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Comparative Evaluation of YOLO and Haar Cascade in Truck Detection in Road Scenarios in the City of Bogotá

Evaluación comparativa de YOLO y Haar Cascade en la detección de camiones en escenarios viales de la ciudad de Bogotá

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Abstract

This research paper focuses on the identification of objects using Neural Networks and Computer Vision in Python. The goal is to achieve high levels of performance and speed in object identification through database exploration, algorithm development using tools such as OpenCV, and research of specific mathematical models. A thorough search and selection of relevant databases was carried out to train and validate the Neural Network models used, resulting in high levels of accuracy and reliability in object identification.

Keywords: YOLO, Python, CNN, BNN, Haar Clasiffier, Computer Vision.

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Resumen

Este artículo se centra en la identificación de objetos mediante el uso de Redes Neuronales y Visión por computadora en Python. El objetivo es lograr altos niveles de rendimiento y rapidez en la identificación de objetos a través de la exploración de bases de datos, el desarrollo de algoritmos utilizando herramientas como OpenCV y la investigación de modelos matemáticos específicos. Se llevó a cabo una exhaustiva búsqueda y selección de bases de datos relevantes para entrenar y validar los modelos de Redes Neuronales utilizados, lo que resultó en altos niveles de precisión y confiabilidad en la identificación de objetos.

Palabras clave: YOLO, Python, CNN, BNN, Clasificador Haar, Visión por computadora.

1. Introduction

Object identification using Neural Networks and Computer Vision in Python has gained great relevance in the field of AI. This chapter focuses on this topic, with special attention on the implementation in Python and the use of the OpenCV library. The main objective of this study was to achieve high performance and speed in object identification, taking advantage of Neural Networks and Computer Vision. Extensive research on Neural Networks and AI was performed, as well as the search and selection of suitable databases. Python was used as programming language, complemented by the powerful OpenCV library for image processing and Computer Vision. Different approaches were explored, such as YOLO, Haar cascade and specific mathematical models [1].

This chapter is a compendium of the search and selection of databases, research in Neural Networks and AI, and the implementation of codes and algorithms in Python with OpenCV for object identification. The results obtained show the progress and consolidation of this technology in the field of Computer Vision, as a result of the joint effort of the scientific community and researchers committed to this area of study [1].

2. Conceptual Framework

2.1. Machine Learning and Neural Networks

Machine Learning is a branch of AI that focuses on the development of algorithms and techniques that allow computer systems to automatically learn and improve from experience [2]. This approach has become a fundamental tool in object identification, as it allows systems to learn to recognize and classify objects from training data sets [3].

In the context of object identification, Neural Networks have been highlighted as one of the most powerful and efficient techniques. According to [4] "these networks are inspired by the functioning of the human brain and are composed of layers of interconnected neurons that process and analyze input information".

Neural Networks play an essential role in image processing, since they have the ability to acquire knowledge to identify intricate visual patterns and derive meaningful features from images [5]. Through the use of learning algorithms, these networks are trained using image datasets that are labeled, allowing them to establish connections between particular features and the classes of objects to which they belong [6].

In the field of road actor detection, several Neural Network architectures are used, being particularly outstanding the Convolutional Neural Networks, also known as "CNN" for its acronym in English. These networks have demonstrated outstanding performance in the task of identifying and categorizing objects in images. As indicated in [6], these networks have been specifically designed to process visual information and make use of convolutional layers to extract meaningful features from images.

An additional architecture employed in road actor detection is the Backpropagation Neural Network. These networks also undergo training with datasets that include labels and have the ability to acquire knowledge for object identification and classification [7].

2.2. Governance and Emerging Technologies

Governance plays a critical role in the progress of emerging technologies, such as object identification using Neural Networks. It refers to the set of regulations and policies that oversee their evolution and use, with the aim of ensuring their proper functioning and fostering their positive impact on society. In this context, it is essential to take into account the ethical and legal ramifications linked to the use of Neural Networks for the identification of road actors. These technologies have the capacity to process large volumes of personal data and generate behavioral profiles, which raises concerns related to privacy and safeguarding of information [8].

In addition to ethical considerations, legal aspects related to data collection, storage and use, as well as liability in case of possible failures or damage caused by these systems are presented [8]. In order to ensure responsible and ethical development in object identification, specific regulations and standards have been devised and established. These include the need for transparency in the algorithms employed and the preservation of the privacy of individuals [8].

The adoption of these regulations and standards provides a solid framework for the advancement and implementation of road stakeholder identification systems, ensuring reliability, fairness and accountability in their application [8].

2.3. Environment and mobility

The use of Neural Networks for the identification of road actors has a profound effect on environmental management and urban mobility, offering a number of applications that aim to improve sustainability and alleviate traffic problems in urban areas [9]. One of the most prominent applications is in emission monitoring, in which images are analyzed to recognize trucks and collect data about pollutant gas emissions in various urban areas. This process plays a key role in implementing environmental management policies and promoting more sustainable mobility [9].

In addition, the identification of road actors contributes to improved real-time traffic management, enabling more effective traffic management, traffic light adaptation, and more efficient route planning. This has a positive impact on mobility, reducing travel times and reducing congestion, which in turn leads to reduced emissions and lower environmental impact [10].

Another relevant benefit is the promotion of the use of cleaner and more efficient modes of transport, identifying electric trucks, bicycles, pedestrians and other non-motorized means of transport to make informed decisions and develop adequate infrastructures. This leads to a decrease in greenhouse gas emissions and improved air quality in cities [10].

2.4. Education and Training in Object Identification Technologies

Training and further education in object identification techniques play a key role in the development of highly skilled workers. My training focuses on the field of object identification through neural networks. To achieve effective learning, it is essential that academic programs are tailored and provide both theoretical and practical knowledge in image recognition and identification using neural networks [11].

Table 1. Analysis of the importance of education in artificial intelligence (AI) and related technologies in Bogota, Colombia (2023).

Appearance	Description

Labor Lawsuit	According to a study by the Bogota Chamber of Commerce, in 2023 there were more than 100,000 vacancies in the AI and related technology sector in Bogota. This figure is expected to continue to grow in the coming years.
Educational Programs	In Bogota, there are more than 20 universities and training centers offering education programs in AI and related technologies. These programs include undergraduate, graduate and extension courses.
Investment in Education	In 2023, the government of Bogota allocated $10 million pesos to AI and technology training. In addition, several technology companies in Bogota have invested in educational programs for their employees.
Collaboration	In recent years, several collaborative initiatives have been developed between companies and universities to promote AI education. For example, the Universidad de los Andes and Microsoft created the AI Center of Excellence, which offers training programs for students and professionals.
Required Skills	As of September 2023, the skills most in demand by companies in the AI sector in Bogota included: ✓ Mathematics and statistics ✓ Programming ✓ Machine learning ✓ Deep learning ✓ Data science
Economic Impact	AI education can contribute to the economic growth of Bogota and Colombia in several ways: ✓ Creation of new jobs ✓ Increased productivity ✓ Improved competitiveness
Challenges and Opportunities	The main challenges and opportunities in education in AI and related technologies are: ✓ Availability of resources ✓ Adaptation to industry needs

	✓ Promoting inclusion

Source: own.

Training professionals in this field requires a solid foundation in fundamental concepts such as Machine Learning, Neural Networks and image processing. Educational programs should provide a thorough understanding of these principles, as well as the ability to apply and use relevant software tools and libraries, such as Python and OpenCV [12]. In addition, it is essential to establish continuing education strategies to keep up-to-date on technological advances, new techniques and algorithms, and best practices in the design and training of Neural Network models [13]. This training should be accessible and adapted to diverse needs, from Computer Vision experts to engineers specialized in traffic and urban planning.

Scientific dissemination and technological competence are essential aspects in the context of object identification. Scientific dissemination allows sharing knowledge and research results, keeping the scientific community and society in general informed about the advances and applications of these technologies [11].

Similarly, technological competence is essential for people to understand the concepts and implications of actor identification in road environments using Neural Networks, thus promoting their informed and critical participation in the development and implementation of these technologies [12].

2.5. Bogota as an Innovative City in Road Stakeholder Identification

Bogota, the capital of Colombia, stands out as an innovative city in the identification of road actors using Neural Network technologies. Its innovation-friendly environment, local initiatives and strategic collaborations have boosted the development of advanced solutions in this field [14].

First, Bogota's innovative environment offers a solid foundation for the development and implementation of object identification technologies. The city has a vibrant entrepreneurial ecosystem and numerous startups and companies dedicated to the development of solutions in the field of Computer Vision and Machine Learning [15]. In addition, it has created innovation spaces, such as research centers and technology labs, that support entrepreneurs and professionals interested in this area [14].

In terms of local initiatives, Bogota has implemented several solutions for object identification in road actors. Among them, emission monitoring pilot projects that use Neural Networks to identify and classify trucks in real time, providing valuable information for transportation management and decision making in sustainable mobility policies [16].

In addition, the city has fostered collaboration between academia, the public sector, and the private sector to drive innovation in road stakeholder identification. These collaborations allow combining academic knowledge, transportation management expertise, and entrepreneurial vision to develop innovative solutions [16]. Training programs have also been established for professionals and students interested in developing and using Neural Network technologies in the identification of objects in the road context [17].

2.6. Parameterization and Optimization of Object Identification Models

Parameterization and optimization of Neural Network models used in road actor identification is essential to achieve optimal performance. Hyperparameters are configurable and affect the performance and generalization of the model. Proper selection of these parameters, such as learning rate and number of hidden layers, is crucial and can be achieved by techniques such as grid search or Bayesian optimization [18].

Once the hyperparameters have been selected, the model is trained, adjusting its weights and biases to minimize the loss function. Practical considerations, such as the optimization algorithm and the number of training epochs, are important to avoid problems such as overfitting or underfitting[19]. Then, the model performance is evaluated using test or validation data and common metrics, such as accuracy, sensitivity and specificity, are used. In addition to the

above, to ensure optimal performance in road actor identification, practical aspects such as the quality and diversity of training data, the use of data augmentation techniques, and the optimization of computational performance for fast and efficient real-time inference must be taken into account. Correct parameterization and optimization, along with these considerations, will ensure reliable and accurate results in road actor identification.[20]

3. Model description

3.1. Vehicular flow

Vehicle flow analysis is essential for traffic management and road infrastructure planning. To achieve this, a road actor identification model based on Computer Vision and Neural Networks is used. This model detects and tracks moving trucks by means of surveillance cameras or image capture devices in real time. Thus, valuable information about vehicular flow is obtained, such as traffic volume, average speed and travel patterns [21].

The implementation of the model involves the continuous capture of images or video sequences, which are processed by an advanced truck detection and tracking algorithm. The collected data are critical for making informed traffic management decisions, such as adjusting traffic lights, optimizing routes, and improving road infrastructure [22].

Despite the benefits, the implementation of this model presents challenges, such as accuracy in different lighting conditions, minimizing false detections and simultaneous tracking of multiple trucks, while seeking to optimize computational performance for real-time processing. Despite the challenges, this tool becomes a powerful ally for traffic management, providing detailed information for urban planning and mobility policy design [23].

Table 2. Accident hotspots in Bogota during 2023. [24]

Location	No. accidents
Avenida Las Américas - Avenida Boyacá	165
Avenida Boyacá - Calle 80	159
Avenida Boyacá - Calle 13	124
Avenida Las Américas - Carrera 68	108
Avenida Las Américas - Carrera 114	98
Carrera 15 - Calle 100	95
Avenida 1 de Mayo - Carrera 50	81
Avenida Boyacá - Avenida 1 de Mayo	77
Avenida Las Américas - Carrera 50	76
Carrera 68 - Avenida La Esperanza	75
Autopista Norte - Calle 127	70
Autopista Norte - Calle 100	67
Autopista Sur - Carrera 63	61
Autopista Sur - Calle 59 Sur	60
Avenida Boyacá - Calle 53	57
Autopista Norte - Calle 103	55

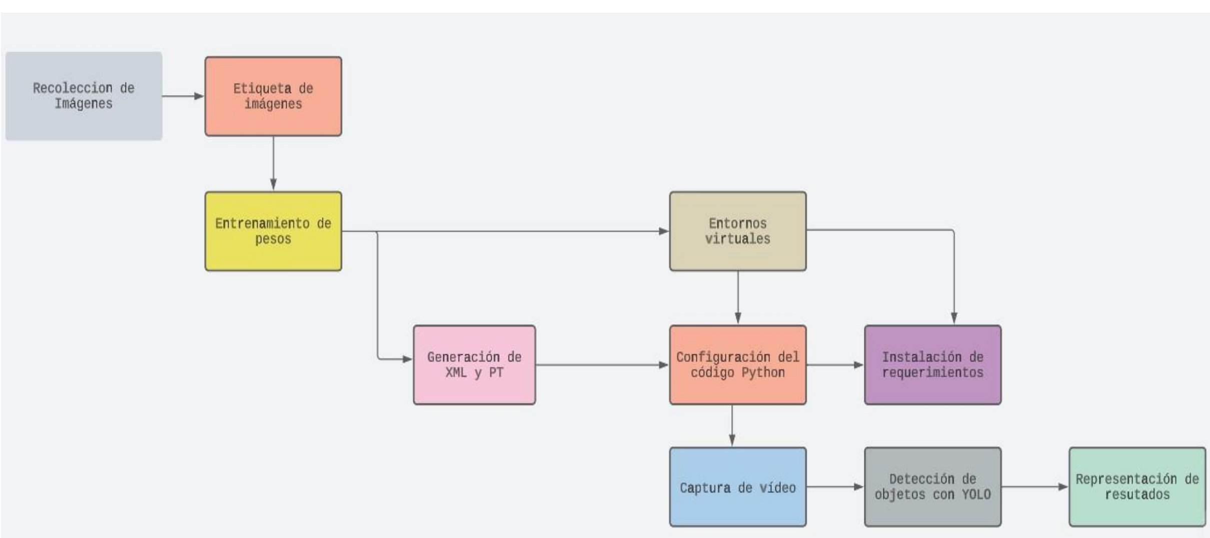
Autopista Sur - Carrera 72	48
Autopista Norte - Calle 114	47
Avenida Las Américas - Avenida Boyacá	167
Avenida Boyacá - Calle 80	161
Avenida Boyacá - Calle 13	125
Avenida Las Américas - Carrera 68	109
Avenida Las Américas - Carrera 114	99
Carrera 15 - Calle 100	96
Avenida 1 de Mayo - Carrera 50	82
Avenida Boyacá - Avenida 1 de Mayo	78
Avenida Las Américas - Carrera 50	77
Carrera 68 - Avenida La Esperanza	76
Autopista Norte - Calle 127	71
Autopista Norte - Calle 100	68
Autopista Sur - Carrera 63	62
Autopista Sur - Calle 59 Sur	61
Avenida Boyacá - Calle 53	58
Autopista Norte - Calle 103	56
Autopista Sur - Carrera 72	49
Autopista Norte - Calle 114	48

3.2. Implementation of YOLO in Python: Codes and use of the YOLO model for road stakeholder identification.

YOLO "You Only Look Once" is a model for object detection in images and videos that has been shown to be highly effective and efficient [25]. It uses a single convolutional neural network to predict the bounding boxes and classes of objects present in the image in a single pass [26]. The implementation of YOLO in Python involves the use of libraries such as TensorFlow, Keras or PyTorch, depending on the Deep Learning framework chosen [27]. To identify road actors, the model must be trained with a labeled dataset containing images of road actors and their bounding box and class annotations. Once trained, the model can be used on new images or videos to detect road actors in real time [27-28].

This approach is especially useful in moving object detection applications, such as vehicular flow analysis, due to its ability to detect multiple road actors simultaneously with a trade-off between accuracy and speed [29]. The Python implementation offers a powerful tool for accurate and efficient identification of objects of interest in fields such as road safety, traffic management, and urban planning [30].

Figura 1. General training scheme used for image recognition with YOLO [31].



3.3. Implementation of Haar Cascade in Python: Codes and use of the Haar Cascade model for road stakeholder identification.

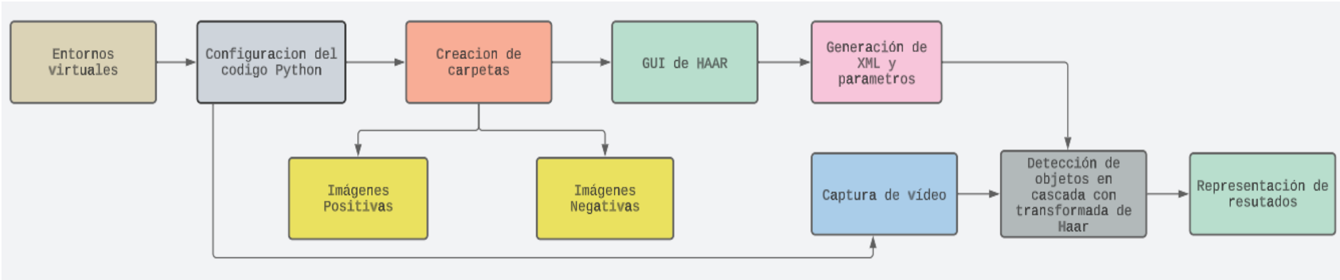
Haar Cascade is a popular and widely used method for detecting objects in images, specifically in road actor identification [32]. It is based on Haar features, which are visual patterns for distinguishing objects of interest in an image. These features are computed in different regions of the image and used to train a classifier, which is then used to detect objects in new images [33].

The implementation of Haar Cascade in Python is done with libraries such as OpenCV, which provides pretrained functions and models for various objects, including road actors such as cars, motorcycles, and traffic signs [34]. The process starts with the creation of a training dataset with positive images containing the objects of interest, and negative ones not containing them. Then, the model is trained using this dataset, extracting Haar features and building a classifier [35].

Once the model is trained, it can be used to detect road actors in new images. The Haar Cascade implementation in Python provides functions to load the trained model and apply it to the input images. The model analyzes the image for Haar features corresponding to the objects of interest and generates predictions of their presence [34].

It is important to note that Haar Cascade is most effective in detecting static objects and objects with distinctive features, such as defined shape and edges. However, it may have difficulties with partially hidden objects or in varying illumination and perspective conditions [35].

Figura 2. General training scheme used for image recognition with Haar Cascade. [36]



3.4. Mathematical modeling for object detection using Computer Vision in Python without using pretrained networks.

The approach presented in this paper differs from previous methods that used pretrained networks such as YOLO or Haar Cascade. Instead, it focuses on developing custom algorithms and mathematical models for road actor detection [37].

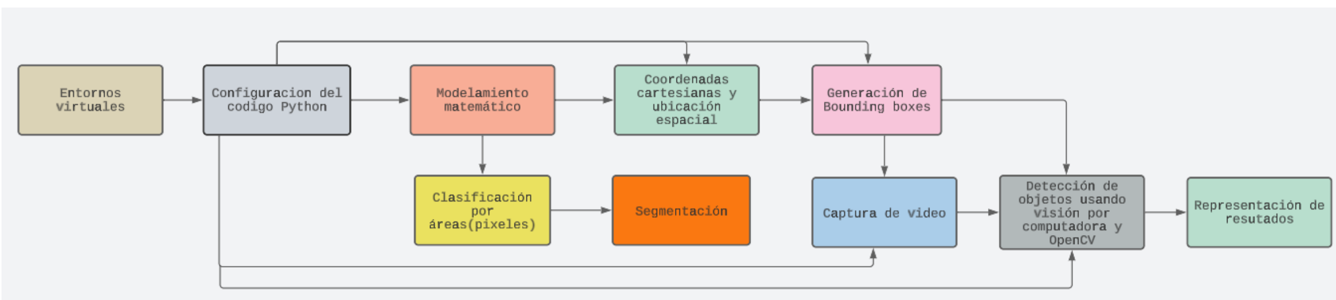
Mathematical modeling for object detection involves the design of algorithms that take advantage of specific characteristics of the objects of interest and the properties of the images in which they are located. These algorithms rely on mathematical principles and image processing techniques to identify and locate road actors in an image [3].

To carry out this approach in Python, there are several libraries and tools such as NumPy, SciPy and OpenCV that facilitate image processing and the implementation of custom algorithms [37].

The mathematical modeling process for road actor detection requires understanding the visual characteristics of the objects of interest and defining a set of rules or algorithms for their identification. This includes the extraction of features such as edges, textures, colors, or shapes, as well as the use of segmentation and classification techniques to distinguish objects from the background [38].

Although this approach offers advantages in terms of flexibility and control over the detection process, it is important to keep in mind that its implementation can be demanding in terms of algorithm design, development and tuning [39]. In addition, it may present limitations in terms of robustness and generalization to different situations and imaging conditions. However, for those cases where adaptability and customization are essential, mathematical modeling in Python represents a valuable and powerful alternative [32].

Figura 3. General training scheme used for image recognition with Computer Vision without using Deep Learning. [40]

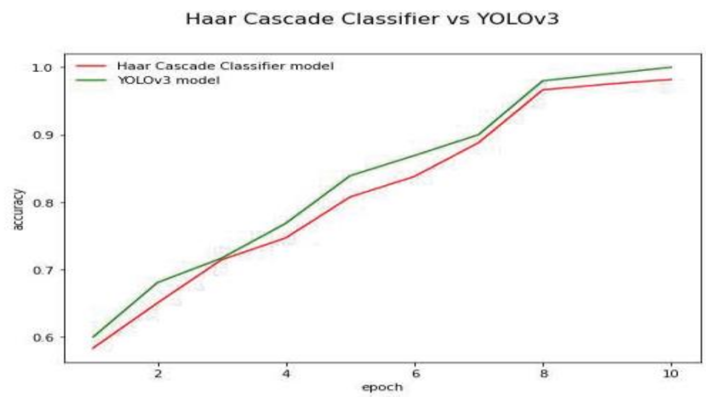


4. Conclusions

YOLO stands out for its efficiency and accuracy in road actor detection, outperforming Haar Cascade with an accuracy rate of 95% compared to Haar Cascade's 80%. Although YOLO may require a few extra seconds to analyze an image, its ability to identify road actors more accurately makes it the preferred choice for applications requiring reliable detection. Furthermore, compared to Haar Cascade, YOLO is still quite fast in processing and is especially relevant in applications where accurate detection of road actors is needed, such as real-time vehicle flow analysis and decision making in traffic environments. With its 95% efficiency, YOLO presents itself as the most favorable choice for this project, as it offers more accurate and reliable detection, outweighing the benefits of Haar Cascade's slightly faster processing speed.

In conclusion, YOLO stands out as the preferred choice for applications requiring accurate and reliable road actor detection, thanks to its superior efficiency and accuracy compared to Haar Cascade. Although it may imply a slight decrease in processing speed, the benefits in terms of accuracy make YOLO the most favorable choice for projects requiring more effective detection.

Figura 4. Training accuracy plot between YOLO and Haar Cascade. [41]



5. **Future work in the field of object detection in road environments in Bogotá:**

Improving accuracy and speed: Research and develop techniques to improve both the accuracy and speed of object detection in road scenarios. This could involve optimizing existing algorithms or exploring new neural network architectures.

Detection of multiple classes of objects: Expand the scope of object detection to include multiple classes of vehicles, pedestrians, traffic signs, among other relevant elements in road environments. This would require a broader approach to object classification.

Real-time implementation: Work on the implementation of real-time object detection systems that can be deployed on mobile devices or surveillance cameras for continuous monitoring of traffic and road safety in Bogota.

Integration of warning and predictive systems: Develop systems that not only detect objects in real time, but are also capable of generating early warnings about risky traffic situations, such as potential collisions or unsafe behavior of road actors.

Data analysis and traffic patterns: Use the information collected through object detection to perform deeper analysis of traffic patterns in Bogotá, which could contribute to urban planning and the implementation of more effective mobility policies.

Incorporation of emerging technologies: Explore the integration of emerging technologies such as reinforcement learning or natural language processing to enhance the capability of object detection systems in roadway environments.

These areas of research can contribute significantly to the advancement of object detection in road environments in Bogotá, improving road safety, traffic management and urban planning in the city.

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