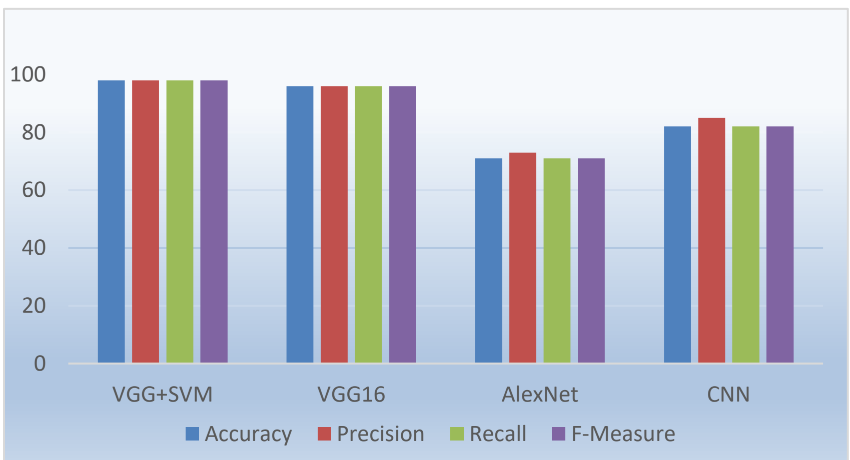
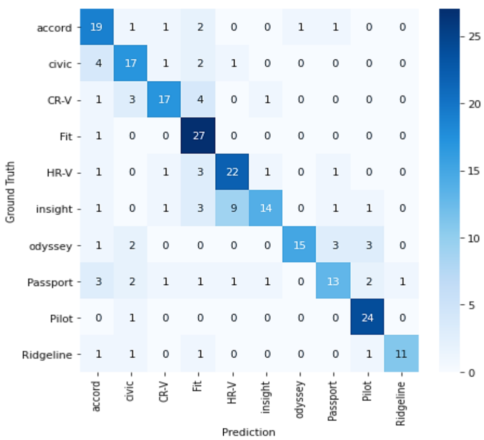


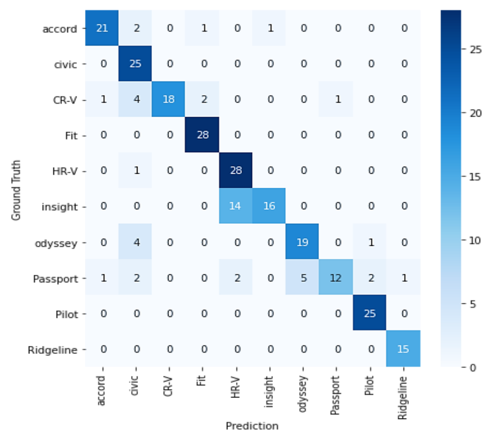
Figure 5. Graphical Representation of Performance Result Achieved for Honda Dataset

5. CONCLUSION

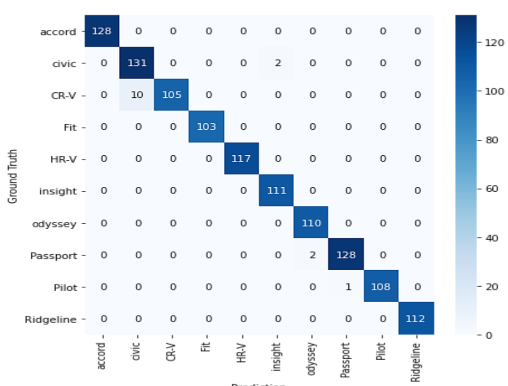
This study suggested utilizing VGG and SVM for automobile model categorization. In the domain of automobile model categorization, three models VGG, AlexNet, and CNN are proposed as a further comparison to our suggested model. The entire simulation is run using Python and associated libraries, including Tensor Flow, Keras, and Sklearn. Two different datasets of car categories like TOYOTA and Honda are used for simulation purposes. The proposed SVM-Based VGG model for Car Classification" combines the strengths of the VGG convolutional neural network (CNN) and Support Vector Machine (SVM) to achieve efficient vehicle classification. The VGG model, pretrained on large datasets like ImageNet, is used as a feature extractor by retaining its convolutional and pooling layers. These extracted features are then flattened and passed to an SVM classifier, replacing the traditional fully connected layers for classification. The model is trained by first optimizing the VGG network for feature extraction and then freezing the layers to train the SVM on the extracted features. Evaluation metrics such as accuracy, precision, recall, and F1-score are used to assess the hybrid model's performance. This approach leverages VGG's ability to capture detailed visual features and SVM's effectiveness in handling complex decision boundaries, particularly for smaller datasets. The novelty of the model lies in this hybrid design, balancing deep learning feature extraction with robust SVM classification for improved car classification accuracy and efficiency. The results of all the simulations showed that the proposed model (VGG + SVM) outperformed existing deep learning models including CNN, VGG, and AlexNet in terms of accuracy, precision, recall, and F-Measure. Our proposed model achieved accuracy of 98% and 99%. While the accuracy of VGG16 model is 96% and 66%. Further the accuracy of CNN model is 82% and 65%. While AlexNet shows poor performance as it achieved the accuracy of 71% and 52% respectively. So, it has been discovered that the recommended method (VGG + SVM) outperforms other algorithms for deep learning and machine learning that are now in use.



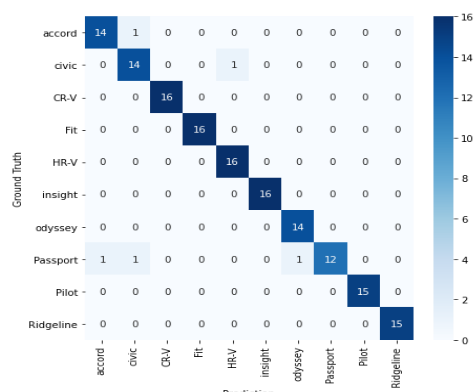
AlexNet Model



CNN Model



Proposed (VGG+SVM) Model



VGG Model

Figure 6. Confusion Matrix of Used Model for Honda Dataset

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CONFLICT OF INTERESTS

The authors have no conflict of interests.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

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