Recognition Module for the Identification and Classification of Patterns in Vehicles Using Deep Learning Techniques.

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***Abstract*— In Mexico, vehicle theft is a serious problem that affects a considerable number of citizens. In the state of Veracruz, 61,796 cars have been reported stolen in one year. This paper presents a pattern recognition system using Artificial Intelligence techniques. This system uses video image analysis and a Deep Learning module to classify vehicles into two categories: automobiles and motorcycles. A case study used video surveillance cameras to capture more than 1,000 vehicles. The Deep Learning model achieved 85% classification accuracy. This solution will improve the identification of suspicious and stolen cars, contributing to security and traffic control.**

***Keywords*— vehicle theft, pattern recognition, Deep Learning, road safety.**

I. Introduction

According to AMIS (The Mexican Association of Insurance Institutions), in the state of Veracruz alone, from July 2021 to June 2022, 61,796 cars were reported stolen, representing 169 cars per day. Of the total number of vehicles, 44% have been recovered, which makes it necessary to solve this problem. Some platforms are based on detection but do not consider important factors. [1]

Vehicle theft control is a field that offers exciting challenges in applying artificial vision techniques. Thus, multiple researches have been directed to solve or lessen this problem, using an optimal network infrastructure and various techniques ranging from classical digital image processing and moving images to heuristic methods such as artificial neural networks.

In this work, an artificial intelligence-based pattern recognition system for vehicle detection has been developed. The system uses video image analysis that is notable for incorporating a Deep Learning module that enables accurate vehicle classification. This additional feature potentiates predictive capabilities and significantly improves the identification of suspicious and stolen vehicles, providing a valuable tool for security and traffic control.

The following sections are addressed below: the second section contains a summary of the work related to this research and a comparative analysis of the contributions and technologies that helped to solve the problem presented; the third section presents a detailed description of the architecture proposed to solve the problem detected; the fourth section presents a case study of a vehicle theft; and the fifth section presents the conclusions and future work.

II. RELATED WORD

This section presents several related papers addressing vehicle detection and pattern recognition using artificial intelligence technologies.

Pattern recognition system with artificial intelligence to detect vehicle license plates for the National Police of Peru [2], the situation of the organization before the implementation of the web system presented deficiencies in terms of search, control, and monitoring concerning the rate of compliance and conformity by eleven police stations belonging to the National Police of Peru.

Artificial intelligence-based facial recognition using machine learning to identify, through Python language, people who are missing, abducted, or have committed crimes [3]. They use a Jetson Nano development platform that identifies and sends an alert via SMS text message to information monitoring and control units for decision-making and response.

Visual detection of vehicles in natural environments [4]. The OpenCV implementation has been used, which has allowed changes in the performance of HAAR-like features to add several features capable of increasing vehicle recognition power. These features and those initially implemented by OpenCV have allowed us to improve the vehicle detection levels in image sequences. In addition, with the training performed, it was possible to observe a specific reduction in false negatives.

Vehicle license plate detection using a cascade classifier model based on Python language [5]. The development of a cascade classifier model for license plate detection using

Python, OpenCV, and Cascade Trainer GUI tools, based on open source, is presented. The images used for processing were captured using a camera for Raspberry Pi connected to the embedded plate at various points in the downtown area of the border city of Cucuta, Colombia; then sent to a personal computer and redirected through geometric transformations to ensure high-performance of the classification system, data augmentation processes are applied, going from 245 to 1867 images for training the cascade detector. The classification model took 17.4 minutes to create and was tested with photos and videos in natural environments in the city of Cúcuta, achieving the detection of Colombian and Venezuelan license plates with an effectiveness of 90.26%.

Implement a vehicle detection system based on convolutional networks from IP traffic cameras [6]. The project focuses on implementing a system for various public services, such as counting traffic statistics or implementing a ticketing system. For this purpose, a database of images captured by IP traffic cameras was used. These images were used to train a model that correctly learns the appearance of a vehicle and can generalize that appearance to detect other cars when shown images other than those in the database. The model will be based on a neural network with convolutional layers, which are ideal when dealing with images, as they allow to reduce the large amount of information provided by so many pixels, extracting, in turn, several features that will be vital to detect cars.

From the above, these studies focus on improving the efficiency of vehicle detection and pattern identification in various situations, from detecting vehicles by the National Police of Peru to the title of missing persons or persons involved in crimes. These works explore technologies such as Deep Learning, Machine Learning, OpenCV, and convolutional networks to achieve accurate vehicle detection and classification results.

Table 1 presents a comparative analysis of the most relevant works related to vehicle detection and their characteristics to analyze similarities and differences.

TABLE I. COMPARATIVE ANALYSIS OF WORK AND RESEARCH RELATED TO VEHICLE DETECTION.

Work research	***Problem***	***Contribution***	***Technology***
Pattern recognition system with artificial intelligence to detect vehicle license plates for the National Police of Peru.	Deficiencies in terms of search, control, and follow-up	The vehicle license plate pattern recognition system (SRP) is developed using Scrum and XP.	MongoDB, Python
Recognition of facial expressions and personal characteristics as a tool to identify people in a public transportation system.	Deficiencies in the search for missing persons, abducted, or have committed crimes.	Development of Jetson Nano, which identifies and sends an alert via SMS text message to monitoring and control information units for decision-making and response.	Python, Ubuntu
Visual detection of automotive vehicles in natural environments.	Worldwide traffic problems are becoming increasingly large and diverse.	Develop an algorithm to demonstrate good real-time detection results.	OpenCV
License plate detection using a cascade classifier model based on Python language.	Identifying vehicle license plates is time-consuming and tedious.	Development of a cascading classifier model for license plate detection.	Python, OpenCV and Cascade Trainer GUI
Implement a vehicle detection system based on convolutional networks from IP traffic cameras.	Mechanize vehicle identification processes.	Develop a vehicle identification system that applies quickly, efficiently, and robustly to any traffic camera.	Deep Learning algorithms based on convolutional networks.

According to the above, the proposal differs from existing solutions due to incorporating a deep learning module. This module stands out for its ability to accurately classify vehicles. This additional feature significantly expands the search options and translates into more accurate results in the vehicle identification process.

III. ARCHITECTURE DESIGN

The developed system employs a Deep Learning infrastructure and module with a classification model designed for pattern recognition in vehicles.

The following deployment diagram (Figure 1) visually shows the different components' interactions. At the center is a server that hosts the system, and two key APIs are highlighted: the first is responsible for the internal administration of the system, while the second uses the classification model. A database has also been incorporated, essential for storing relevant information.

The system is complemented by a client that accesses the system, and a DVR has been integrated along with security cameras, to which the APIs located in the server have access.

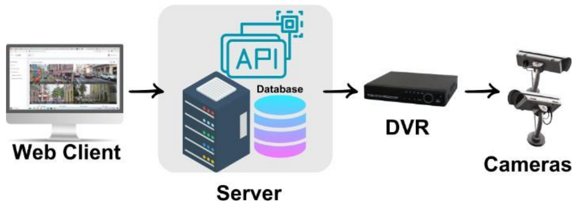

Fig. 1. Deployment Diagram of the system.

The system architecture is centered on a central server that hosts the application and runs the Deep Learning module. This application uses a neural network model based on Deep Learning to classify vehicles into two categories: automobiles and motorcycles (Figure 2).

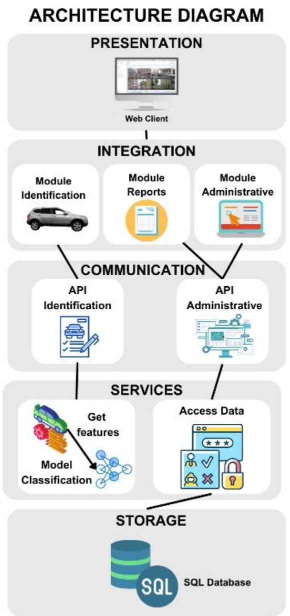

Fig. 2. Architecture of the proposed system.

A. *Description of the architecture*

Presentation Layer:

- User Interface: This is the part of the system with which users interact directly. It allows users to send requests for pattern recognition on vehicles and receive the corresponding results.

Administrative integration module layer

- This module is responsible for the fundamental administrative management of the system, such as authentication and CRUD operations to manage data.
- Identification module for vehicle image capture.

Communication Layer

- Provides specific services and functionalities in the system.
- Administrative API for report and user control.
- Algorithms API for plate and color identification.
- Model API to identify vehicle type.

Service layer

- Vehicle analysis is based on a Deep Learning model that allows the classification of vehicles into two classes: automobiles and motorcycles.
- Data access allows administration of data access.

Data Storage Layer

- Data Repository: Stores and manages information about identified vehicles, such as color, license plate, and model, by a relational database.
- Database Connector: Provides access and manipulation of data in the repository. Allows to perform read and write operations on the database and establish secure connections.

IV. CASE STUDY

A case study was conducted in Fortín de las Flores, Veracruz. An infrastructure consisting of two HiLook THC-B120-PC surveillance cameras and a DVR (Digital Video Recorder) was implemented to ensure effective image capture of moving vehicles. These cameras were placed strategically to obtain optimal viewing angles.

All this infrastructure was implemented and configured so that the system containing the Deep Learning module could perform vehicle classification using a previously trained neural network model (Figure 3).

Fig. 3. Video security cameras.

The Deep Learning module within the system refers to the integration of the deep learning model to perform the image processing and its classification into two categories: automobiles and motorcycles. The construction of this module is described below.

Development of the Deep Learning model: Before integrating a Deep Learning model into the system, the model was first developed and trained. This involved the collection of data (images), the creation and training of the neural network, and the tuning of the epochs to obtain a good performance.

Model export: Once the Deep Learning model was obtained, it was exported to TensorFlow js, saving the model in HDF5 format.

HTML document of the model: The HTML document of the model was created using HTML, CSS and JavaScript, and the Tensorflow.js library was leveraged for the implementation of the model. Model loading was achieved via HTTP, supported by a Python web server.

Integration into the web application: To integrate the model into the web application, a window was incorporated to allow the reception of images for subsequent classification, and the presentation of the results in the user interface, which facilitates the identification of vehicles in the images.

For this purpose, the system's access to video surveillance cameras was used to capture video of 1,016 vehicles recorded while in transit. (Figure 4).

Fig. 4. Vehicle image captures.

To guarantee that the classification algorithm received suitable images, we utilized TensorFlow to uniformly resize all pictures to 256 pixels in height and 256 pixels in width. This streamlined the processing and input for the Deep Learning model.

Upon resizing the images, we proceeded to classify the vehicles into two distinct groups: motorcycles and automobiles. These resized images served as inputs for our classification model, which we developed with the aid of TensorFlow/Keras. In order to enhance the model's accuracy, we increased the number of epochs by 50 during the training phase. Furthermore, we conducted 25 unit tests for each vehicle type to optimize its classification capabilities. The outcome of these efforts was a model that achieved 85% accuracy in classifying motorcycles and automobiles.

To estimate the 85% classification efficiency of motorcycles and automobiles, training experiments were mainly used. These experiments involved fitting and optimizing the image classification model using TensorFlow/Keras. The training experiments were conducted with different numbers of epochs (or "epochs") to evaluate how the model performance was affected. Here are the details of the experiments:

First Experiment (10 epochs): In this experiment, the model was trained with 10 epochs. The model was exposed to the training dataset for 10 full iterations to learn how to perform motorcycle and automobile classification.

Second Experiment (20 epochs): In this experiment, the number of epochs was increased to 20. The model was trained for 20 full iterations of the training dataset to see if more epochs improved performance.

Third Experiment (50 epochs): The last experiment was conducted with 50 training epochs. Here, the objective was to determine whether further increasing the number of epochs would lead to improved performance. As a result, it was found that with 50 epochs, a balance between fit to the training data and generalizability was achieved, reaching an accuracy of 85%.

These training experiments made it possible to evaluate how the number of epochs affected the performance of the model and, ultimately, to determine that 50 epochs provided the best performance for motorcycle and automobile classification. Optimizing the number of epochs is an example of how training experiments can help improve the effectiveness of a machine learning model.

The model achieved high accuracy and the results were clearly visualized. By resizing the input image to 256 by 256 pixels and displaying it using Matplotlib, the classification model was able to assign a label to the image, accurately identifying it as either a motorcycle or a car. This convenient display of both the resized image and its classification result on a single screen greatly facilitated the evaluation and verification of the model's classification capabilities, as shown in Figures 5 and 6.

Fig. 5. Car classification result.

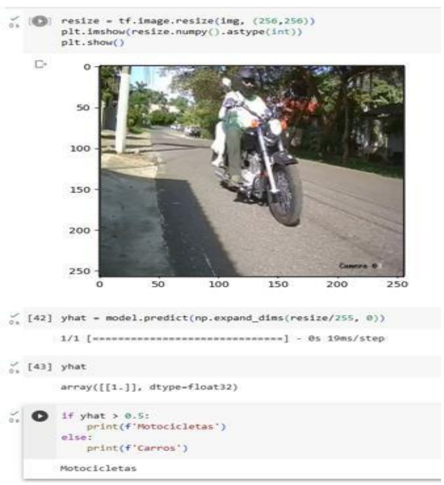

Fig. 6. Motorcycle classification result.

In order to optimize the effectiveness of vehicle identification and classification, it is imperative to integrate the Deep Learning module into the system. This valuable feature enables the recognition of patterns in vehicles, enhancing the system's overall capability. By seamlessly combining this module with other license plate and color detection algorithms, the Deep Learning technology can proficiently detect vehicle patterns. This will prove to be an invaluable tool in identifying suspicious vehicles and those with theft reports.

V. CONCLUSIONS AND FUTURE WORK

The implementation of a Deep Learning module for vehicle classification utilizing a neural network model has been proven highly effective. It has demonstrated the ability to accurately evaluate vehicles captured in videos and successfully classify them into two categories: cars and motorcycles. With an accuracy rate of 85%, this technology showcases its proficiency and effectiveness in identifying vehicle types for vehicle pattern recognition.

The Deep Learning module enabled accurate classification of vehicles, in our case automobiles or motorcycles, thus providing an additional tool to identify patterns in cars, which can speed up their search and identification in situations of suspicion or theft.

In order to enhance the Deep Learning capabilities of our system, it would be advantageous to expand the range of vehicle categories recognized, such as buses, SUVs, and trucks. This would entail training the model to identify a broader range of vehicles. Furthermore, we could explore the option of incorporating a new module that utilizes Machine Learning algorithms to predict and ascertain vehicles based on attributes such as color and license plate number.

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