Innovations

Modeling Vehicles Image Detection at Nigerian Higher Institutions

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Abstract: *Vision has been the primary method for extracting information for judgment and decision-making. Visuals are now being used by gate and traffic systems to automate their operations. Identifying innate patterns in the flow of vehicles into and out of the Universities may provide useful information for security-focused decision-making in order to be prepared for this future. The work aim to integrate statistical learning methods with image processing to identify traffic trends in higher institutions.At the entrance and exit locations of the gates of five southwest higher institutions in Nigeria, pictures were taken using a stationed long-range camera. These institutions selected are the Polytechnic of Ibadan, Ladoke Akintola University of Technology (LAUTECH), University of Ibadan (UI), University of Lagos (UL) and Obafemi Awolowo Universities (OAU. Three thousand and eighty observations make up these data. At the entry point, 1,802 observations were collected, and at the exit position, 1,278 observations were collected. Two deep learning models were considered, the Convolutional Neural Network (CNN) and the Gaussian Mixed Modelling (GMM) models for classification of the vehicle images. The result shows that CNN outperformed GMM in terms of classification accuracy, achieving 85.48% compared to 71.77% for GMM.The findings suggest that for complex pattern recognition tasks like vehicle image identification, deep learning architectures can overcome fundamental limitations. The management of the Nigerian Institution can use the algorithms and outcomes to control vehicle movement as well as for security inspections within the school.*

Keywords: *Convolutional Neural Network, Image Recognition, Gaussian Mixed Modeling, Deep Learning, Transportation System*

1.0 Introduction

As the pace of urbanization in our higher institutions continues to accelerate, the number of roads and family cars in our cities is increasing, and road traffic pressure is increasing day by day. The research of intelligent transportation system is very important to ensure the smoothness and safety of roads. Intelligent transportation system uses information technology, such as image recognition, computer vision, etc. to realize more intelligent and automated road transportation system. It improves the throughput capacity of the road area and greatly facilitates the dispatch of the traffic management department. However, real-time acquisition of road traffic information is the basis for the realization of an intelligent transportation system. How to obtain high-quality road vehicle information has become an urgent problem to be solved.

At present, the collection methods of vehicle information mainly include loop coil detection, infrared detection and intelligent video surveillance detection. Among them, the loop coil detection work is stable, the detection accuracy is high, and the traffic information can be counted. It is easy to install and set up, and is mostly used in areas such as traffic toll crossings and parking lots. Infrared detection mainly uses light-emitting diodes to detect vehicle speed, with high detection sensitivity. But it is easily affected by the environment, such as temperature, humidity, etc., resulting in low detection accuracy and low robustness. With the development of technologies such as image recognition and computer vision, intelligent video surveillance and detection has taken up an increasingly important position in traffic information collection. Intelligent video surveillance detection uses a camera set up at a traffic intersection to perform target analysis on the camera monitoring area to obtain unstructured information of the target in the video. The traffic monitoring video contains a wealth of information and is an important data source for intelligent traffic monitoring systems. However, the data resources acquired by fixed cameras are limited. With the development of drone technology, it has begun to be widely used in traffic monitoring, with rich data types and efficient data acquisition. But how to detect the vehicle from the massive data is the difficulty of the research.

With the rapid development of computer technology, machine learning algorithms have also been widely used in the field of image recognition. Bugeja, etal(2020) compares several commonly used video vehicle recognition methods including deep learning models and computer vision methods. The average accuracy, the semantics of recognizing vehicles, and the robustness of recognition when applied to data sets containing images with different lighting conditions are used to compare detection accuracy. The results show that the proposed deep learning method has better recognition performance. Peng X.etal(2020) proposed a driver warning and collision avoidance system based on vehicle trajectory characteristics and long- and short-term memory neural network. By judging the video behavior of vehicles, road safety is effectively improved. However, the initial detection performance of the vehicle in the video still needs to be optimized. Appathuraietal(2020) proposed a new type of hybrid artificial neural network and a mobile vehicle detection system based on the opposing gravity search optimization algorithm. Used to detect moving vehicles in traffic scenes to achieve effective traffic video surveillance. Optimizing the selection weights through the opposing gravity search optimization algorithm, effectively improving the recognition accuracy and speed of the artificial neural network. Priyadharshini etal(2020) proposed a region-based Convolutional Neural Network (CNN) in vehicle detection algorithm.In order to obtain a better feature extraction effect, the method adds focus loss to the basic DWT for optimization to improve the detection accuracy.Transport system represents a major interface between the location of activities and the general movement of people in an urban system (Estahlani, 2019). Hitherto, urban transport problems are becoming more and more acute in the cities in Nigeria (Feng etal, 2020; Asthanesiousetal, 2020; Martinez and Barczyk, 2019; Lee and Lin, 2019; Houben etal, 2019; etc.) World Health Organization (2000) recently articulated that health concerns related to traffic and transportation have become a worldwide phenomenon and will likely become more of an issue in the future. Findings from other recent studies suggest that stress from transportation may represent an important factor that influences the well-being of urban population (Ycaetal, 2020; Ogundunmade, 2024).The trend of urbanization and city growth in developing countries are characterized by rapidity of urban increase, urbanization outpacing industrialization, and a high rate of urban population growth by natural increase and migration (Houben etal, 2019).

In Nigeria, urbanization has a fairly long history in its growth and development. Historical account shows that extensive urban development in Nigeria predates the British colonial administration. Early explorers, missionaries and merchants estimates of population of towns show the existence of substantial human settlements in this part of the world in the 19th century (Nobel etal, 2024). During this period, the major factors crucial to the growth and development of cities were trading, marketing and administration. The second half of the 20th century witnessed rapid rate of urbanization and emergence of cities in various parts of Nigeria due to a number of factors among which are: introduction of wheeled transportation, particularly railway and road; categorization of settlement into hierarchical order of township; introduction of monetized economy and consequently production of cash crops and exploitation of mineral resources; continuous geopolitical restructuring, through creation of states and local governments in 1967, 1976, 1987, 1991 and 1996, and the industrialization process between 1960 and 1975, which was based on import substitution strategies and consumer market for imported goods and services (Nobel etal, 2024).

According to Mputu etal, (2024), sates in his Road Safety Practice in Nigeria that "the method of vehicle and plate number registration and identification has caused a lot of people pains, a pregnant woman die on the queue in her quest for vehicle registration". According to Nuthakkietal, (2024), states that "our vehicle registration offices today are faced with potential rise and inefficiencies associated with manual i.e. paper-based processes which are costly, prone to error and require mental and manual labor. Heightened regulation in the country is also placing these vehicle owners under pressure to meet litigation needs".According to Kathiriya et al (2024), states in his stand in his Stand in Road Traffic Administration states "the level of tediousness the manual system of vehicle registration is so alarming that requires a new modified method that will be easy and simple." According to Alves et al (2024), "most vehicle owner findsit difficult to register their vehicle on time due to the manual process which consumes time. For you to register your vehicle within a short period, you need to know one or two persons in the licensing office. This factor is peculiar to most Nigerian offices".According to Nuthakkiet al, (2022), vehicle crime accounts for a quarter of all recorded crime; it costs over £3 billion a year and causes immense distress and inconvenience to its victims to track their records. That is why there is need to setup a national target of reducing vehicle crime by 30% over the next five years in Nigeria. The rapid aggregation of road traffic data is effectively realized to improve traffic automation management. However, the above method is limited to the transmission image of the fixed camera for traffic video, and the flexibility is poor. Compared with ordinary video surveillance scenes, the video collected by drones has the advantages of wide surveillance range, less target occlusion, and more macroscopic traffic information provided. However, most existing machine learning methods are difficult to process real-time and massive drone video data. For this reason, a vehicle image detection method using deep learning in for Nigerian institutions is proposed.

2.0 Methods and Materials

2.1 Data

At the entrance and exit locations of the gates of five southwest universities in Nigeria, pictures were taken using a stationed long-range camera. These Institutions are the Polytechnic of Ibadan (PI), Ladoke Akintola University of Technology (LAUTECH), University of Ibadan (UI), University of Lagos (UL) and Obafemi Awolowo Universities (OAU). Three thousand and eighty observations will be collected. At the entry point, there were 1,802 observations made, and at the exit position, there will be 1,278 observations made. The two categories were modelled using CNN and GMM models. Figures 1 and 2 show the 10 sample cars each taken at the entrance of the universities for the incoming and outgoing cars.

Fig 1: Sample Incoming cars at University's entrance

Fig 2: Sample outgoing cars at University's entrance

2.2 Models

2.2.1 Gaussian Mixed Modelling(GMM)

The GMM is a probabilistic model that represents a mixture of multiple Gaussian distributions, allowing it to cluster facial features into student identities. Unlike the discriminative approach of ResNet-50, GMM is generative, modeling the probability distribution of the input features.The probability of a feature vector x is given by:

$$\mathbf{P(x)} = \sum_{i=1}^{k} \pi_i \mathcal{N}\left(\frac{x}{\mu_i}, \Sigma_i\right) \quad \dots \qquad (1)$$

Where:

- π_i is the mixing coefficient (weight) for the ith Gaussian component, satisfying;
  $\sum_{i=1}^{k} \pi_i = 1, \text{ or } 0 \leq \pi_i \leq 1 \quad \dots \qquad (2)$
  This ensures the model represents a valid probability distribution.
- $\mathcal{N}\left(\frac{x}{\mu_i}, \Sigma_i\right)$ is the probability density function of a multivariate normal distribution.
- $\mathbf{K}$ is the number of Gaussian components.
  Model Training: Expectation-Maximization (EM) Algorithm

The model is trained using the EM algorithm, an iterative method that maximizes the log-likelihood of the data. The steps include:

- E-Step: Estimating the expected value of the latent variables (cluster memberships) given the current parameters.

$$\boldsymbol{\gamma}(\mathcal{Z}_{\mathbf{ij}}) = \frac{\pi_j \mathcal{N}(x_i|\mu_j,\Sigma_j \quad)}{\sum_{k=1}^{K} \pi_k \mathcal{N}(x_i|\mu_k,\Sigma_k)} \quad \ldots \quad (3)$$

where $\boldsymbol{\gamma}(\mathcal{Z}_{\mathbf{ij}})$ is the responsibility of component $\mathbf{j}$ for data point $\mathbf{x_i}$.

M-Step: Updating the parameters to maximize the expected log-likelihood:

$$\boldsymbol{\pi}_{\mathbf{j}} = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{\gamma}(\mathcal{Z}_{\mathbf{ij}}) \quad \ldots \quad (4)$$

$$\boldsymbol{\mu}_{\mathbf{j}} = \frac{\sum_{i=1}^{N} \gamma(\mathcal{Z}_{ij}) x_i}{\sum_{i=1}^{N} \gamma(\mathcal{Z}_{ij})} \quad \ldots \quad (5)$$

Loss Function for GMM: Negative Log-Likelihood

The optimization is carried out using the Negative Log-Likelihood Loss:

$$\boldsymbol{\mathcal{L}}_{\mathbf{CE}} = \sum_{i=1}^{N} \log \sum_{k=1}^{K} \boldsymbol{\pi}_{\mathbf{k}} \mathcal{N}(\mathbf{x_i}|\boldsymbol{\mu}_{\mathbf{k}}, \boldsymbol{\Sigma}_{\mathbf{k}}) \quad \ldots \quad (6)$$

$\mathbf{N}$ is the number of data points.

$\mathbf{K}$ is the number of Gaussian components.

$\boldsymbol{\pi}_{\mathbf{k}}$ is the mixing coefficient for the k-th Gaussian,

Where,

$\sum_{k=1}^{K} \boldsymbol{\pi}_{\mathbf{k}} = 1$.

$\mathcal{N}(\mathbf{x_i}|\boldsymbol{\mu}_{\mathbf{k}}, \boldsymbol{\Sigma}_{\mathbf{k}})$ is the Gaussian probability density function (PDF) with mean $\boldsymbol{\mu}_{\mathbf{k}}$ and covariance $\boldsymbol{\Sigma}_{\mathbf{k}}$

2.2.2 Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a type of neural network that is particularly well-suited for image and video processing tasks.The convolutional layer is the core component of a CNN. It applies a set of filters to the input data, scanning the data in both horizontal and vertical directions, and performing a dot product at each position to generate feature maps.The fully connected layer is used to process the output of the convolutional and pooling layers.The mathematical representation of a fully connected layer can be described as:

Output = σ(W × Input + b)

Where:

- Output is the output of the fully connected layer
- σ is the activation function (e.g. ReLU, Sigmoid)
- W is the weight matrix

- Input is the input data
- b is the bias term

A CNN architecture typically consists of multiple convolutional and pooling layers, followed by one or more fully connected layers.The mathematical representation of a CNN architecture can be described as:

Output = FC(σ(Conv(σ(Conv(Input)))))

Where:

- Output is the output of the CNN
- FC is the fully connected layer
- Conv is the convolutional layer
- σ is the activation function
- Input is the input data

3.0 Results and Discussion

In this section, the results for the GMM and Recurrent Neural Network(RNN) in modelling the incoming and the outgoing vehicles in Nigerian institutions are presented and discussed.The model was trained for 50 epochs with a batch size of 20 and an initial learning rate of 0.01. The dataset was partitioned into training and testing subsets, with training (80%), validation (10%), and testing (10%).

Table 1: Distribution of cars by Institution

Institutions	Incoming	Outgoing
PI	213	198
LAUTECH	341	248
UI	456	375
OAU	394	235
UL	398	222
Total	1802	1278

This section explores the dataset's patterns and distributions of key features, providing insights that guide the modeling phase.

3.1 Popular Car Brands

Table 2 presents the Top 10 Most Popular Car Brands in the dataset. Toyota dominates with 900 vehicles, significantly outpacing other brands. Honda (635) and Lexus (422) follow, indicating strong demand for reliable and mid-range vehicles. Mercedes-Benz (317) is the most popular luxury brand, while Hyundai (306), Ford (180), and Nissan (169) reflect the presence of budget-friendly options.The distribution suggests a preference for durability, affordability, and resale value, with Toyota leading the market. A corresponding bar chart in figure 1 further illustrates these brand preferences.

Table 2: Top 10 Most Popular Car Brands

Car Brand	Count
Toyota	900
Honda	635
Lexus	422
Mercedes-Benz	317
Hyundai	306
Ford	180
Nissan	169
Kia	64
Acura	45
Land Rover	37

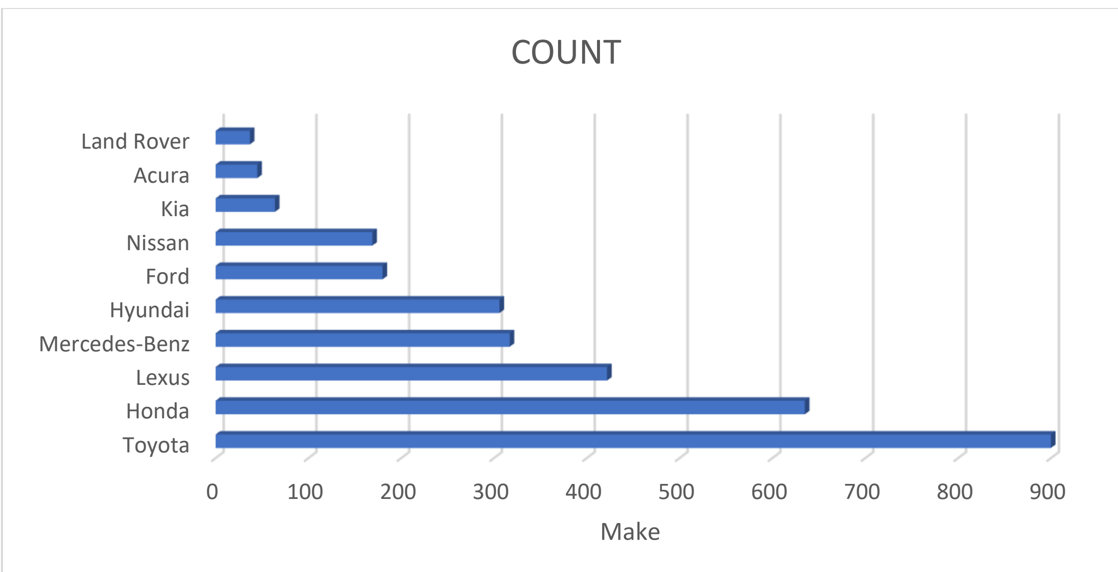

Figure 1: Top 10 Most Popular Car Brands in the Institutions

3.2 Popular Car Colours

As shown in Table 4.2, black is the most preferred car color, accounting for 839 vehicles, followed by gray (672) and silver (552). These neutral tones dominate, likely due to their professional appeal and ease of maintenance.Brighter colors such as blue (417), white (178), and red (148) also have a notable presence, while niche choices like gold (99), green (82), brown (58), and burgundy (35) are less common.

Table 3: Top 10 Most Popular Car Colours

Colours	Count
Black	839
Gray	672
Silver	552
Blue	417
White	178
Red	148
Gold	99
Green	82
Brown	58
Burgandy	35

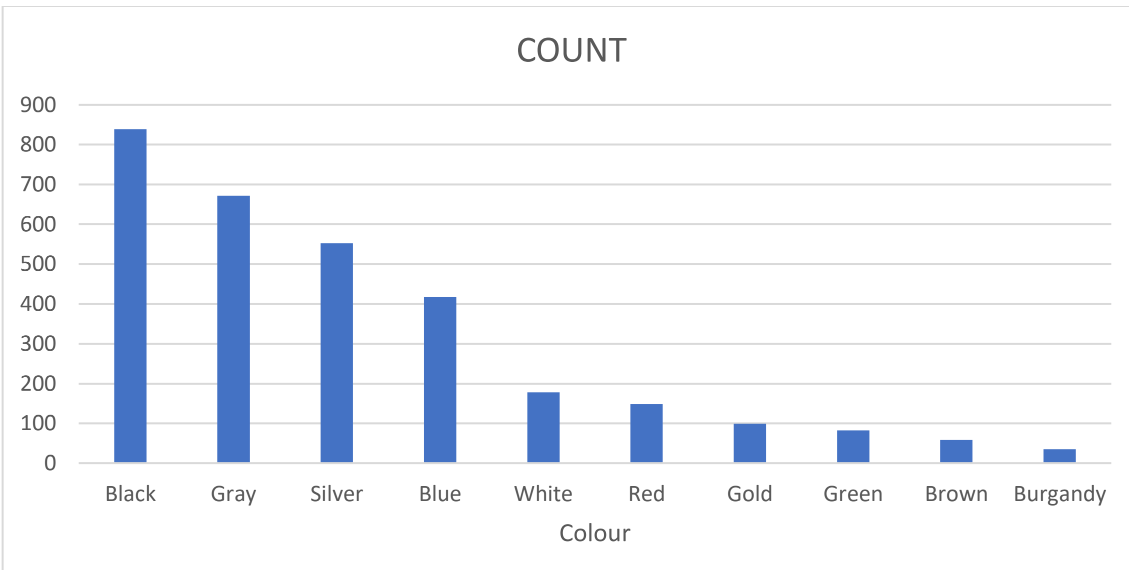

Figure 2: Top 10 Most Popular Car colours in the Institutions

3.3 Image Modelling

This chapter presents the results derived from the predictive models employed in forecasting vehicle images using machine-learning approaches. The focus is on showcasing the outcomes of each model's application, highlighting their effectiveness in producing accurate predictions. The machine learning techniques used are the GMM and CNN models.

Table 4a: Gaussian Mixture Model (GMM) evaluation

Metric	Value
In-coming	
AIC	27286.8735
BIC	47480.0895
Log-Likelihood	-6483.4368
Out-going	
AIC	27286.8735
BIC	47480.0895
Log-Likelihood	-6483.4368

Table 4b: Gaussian Mixture Model (GMM) overall metrics

Metric	Value
In-coming	
Accuracy	71.77
Macro Avg	0.73 (Precision), 0.73 (Recall), 0.72 (F1-Score)
Weighted Avg	0.75 (Precision), 0.73 (Recall), 0.72 (F1-Score)
Out-going	
Accuracy	0.72
Macro Avg	0.73 (Precision), 0.73 (Recall), 0.72 (F1-Score)
Weighted Avg	0.75 (Precision), 0.73 (Recall), 0.72 (F1-Score)

The report provides in Tables 4a and 4b shows the performance metrics such as precision, recall, and F1-score for different classes. The overall accuracy of the model is 71.77%, with a macro average F1-score of 0.72 and a weighted average of 0.71. This suggests that the model performs reasonably well but has inconsistencies across different classes. Some classes achieve perfect precision and recall, while others show lower values, indicating varying classification performance across individuals.

Table 5: CNN Overall Metrics

Metric	Value
In-coming	
Accuracy	0.85
Macro Avg	0.86 (Precision), 0.87 (Recall), 0.85 (F1-Score)
Weighted Avg	0.88 (Precision), 0.85 (Recall), 0.85 (F1-Score)
Out-going	
Accuracy	0.85
Macro Avg	0.86 (Precision), 0.87 (Recall), 0.85 (F1-Score)
Weighted Avg	0.88 (Precision), 0.85 (Recall), 0.85 (F1-Score)

The classification report indicated in Table 5 shows that the majority of precision and recall values for CNN were 0.86 and 0.87 respectively. CNN shows an accuracy value of 85% with weighted average precision, recall and F1-score values of 88%, 85% and 85% respectively.

Table 6: Models Performance Comparison

Metric	GMM	RNN
Accuracy	0.7177	0.8548
Precision (Majority)	0.7	0.86
Recall (Majority)	0.7	0.87

Table 6 shows that CNN outperformed GMM in terms of classification accuracy, achieving 85.48% compared to 71.77% for GMM. The improved performance of CNN can be attributed to its deep learning architecture, which is capable of extracting complex hierarchical features from facial images. Conversely, GMM relies on statistical clustering, which struggles with high-dimensional data and intra-class variations in car images.

The classification report indicated that the majority of precision and recall values for GMM were approximately 0.7, while CNN achieved values around 0.87. This implies that CNN not only identifies vehicles more accurately but also maintains a better balance between false positives and false negatives. The improved recall suggests that CNN is less likely to miss identifying a vehicle correctly, which is critical for real-world applications in management and impersonation detection.

4.0 Conclusion

This comprehensive study presents a rigorous comparative analysis between two fundamentally distinct machine learning approaches for automated student identification through facial recognition: a deep learning-based CNN model and a probabilistic Gaussian Mixture Model (GMM). The research was conducted using a carefully curated dataset of 3080vehicle images collected from the entrance of the five higher institutions considered in the southwest states of Nigeria. The images underwent standardized preprocessing including resizing, grayscale conversion, and systematic data augmentation before being partitioned into training (80%), validation (10%), and testing (10%) subsets using stratified sampling to maintain distribution integrity.

The comprehensive evaluation provides compelling evidence that CNN's hierarchical feature extraction capabilities enable significantly better recognition accuracy compared to traditional probabilistic methods. The consistent performance advantage across all metrics (accuracy, precision, recall, F1-score) and the large effect size ($d = 1.24$) demonstrate that this is not merely a statistically significant difference, but one with substantial practical implications for real-world deployment.While GMM offers theoretical advantages in interpretability and computational efficiency, these benefits did not translate to better practical performance for this high-dimensional recognition task. Interestingly, CNN achieved both higher accuracy and more confident predictions (mean confidence 0.0709 vs 0.0339 entropy for GMM) despite its greater complexity, challenging conventional assumptions about probabilistic models providing better uncertainty quantification.

The findings suggest that for complex pattern recognition tasks like vehicle image identification, deep learning architectures can overcome fundamental limitations of traditional statistical models in capturing non-linear feature relationships. The residual connections in CNN appear particularly effective at maintaining gradient flow during backpropagation, enabling the network to learn discriminative hierarchical representations that elude the GMM's more constrained parametric form.

For further research, hybrid architectures combining deep feature extraction with probabilistic modeling should be investigated to potentially achieve both high accuracy and interpretable uncertainty estimates. The development of specialized loss functions or architectural modifications to better handle challenging cases (extreme poses, occlusions) warrants investigation.

Conflict of Interest

The authors have no conflicts of interest.

Author Contribution
Ogundunmade TP handled the writing, methodology, and conceptualization. The article was written, reviewed, and edited by Ganiyu KA. Yahaya TO wrote and curated the data. The submission was approved by all writers after they had read it.

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