DEVELOPMENT OF ~~AN~~ IMAGE PROCESSING TECHNIQUES FOR VEHICLE CLASSIFICATION USING OCR AND SVM

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***Abstract* -** Image processing is a method for enhancing unprocessed images from cameras on aircraft, spacecraft, and satellites as well as images taken regularly for a variety of uses. In general, the following strategies can be used to categorize all image processing operations: Images are represented in several ways, which are referred to as image representation, image preprocessing, image enhancement, image restoration, image analysis, picture reconstruction, and image data compression. The first radiometric normalization, geometric distortion correction, and noise removal of the raw image data been discussed in the past. **The goal of the information extraction procedures is to automate the identification of tone in a scene by replacing the visual examination of image data with quantitative techniques. This entails analyzing multispectral image data and establishing the earth cover identification of each pixel in an image using statistically based decision procedures. The goal of the classification procedure is to sort all of the pixels in a digital image into one of several different earth cover classes or themes. The purpose of this study is to examine various image processing approaches and algorithms, many sorts of image processing algorithms: Optical Character Recognition (OCR) and Supporting Vector Machine (SVM) a feature extraction technique, on the vehicle classification dataset and had accurate results of 90% for SVM and 95% for OCR, to further improve the performance of machine algorithms in terms of accuracy for image processing technique using a vehicle. This study can be used for vehicle classification research, it also advances and improves the performance of the system in terms of accurate detection.**

***Keywords— Support Vector Machine, Object Character Recognition, Image Process Techniques**, Vehicle.*

I. INTRODUCTION

Everything is becoming automated in today's world, with the advent of artificial intelligence. vehicle detection and tracking are essential and a rapidly developing research aspect for intelligent transportation systems. When it comes to spotting automobiles from traffic surveillance recordings, image processing is critical. Traffic surveillance using image processing allows for better traffic flow control as well as the identification of reckless users and speed violators [1].

Vehicle classification, in line with rapid advances in computer vision, shows a lot of promise for reshaping systems for smart transportation. Systems for categorizing vehicles based on image processing and pattern recognition used throughout the last few decades to improve the effectiveness of automated highway toll collecting and traffic monitoring systems. These algorithms, on the other hand, do not take into consideration circumstances involving real-time road traffic because they were trained on a tiny number of hand-crafted features extracted from small datasets [2].

Due to the exponential increase in global vehicle production, vehicle classification systems have a significant potential to contribute to the development of intelligent transportation systems, such as automated highway toll collection, self-driving vehicle perception, and traffic flow control systems. For the classification of vehicle types, laser and loop induction sensors-based methods were developed in the past. These sensors were implanted beneath the road's pavement to gather and analyze data in order to extract essential vehicle information [3].

Attempts have been undertaken over the last few decades to discover a solution to the automated vehicle classification challenge, such as a video-based vehicle classification system that employs length information; a similar technique in classification. The videos are captured by cameras installed on the road's crest. To circumvent the long processing times of video processing, image-based approaches using neural networks to categorize vehicles have been created. Vehicle photos are analyzed for features that can be used in training. In automated vehicle classification, there are numerous solutions to unsolved problems. Vehicle recognition is conducted before classification in free-flowing traffic; nevertheless, it is easier to recognize vehicles in dedicated lanes. Furthermore, compared to open flow, dedicated lanes have slower cruising speeds, which increases sampling performance [4].

Vehicle classification is a difficult topic to solve and a process that is still ongoing. Vehicle classification issues might develop as a result of Unusual vehicle proportions, background and scene changes, vehicle occlusions, sudden vehicle movements, and camera motion. Vehicle classification is typically done in conjunction with higher-level applications that require the vehicle's location at every frame [5].

Deep learning-based feature extraction and classification approaches have recently been created, and they have shown to be more adaptable and applicable than standard classification systems. Recently, algorithms for feature extraction and categorization based on deep learning have been created, and they have proven to be more versatile and relevant than traditional classification methods [6].

However, a CNN-based classification system necessitates a substantial amount of data to maintain accuracy and guarantee generalization. To our knowledge, there has never been a generic benchmark dataset for the development and evaluation of vehicle categorization algorithms. As a result, existing vehicle classification datasets are limited, focused on a small number of classes in specific regions, such as the Comp Cars and Stanford Cars databases. These areas' intelligent transportation systems can accomplish considerable results with these datasets, but their performance is hampered by the presence of non-regional classes. We have contributed the following contributions to overcome the limitations in vehicle classification systems stated above [6].

A generalized vehicle classification architecture based on Convolutional Neural Networks (OCR) and SVM is provided to improve the resilience of vehicle classification systems for Intelligent Transportation Systems (ITS) in low-light settings. From traffic surveillance and driving videos, a local dataset of 10,000 photos based on six types (Car, Van, Truck, Motorbike, Rickshaw, and Mini-Van) was compiled. It's worth noting that these classes have their own design and shape that isn't covered by existing vehicle databases. Changed To ensure network generalization, OCR and SVM were used and trained on the VeRi dataset, which contains 50,000 photos across six vehicle classes. Illustrating the effectiveness of the proposed classification network, a thorough comparison study was conducted between the proposed and existing vehicle classification methods [1].

In this study, OCR and SVM-based approach is suggested to help in enhancing image classification for vehicles. The study is evaluated in terms of accuracy and compared.

II. RELATED WORK

Some academics have used machine learning algorithms in recent years to categorize automobiles using a variety of image processing approaches for vehicle classification datasets. Because they produce accurate categorization results, many specialists choose these algorithms to handle challenging tasks. In particular, the recent advancement of machine learning technology has inspired the advent of sophisticated image processing that uses machine learning methods to examine the magnetic signature of passing autos. Listed below are some works that are connected to this methodology.

Manisha et al., 2013 suggested a method for extracting features that use the Fourier transform to extract characteristics in the time domain. It was discovered that the effectiveness of their algorithm, as well as the system's overall performance, was dependent not just the technique used for feature extraction, but also the quantity or size of vehicle recordings in their database.

[8] have compared various machine learning techniques used for classifying vehicles in their study. Considerations were given to methods including support vector machines, neural networks, and logistic regression. Although it included a huge number of vehicle samples, it was heavily biased towards one of the classes, making it challenging to divide the data into training and validation. [9] presented multi-layer K-means (MLKM), a new data association learning strategy that combined the advantages Deep neural networks and other existing machine learning methods like K-means and KMeans++ theory offered in this research include the fact that it does not explore a more generalized example of road networks, as well as false alarms and missed detection. We evaluated their performance using a sizable dataset of 3074 samples. The categorization rate was rather closely approximated.during the process. The dataset, on the other hand, was one of the study's major limitations.

[10] released a research article on the subject of categorizing vehicles based on their auditory signatures. The samples were acquired using a reliable recording tool, then wavelet analysis was used to remove noise from the signals. A unique energy index method is used to pick the frames to be studied. After that, the most noticeable aspects of the obtained frame were extracted. The required features for analysis are chosen using a unique feature selection method based on mean and variance.

Jobin George et al. have introduced a unique and effective technique for detecting and classifying automobiles based on their acoustic features using ANN and KNN. A method for properly and effectively classifying automobiles In this work, a typical Indian scenario has been constructed and put into practice for several classes. The way this strategy operates is by identifying the area with the highest energy level for the autos that have been recorded. Smoothing the energy contour and finding the peaks belonging to each vehicle were part of the process [11].

[12] divides vehicles into four categories: bicycles, automobiles, trailers and trucks. The brief time strength of the acoustic signal serves as the main foundation for this technology, and a significant amount of spectral information is ignored. As a result, this method is unable to distinguish between two classes of similar size and engine power. For classification, Sampan employed fuzzy logic. The overall categorization accuracy was found to be 92 percent.

[13] To increase vehicle classification accuracy, A k-nearest neighbor classification method based on multiple kernels was created by Pradeep Kumar Mishra. Vehicle detection is accomplished utilizing the background subtraction method after frame extraction from the traffic video has been completed. Then, in order to categorize each detected vehicle, a feature extraction phase that considers wavelet and interest points are performed. In the last stage, vehicles are classified

using the recently proposed multiple kernelbased k-nearest neighbor (KNN) method. However, one of this model's significant flaws is its inability to function well in inclement weather.

[14] employed a median filter to reduce noise in a specific image. by emphasizing the Correlogram, Discrete Wavelet Transformation (DWT), and Edge Histogram as facial recognition methods for facial identification (EH). A facial vector is used to categorize the input faces as single or multiple faces, after which the SVM classifier, using a mixture of DWT, EH, and Correlogram multi-facial detection (MFD). The proposed approach was evaluated on the conventional BAO and Carnegie Mellon University (CMU) datasets, and the precision reached up to 90%.

Kumar et al. developed automated live facial expression detection (FED), in which the Haar Wavelet Transform is utilized to extract and classify RBF-SVM features with support for the radial baseline function (HWT). A genetic algorithm and fuzzy-C-means are used to determine the facial image's edges. The Cohn Kanade (CK+) database and the JAFEE face expression database were used in the experiment to produce the results. CMU+MIT, LFW-a, FEI, and its own site are the additional databases utilized for facial recognition. Finally, 95.6 percent and 88.08 percent of the CK+ and JAFEE data sets, respectively, yielded improved results [14].

[15] Using a multi-class SVM classifier, Alam et al. proposed a suitable method for the early identification and prognosis of lung cancer. Multi-stage classification has been used to detect cancer. This technique can also forecast the likelihood of developing lung cancer. The enhancement and segmentation of the classification image were done separately in each phase. The suggested method attained a 97 percent accuracy for image detection and an 87 percent accuracy for prediction.

[16], on the other hand, proposed an electrocardiogram-derived heart rate variability (HRV) signal-based method for the automatic detection of problems related to both common and coronary artery disease (ECG). Features are extracted from the HRV signal in the time, frequency, and nonlinear domains. To minimize the quantity of the retrieved attributes and expose the hidden characteristics beneath the surface, the key component analysis (PCA) is performed. Ultimately, two classes of data were classified using the Vector Classification Support Machine (SVM) using the extracted attributes.

[17], offer an SVM classifier based on a genetic approach for feature weighting and cataract diagnosis. One of the most serious disorders that can result in blindness is cataracts. The classifier is used to detect and evaluate cataracts, and it outperforms earlier studies in terms of classification accuracy. The upgraded classifier's practical use is a significant step forward. The technique avoids the time-consuming steps of pre-processing fundus images and instead extracts and calculates the features straight from the original photos This encourages the precision of the original fund photos to be preserved as much as possible in the flow chart of cataract classification.

[18], proposed a method for identifying and detecting vehicles called Speed Up Robust Features (SURF). Due to the low computing cost and distinctive characteristics of the ROI, vehicle and model recognition is done using the front or back images of the vehicle. Petrovic and Cootes made the initial suggestion for this for the identification of vehicles and models, which serves as the foundation and approach for later study. Prokaj and Medioni employed an approach based on models for vehicle categorization, matching vehicle imaging attributes with 3D modeling.

[19], proposed a technique for local tiled CNN that could achieve cross-sectional, rotational, and scale invariance by modifying the local tile configurations for the CNN weight-sharing algorithm, enabling make and model recognition. Zhang introduced a deep CNN-based vehicle classification technique, in which a solution was proposed for accurately recognizing cars in real-world photos.

[20], Deep learning is divided into two categories: RBM and auto-encoder. As opposed to the latter, which is based on computation graphs, the former employs probabilistic graphical models. A deep network consists of many levels is better equipped to characterize input data. A deep network can be trained via classic back-propagation, however there are problems with insufficient local optima and high time consumption.

Another problem is that labeled data is needed for backpropagation but is not always available for small datasets, which is a problem. The deep learning technique uses unlabeled data to establish the deep model rather than learning, and learns the p-value to resolve the poor local optima and lengthy time frame (image). This method generates input data by maximizing the likelihood of a generative model.

[21], who demonstrated an SVM-based car color categorization. For 500 outside vehicles with five colors, the implementation results indicated a 94.92 percent success rate. To identify the posture of a vehicle in the 3D environment, Ambardekar et al. utilized optical flow and knowledge of camera settings. This data is utilized by their traffic surveillance program to develop a model-based vehicle identification and categorization method. In a mid-field surveillance framework, Ma et al. developed a method for vehicle categorization. They use edge points and modified SIFT descriptors to differentiate between features. To categorize vehicles into trucks, passenger cars, vans, and pick-ups, Eigenvehicle and PCA-SVM were developed and applied.

(Ghobad and colleagues 2019) the researcher took six apples and used a CCD matrix camera to find the defects. The Active Counter Model [ACM] technique was used to recover the shape of the apple photos, and the accuracy of the statistical histogram-based EM method for healthy apples was calculated by counting the pixel values.pixels, which was 94.86 percent.

III. METHODOLOGY

Each country's vehicle registration number is printed on the license plate. This number separates one car from another, which is helpful, especially if they are both the same make and model. A vehicle's license plate can be recognized by an automated system, which can also extract the characters from the area where the plate is located. By using the license plate number, more details about the car and its owner can be obtained and used for processing. A portable, compact design is essential for such an automated system.

IV. DATASET DESCRIPTION.

A dataset from the random Nigerian vehicle plate numbers was accessed. This dataset includes default plate numbers which were assessed and examined with the predicted accuracy of default likelihood across the methods of data mining.

An Automatic car number plate detection using a morphological image processing system is proposed, it allows the detection of a a car entering the restricted region is shown by its license plate on the picture. The method is meant to be the first step in an identification process that also has a second step, which is the identification of characters that have been discovered. By using mathematical morphology, automatic car number plate detection is accomplished. The input image is intelligently filtered using a series of filters that remove extraneous image components while keeping the location and shape of the characters on the vehicle number plate. Old and new license plates are available.

The car number plate's two characteristics—that it is an item with a white backdrop and that its position is such that its edges are parallel to the image's x and y axes—are used by the detection technique. All processing steps have operations that depend on certain characteristics (such the opening's size, etc.). The size of the license plate in the input image determines which option they select. Due to the variable nature of the number plate's size and input image resolution, this cannot be totally automated. In contrast, the location of the camera and the position of the car in reference to the camera are fixed in the actual identification system. As a result, certain settings can be simply set by a human operator only once for the specific installation (a camera calibration phase). It is sufficient to include just one of these as an algorithm input parameter because the size of the characters on the image, its thickness, and the x and y sizes of the number plate are all dependent on one another. The parameter used for the tests detailed in this paper was the number plate's height, h, in pixels.

The algorithm has five steps, which are broken down into the following sections.

Step 1 - contrast enhancement
Step 2 - background cleaning
Step 3 - plate area detection
Step 4 - extraction of characters
Step 5 - Optical Character Recognition

The overall system design of the proposed work is shown in figure 3.1

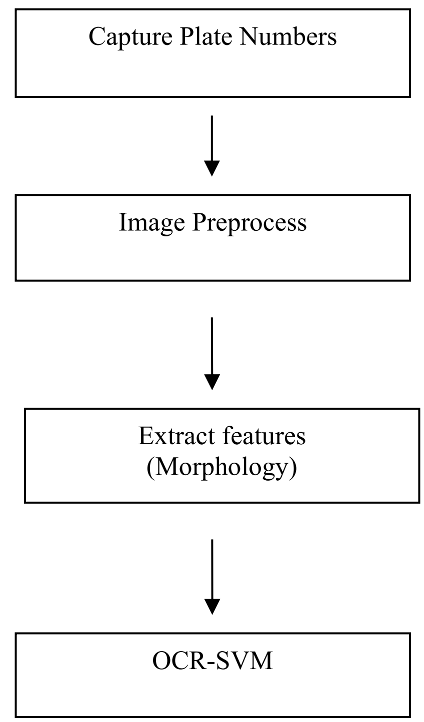

Figure 1 Proposed System Design

Image set

To achieve the desired goal, the proposed system uses captured pictures of plate numbers at the school using a powerful camera, as the image set and experimented using MATLAB. The image set contains 30 plate numbers.

V. SUPPORT VECTOR MACHINE

Support Vector Machine's decision boundaries are created to minimize generalization error. It is a comprehensive and flexible machine learning model that can handle regression, outlier identification, and both linear and nonlinear classification. [22].

Support vector machine models could classify any new text after feeding them sets of labeled training information for each category. The advantage is that you may monitor far more intricate connections between your data components without having to do difficult changes yourself. [23].

The consequence is that because of the higher computational cost, training is considerably longer. Support Vector Machine may be trained to recognize fraudulent credit card activity by reviewing thousands of records of both fraudulent and legitimate credit card activity. An SVM may learn to recognize handwritten digits by examining a vast collection of scanned images of handwritten zeroes, ones, and other characters. In a growing variety of biological applications, support vector machines are currently being used with tremendous success. The automatic classification of microarray gene expression profiles is another common biomedical use of support vector machines. To provide a diagnosis or prognosis, a Support Vector Machine could theoretically evaluate the gene expression profile generated from peripheral fluid or tumor sample. Protein and DNA sequences, microarray expression patterns, and mass spectra are all classified by SVMs in biology. (Schoelkopf and Tsuda, 2004)

OPTICAL CHARACTER RECOGNITION

The area of artificial intelligence known as computer vision studies how computers perceive digital images. Images must be transformed into integer arrays, where each array corresponds to the value of each color on each pixel. For example, an RGB (Red, Green, and Blue) image has three arrays, each representing the intensity of the red, green, and blue colors, while a grayscale image only has one array representing the intensity of the gray colors. Computer vision is a dependable image processing method. To back up this claim, a model was trained to classify 10.982 different bird species, 14.553 different butterfly and moth species, 409 different aircraft types, 92.3%, 85.4%, 93.4%, and 80.8% accuracy for 515 distinct dog breeds, respectively. [1].

Computer vision may be used for a variety of purposes; for example, it can be used to investigate how Instagram users' personalities and photo attributes are linked. According to one of the study's findings, the number of faces in a photo is related to the user's extraversion, agreeableness, and openness. Even while past research has shown that computer vision is capable of handling complicated scenes, uneven lighting, skewness or rotation, blur and degradation, and fonts, it still faces a number of obstacles [24].

Another application of computer vision is Optical Character Recognition, which recognizes characters in images and converts them into strings or text (OCR). OCR is extremely valuable since It not only helps computers interpret the data in the image, but it also enables us to edit documents that have been extracted. Tesseract, an open-source OCR engine, makes it simple to execute OCR. If used appropriately, Tesseract is already a strong engine. A study that tested the use of Tesseract on handwritten Chinese characters. Because Tesseract was designed to recognize numerals and alphabets, the result is poor, and handwritten Chinese characters are similarly difficult. With an average accuracy of 64% across all characters, the accuracy ranged from 100% to 4%. Yet, additional preprocessing significantly increased each Chinese character's accuracy to above 92%. Another benefit of Tesseract is its adaptability; it works with Linux, Windows, Mac OS X, Android, and iPhone10. It was evident that this technology was prepared for deployment based on the encouraging results of prior research on OCR and tesseract. OCR and Tesseract were chosen as the engine because of this. study [25].

Recognition of characters on vehicle license plates is important in Nigeria, especially when traffic lights are violated. In this study, an experimental work has been performed using morphological techniques that are based on the characters' initial binary images and the suggested system uses gray scale, edge detection and optical character recognition to fetch out figures and characters on a Number plate clearly.

This study has also demonstrated that combining several techniques can enhance plate matching's beneficial results. This combination can be carried out after collection, at the detection stage. It is recommended to choose detection methods or approaches with good value but limited calculation cost. Acceptable template matching can also be achieved using extraction techniques like extracting features and flexible iterative threshold holding.

Another area where good documentation from database template matching organizations is strongly advised. The proper names, addresses, and other documents must be completed during the vehicle user's biodata registration stage in order to prevent system failure during plate matching. This is important because personnel at these agencies have historically lacked concern for accurate documentation due to laziness and a failure to assign the task to the most qualified person.

PERFORMANCE METRICS

Accuracy in tasked with the responsibility is measured by the proportion of accurate predictions made by the model.
In the data's target variable classes which are nearly balanced, accuracy is a useful statistic.

$$\textbf{Accuracy} = \frac{\textbf{TP+TN}}{\textbf{TP+FP+FN+TN}}$$

Precision is a metric that shows us how much the forecasts are right.

$$\text{Precision}= \frac{TP}{TP+FP}$$

The fraction of true positives that are accurately identified as positives is measured by sensitivity.

$$\text{Sensitivity}=\frac{TP}{TP+FN}$$

The proportion of true negatives that are accurately detected is what is meant by specificity detected as opposed to positive, known as selectivity or real negative rate (TNR).

$$\text{Specificity}=\frac{TN}{FP+TN}$$

The F1 Score measures the accuracy of a test, defined as the harmonic mean of precision and recall.

$$\text{F1 score}=\frac{2TP}{(2TP+FP+FN)}$$

VI. RESULTS AND ANALYSIS

The implementation of plate number recognition system using morphological image processing to perform analysis on captured images representing the database. To demonstrate, mathematical morphology was applied to plate number images for detecting car number plates. From these data, the detection of old and new plate numbers was designed, as sensitivity to lighting conditions, preprocessing, and detection of different sizes of plate numbers from a certain interval.

The analysis and interpretation of data use MATLAB. The data collected was compiled and processed using JPEG. MATLAB software was used to contrast image enhancement, clean the background, detect the plate, extraction of the plate number, and recognition of the in-texts.

Nigerian automobile license plates are intended to be identified and recognized by the designed recognition system. The system receives as its input a digital camera-captured image of the car, and its output is the license plate that has been detected and identified. On MATLAB 15a, the program's implementation was created. This procedure involves converting the color input image to a grayscale version, binarizing the character, and removing noise during the preprocessing stage.

The colors in the vehicle image vary. The NTSC standard approach is then used by the system to convert the RGB images to grayscale images.

Gray = 0.299 * Red + 0.587 * Green + 0.114 * Blue.

The technique presented here for converting a colored image to a gray image is independent of the type of colors present in the image and depends mostly on the gray level of an image for processing and extracting the necessary information. The red, green, and blue values of colors are not used anywhere in this algorithm. So, before further processing, a 2-dimensional gray image is created if the input image is a colorful image that is represented by a 3-dimensional array in MATLAB. It displays a sample of the original input image along with a grayscale image is shown in figure 2

Figure 2 Gray Scale Image

Several kinds of noise are introduced into the original image during image capture, making it useful for us to identify image edges. Many procedures are anticipated in order to acquire a trustworthy localization of license plate in real time. Steps with a higher time complexity are used in order to make the technique suitable for real-time systems at various stages. The steps listed below are nominally included in this part:

i. Plate modification intensity
ii. Edge detection
iii. Distinguishing objects from background
iv. Locating associated component
v. Candidate selection Detecting Edges and Separating Objects from Background

A. Detecting Edges and Separating Objects from Background

In order to just have better edge detection, the license plate is enhanced and sharpened. Histogram equalization is used to expand the range of the plate's levels of intensity, as well as the feature extraction operator is utilized for edge detection, as shown in Figure 3.

The optimum use of thresholding in this stage is to differentiate items from a background, as seen in Figure 4. To choose rows with a concentration of white pixels, apply the threshold. Separating object and background information is done through the thresholding procedure. A grayscale image of a license plate is translated into a binary image as the basis of the technique. Local thresh olding and global thresholding are two different threshold operations that can be used for the conversion.

Figure 3: Detection of Edges and Separating Objects from background

After identifying the linked elements, the remaining objects in the image were examined for using the license plate's area, aspect ratio, and density. As a result of these features, elements other than the likely number plate designation were removed from the license plate space. After that, using the coordinates—which are the precise locations of the automobile license plate—the bounding box around the item was calculated.

Figure 4: The actual license plate for a car.

To put the recognition system to the test and gauge the success rate, experiments were carried out. Version 8.0 of MATLAB was used to implement the approach, and Windows 8 with an Intel(R) Corei5 processor running at 2.3 GHz and 4GB of Memory were the computer's specifications. Captured colored photos will be used as the system's input.

The test photos were captured using three kinds of plate numbers and various illumination conditions.

Figure 5: Shows the confusion matrix plot using the random forest classifier. The false-positive rate yields = 0.0216 and the false-negative rate yields = 0.0122

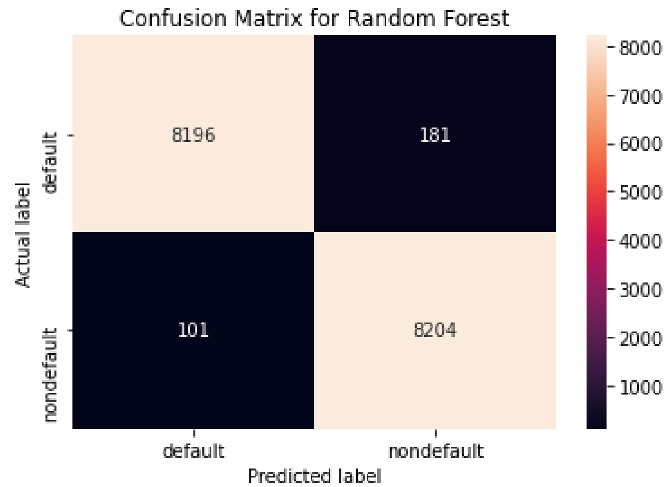

Figure 5 OCR-SVM Confusion Matrix (TP= 8196 FP= 181 FN= 101 TN=8204).

The confusion metrics obtained are evaluated using agglomerative hierarchical clustering, Decision Tree, and Random Forest with evaluation such as Accuracy, Precision, Specificity, Sensitivity, F1 score, and Matthew Correlation Coefficient.

Table 1 Performance Evaluation

Performance Measures (%)	**OCR + SVM**	**Formulas**
Accuracy	98.3	ACC = (TP + TN) / (P + N)
Specificity	97.8	SPC = TN / (FP + TN)
Sensitivity	98.8	TPR = TP / (TP + FN)
Precision	97.8	PPV = TP / (TP + FP)
F1 Score	98.3	F1 = 2TP / (2TP + FP + FN)
Matthews Correlation Coefficient	96.6	TP*TN - FP*FN / sqrt((TP+FP) *(TP+FN) *(TN+FP) *(TN+FN))

In this study, several experiments were carried out and table 4.1 shows the evaluation with an accuracy of 98.3%. table 2 compares existing works

Table 2 Comparison with Related Works

S/N	Authors / Year	Methods	Results (Accuracy)%
1	(Mustafa Abdullah & Mohsin Abdulazeez, 2021)	SVM Classifier	90.0
2	(Alam et al., 2018)	SVM Classifier	97.0
3	Mohsin Abdulazeez, 2021)	OCR Classifier	88.08
4	(Sampan, 1997)	Acoustic Classifier	92.0
5	(Chen et al., 2009)	SVM Classifier	94.92
6	(Ghobad and colleagues 2019)	CCD Matrix	94.86
7	Proposed System	OCR, SVM	98.3

VII. CONCLUSION

In Nigeria, it is crucial to recognize the characters on vehicle license plates, particularly when there are violations of traffic lights.

In this study, In order to clearly extract the figures and characters on a number plate, experimental work has been done utilizing morphological approaches that are based on the original binary pictures of the characters. The suggested system uses gray scale, edge detection, and optical character identification.

This study has also demonstrated how combining several strategies might enhance plate matching's beneficial results. After acquisition, this combination can be performed as soon as detection. It is recommended to choose detection methods or procedures that will be effective yet require less computational power. Adequate template matching can also be achieved using extraction processes like feature extraction and adaptive iterative threshold-holding.

Another area where good documentation from database template matching organizations is strongly advised. In order to protect against system failure during plate matching, the proper names, addresses, and other paperwork must be completed during the stage of vehicle user's biodata registration. This is required since personnel at these agencies have a history of disregarding proper documentation due to laziness and failing to assign the task to the most qualified individual. This part provides a thorough discussion while also explaining the research findings. Findings can be presented in ways that the reader will easily understand, such as figures, graphs, and tables [14], [15].

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