EVALUATION OF TRANSPORT EVENTS WITH THE USE OF BIG DATA, ARTIFICIAL INTELLIGENCE AND AUGMENTED REALITY TECHNIQUES.

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ABSTRACT

The phenomenon of "smart cities" generalizes the use of Information and Communication Technologies. The generation and use of data to manage mobility is a challenge that many cities are betting on and investing in. Through the Internet of all things (IoT) and the use of sensors and mechanisms for capturing information, the number of data analysis tools such as Big Data, Artificial Intelligence (AI), and Augmented Reality (AR) has increased.

The tools that are used to interpret events are applied to the analysis of video and photographic images and comprise of a set of programs, mathematical algorithms and protocols. The implementation of procedures could enable the automatic interpretation of image information, from the most basic such as changes in the presence of objects or people, to the identification of complex shapes and relevant event detection. With the constant use of the assisted process learning (Machine Learning), it's possible to improve event interpretation through the customization of learning protocols.

Repetitively trained software can identify relevant events and report changes in critical scenarios that can trigger a series of protocols. The use of artificial intelligence techniques makes it possible to automate monotonous processes and improve transport management.

This article analyzes different technologies used to generate transport information and data validation. It is intended to experiment with the use of technologies in the detection of relevant facts, changes of state, and identification of events. It also measures the reliability level when detecting events, and studies the implementation of possible solutions into the transport management system, in order to assist in decision making processes.

1. INTRODUCTION

There is an increasing interest in the potential of the Information and Communication Technologies to manage and police urban transport issues. Recent advances in urban monitoring and sensoring applications have broadened the landscape of managing transport operations and infrastructures. Monitoring of transport processes is a key issue in efficient mobility. Sensoring and monitoring not only reduces the need for expert operators, thereby lowering costs, but it also allows quicker incident detection and consequently its prompt risk management.

This article aims to show a series of experiments in the field of transportation management in which Big Data, Artificial Intelligence and Augmented Reality techniques are used with different levels of interaction and integration. The experiments carried out are intended to show in an empirical way potential uses of these technologies separately and with different degrees of integration in order to try to manage specific situations of parking places management in urban sections.

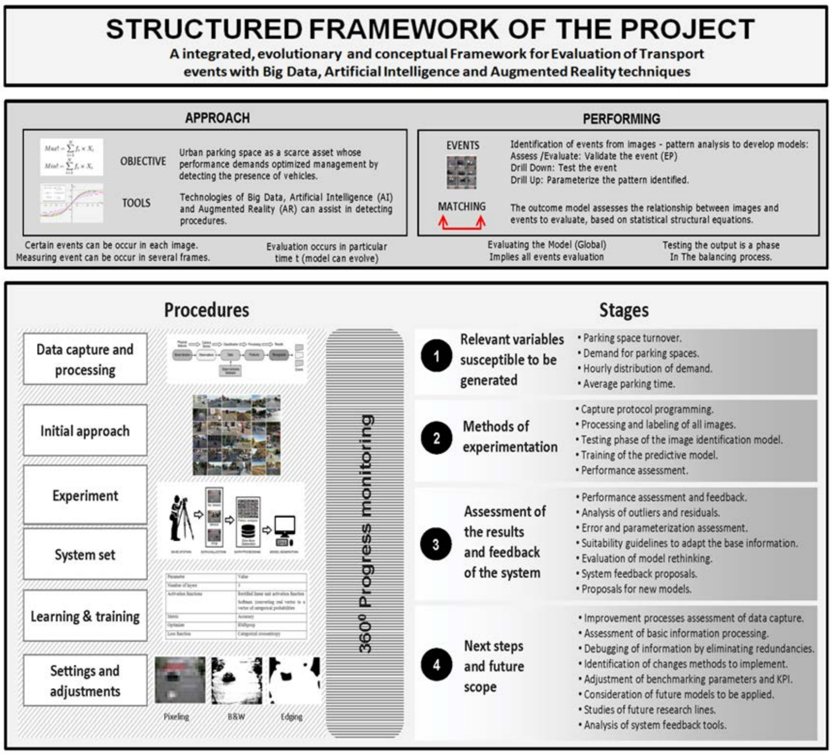

Figure 1. Structured framework of the project.

The purpose of the experiments carried out in this study is to provide better tools for managing parking spaces. Vehicles detection is considered as a challenging field in computer vision. The experiments are based on the recognition of traffic-related events, specifically the identification of changes in traffic and parking status. Artificial Intelligence protocols will be used for this purpose. Next, management and communication techniques of relevant information and assistance in decision making by the agents involved in mobility management will be used, evaluating in some cases the introduction of Augmented Reality methods. Finally, Big Data techniques have a transversal character as they are present in the implemented applications of Artificial Intelligence and Augmented Reality.

The article frames some applications in the domain of mobility, Smart Cities and urban space Management. In addition, several experiments were carried out to develop a vehicle detection system. Various smart technologies have been repurposed to inform appropriate response measures. It has been evaluated as the combination of AI and AR technologies yielded the best results.

2. AWARENESS OF THE PROBLEM

2.1. Urban parking space as a scarce asset that should to be optimized.

In urban environments, motorized vehicle trips require the reservation of space for circulation and parking, especially in areas with high demand and intensive land use. Traffic space is shared by private vehicles, but also by public transport, bicycles and pedestrians. For the authorities in charge of managing public space, it is a challenge to distribute uses for transit, private vehicles, pedestrian and parking mobility.

In urban central districts, public space is a scarce resource that is assigned to different uses. It can be considered, that much of the public areas are divided between the surface reserved for pedestrian traffic, mainly sidewalks and roads dedicated to traffic. The sidewalks are reserved for the priority transit of pedestrians, although in certain sections the circulation of bicycles and the parking of two-wheeled vehicles are allowed. In turn, there are areas of unique access to pedestrians (parks, gardens, beaches ...). The circulation routes are dedicated to the vehicles with reserved sections according to uses (bus-taxi lane, bike lane ...). A part of the road is reserved for parking vehicles on the surface with different types of regulations and different reservations.

The great demand for public space in dense urban environments pressures the specialization of land uses and its reserve for specific uses, both dedicated and by time slots. The management of such a scarce resource requires the application of different techniques and technologies that allow optimizing its use. In this sense, different technologies can contribute decisively in the management of mobility and optimization of public space uses.

The use of Big Data, AI, AR applications in the field of urban mobility can bring advances in the control of the mobility that can result in the improvement of safety conditions and the transports system efficiency.

The allocation of public space and its distribution among different users and modes of transport is one of the most important policy areas of territorial management in general and mobility in particular. The management of public space includes traffic management, integrating measures aimed at adjusting the supply of public space with the demand for mobility, taking into account the different modes of transport and their road space requirements.

The city of Barcelona has 1,362 kilometers of roads. The basic network comprises 27.5% of the streets of the city, which absorb 82.04% of circulation. The City Council has carried out, in recent years, pacification projects, especially in the central areas of the different neighborhoods. The measures implemented consist of reconverting areas for pedestrians, widening sidewalks, raising roadways and creating unique platforms, as well as reducing the accessibility of motor vehicles and speed of traffic to ensure the safety conditions.

From the data of the statistical yearbook of Barcelona, table 1 shows the evolution of the surface of sidewalks, road and the length of the streets. It can be observed how the extension of surface area for pedestrians has expanded in recent years, while that for cars has decreased (AJUNTAMENT de BARCELONA 2015; 2018).

Public Road	**2011**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**
Street KM	1361,8	1369	1369	1368	1368	1368	1368
Total Surface of Barcelona (km^2)	102,6	102,6	102,6	102,6	101	101,3	101,3
Surface intended for the vehicle (km^2)	10,9	11,4	11,4	11,4	11,4	11,4	11,4
Surface intended for the pedestrian (km^2)	15,32	15,81	15,81	16,18	16,83	17,52	17,52

Table 1. Evolution of the distribution of space in the city of Barcelona.

The municipal forecast is that all streets that are not part of the basic network have to become part of a pacified zone. These streets have to have a different character, depending on the hierarchy they occupy within the secondary network (segregated spaces, single platform, etc.) and they have to abide by the restrictions in the speed of the vehicles and priorities of step that regulate them. According to the municipal data, currently, about 56% of the city's road network gives priority to pedestrians or is pacified.

The road network has acquired a great specialization. It has gone from a wide basic road network, to a greater segregation of the road by uses, so that the local road network or non-basic network, is hierarchies in different categories. In urban dense areas such as the City of

Barcelona, mobility management implies acting on a great variety of modes of transport. The priorities are to reduce private vehicles mobility and promote public transport. Although it is desirable to discourage the use of private vehicles, it is also important that those private vehicles that circulate can do it smoothly, without congestion.

The challenges posed by the "smart cities" and their concretion in the "smart mobility" involve the implementation of technologies such as assisted and autonomous driving, sensitization, processing and massive use of data (Big Data), geolocation, systems navigation, Artificial Intelligence (AI) and other areas that make the knowledge of the current behavior of users of motorized two-wheelers have a great future potential and opens the way to a wide field of research (VIDAL TEJEDOR, N. 2015; VIVES, A 2018).

3. USE OF BIG DATA, ARTIFICIAL INTELIGENCE (AI) AND AUGMENTED REALITY (AR) IN URBAN TRANSPORT MANAGEMENT

The Big Data, the Artificial Intelligence (AI) and the Augmented Reality (AR) tools use will reshape the urban transport management, leading to fast adoption of more efficient transport integrated systems at an unprecedented rate. Traffic professionals continuously apply management strategies in order to maximize the productive use of the infrastructures. The use of those technologies could elevate and improve the transport management experience dramatically. This article focus on use of Big Data, Artificial Intelligence (AI), and Augmented Reality (AR) has increased to help solve problems of Transportation Analysis aiding human intelligence in functioning of machine and systems.

Big data implies an exponential availability of information and its accessibility, which enhances the capacity to assess data relevance. The significance of information is proportional to its meaningfulness. Its value lies in how we use it to guide our decisions and place it in a specific knowledge framework.

Some authors have highlighted the potential that Augmented Reality has, so that they consider that a breakthrough is not only machines that think, but machines that allow us to increase our perception and how the fact that officials will have improved cognition systems can transform power relations (Anderson, R. 2020.). Thanks to the development of the Artificial Intelligence (AI) new forms appear in the convergence of machine learning and deep learning. The union of Machine Learning algorithms with artificial neural networks and deep learning are being used in numerous and several fields. Artificial intelligence is already embedded into traffic control the ability to detect the presence of pedestrian and vehicles (BENGTSSON, P. 2018).
The developments that Big Data has brought about in the efficiency processing of huge quantities of data are closely related to Artificial Intelligence and Augmented Reality applications, making possible better learning algorithms (PASTOR, R. (2018).

On the basis of the number-crunching power is the improvements of digital computers. The exponential rise in crunch power lets ordinary-looking computers tackle tougher problems of Big Data and pattern recognition.

The optimal approach to getting machines to solve difficult real-world challenges is to set them up as statistical learning machines that can benefit the most from exposure to massive amounts of data. These technologies can come to learn to solve complicated tasks by detecting patterns, and patterns between and within patterns, hidden from the vast data streams to which they are exposed. Big Data technologies have made it possible to provide a capacity to manage enormous amounts of data with which to feed the algorithms that underlie Artificial Intelligence technologies. Data crunching is at the basis of the operation of deep learning algorithms that make it possible to profoundly examine data flows, yielding systems that work to provide solutions to solve problems, but whose knowledge structures are opaque to the technicians who created the system, so that the resulting algorithms can be used with levels of significance of the results, totally unaware of the reasons that make their significance levels possible. In this way is acceptable that current and future AIs solutions are forms of intelligence feeding off Big Data and crunching statistics in ways that render their operational engines opaque to human understanding.

Artificial Intelligence (AI) applied to the interpretation of video or photographic images comprises a set of programs, mathematical algorithms and protocols that make it possible from a process assisted learning (machine learning), the possibility of interpreting events from the computer processing of images. From the customization of learning protocols, in an automatic way it is possible to interpret events in images, from the most basic ones, such as the presence of objects or people, to the identification of complex shapes.

The use of Artificial Intelligence (AI) can be a valuable tool to assist in the detection, interpretation of events, state vision, and identification of relevant facts. In this sense it can be useful in assisting in case detection, alert triggering and helping in decision making to assist in dealing with situations that demand more or less immediate responses.

There are several areas in which these technologies are used in the management of traffic. One of the main fields is vehicle identification: AI in the area of traffic management can be used mainly in traffic jam recognition and management. These systems could perform the task of tracking and locating vehicles in real time and adapt traffic management according to current or predicted conditions to accommodate lanes or fast sections for emergency services. These technologies can also be used to detect infractions, which will help municipal and traffic authorities to identify them, develop effective prevention systems and apply the corresponding penalty (JIN, J. and DENG, Y. 2017).

However, the adaptation of these technologies to cities and roads must consider safety, so it is necessary to establish systems that prioritize avoiding traffic accidents; one of the additional facilities performed by these technologies are the identification of people at risk, in order to warn or prevent reckless actions of pedestrians, crossing streets inappropriately, identifying motorcyclists who did not wear helmets properly (CHIVERTON, J. 2012) and estimating the driver's workload (MANAWADU, U. E. et al. 2018).

BARLOW,H.(1989) was one of the first to appreciate the importance of unsupervised learning as opposed to reinforced learning, so that unsupervised learning applied to big data and artificial intelligence allows to identifies "statistical regularities", or patterns in its inputs in the form of possible discrepancies that allow it to identify and deal with potential underlying patterns. This information theory-based approach embodies many modern approaches to unsupervised learning in neural networks and Bayesian learning.

4. RELEVANT VARIABLES SUSCEPTIBLE TO BE GENERATED

The purpose of the experiments carried out in this study is to provide better tools for managing parking spaces in urban sections. Vehicles identification is considered as a challenging field in computer vision. We consider the vehicle detection problem as the basis for extracting relevant variables for parking space management in urban areas sections.

We study the case of the vehicle presence identification in parking line section. Our research goal is to test a method to identify vehicles and types of vehicles presence in a street section. Once an object has been detected, the next challenge is object localization in the section. Object detection deals with finding the objects that are present in an picture. The technologies for the recognition of elements in a road section are based on the interpretation of a set of digitized data captured by different means. Based on these data, different tools can create analogies and models that simulate the presence of defined objects on a road section. One of the most common applications of Big Data, AI and ER is the use of photography to identify events. In the case of urban traffic a primary event would be to recognize the presence or not of vehicles on a section road.

Once the presence of vehicles on a stretch has been detected, we can lay the foundations for building variables such as counting vehicles, estimating speeds, identifying vehicle types, calculating parking space turnover, detecting violations and many other different variables relevant to traffic and parking management. With the above technologies we can develop accurate techniques to identify the presence or not of vehicles in a stretch and we can have a basic tool to develop traffic management devices.

A basic stage would be to have a device, in this case that answers the bionomial question: Are there or not vehicles on a specific section, with a Boolean answer.

Knowing whether there are vehicles on a road or in a parking space is relevant information for traffic management. If the information can be obtained periodically, we are able to evaluate changes in status.

So it can be used to detect presence, and count vehicles in a section (measuring capacity) or to determine the rotation of parking spaces. In this way, the dynamic management of information and its analysis can be relevant in traffic management.

Relevant variables related to parking space management that can be expected to be generated in future phases of our experiments are:

- **Parking space turnover:** number of vehicles parking in a space over a period of time.
- **Demand for parking spaces:** Usage ratio, based on the number of vehicles driving on the section and the number of vehicles that end up parking.
- **Hourly distribution of demand:** Use of parking spaces throughout the day and therefore peak and off-peak periods.
- **Average parking time:** Length of time the vehicle is parked in the space.

In order to generate all of the above variables, the basic variable to work with is to detect the presence of vehicles on a section of road. So if it is not possible to detect the presence of vehicles, it is not possible to progress to the following phases. This is why the experiment focuses on identifying the presence of vehicles on a stretch of road. Once a high level of reliability is achieved in identifying the presence of vehicles on a stretch of road, it is possible to move on to more complex phases of information generation, such as identifying parking in a spot and, from there, estimating parking times.

5. METHODS OF EXPERIMENTATION AND PROCEDURES TO DETECT PRESENCE OF VEHICLES IN A STREET SECTION

5.1 Outline of the methodology applied.

The study is forward-looking in approach. The initial objective is to produce a large number of images that will allow the building of a database in which each image will be linked to certain attributes for fields. Starting from the basic information, the learning process is conducted, following which the levels of accuracy are evaluated. Then different techniques are applied to improve the reliability of the results. Finally, the results are presented and a proposal is made for uses and future developments.

The phases of the project are:

1. **Capture protocol programming.** In order to obtain images from the installed cameras, it will be necessary to develop a computer program to capture the images. For this purpose, software will be developed with code that will implement the following operations at each programmed interval: open the browser with the IP address, capture the images for each image, label the images and store them sequentially in a database.
2. **Processing and labeling of all images:** Generation of image database. A database will be designed with the identified attribute fields of the images. Then a specialist will analyze the images one by one and will fill the database with the selected attributes.
3. **Testing phase of the image identification model.** Based on the images and the associated database, it is possible to develop the testing phase for the identification of events in the images.
4. **Training of the predictive model.** The central phase of the application of Artificial Intelligence techniques goes through the training of the model, from different treatments of the images adapted pixel matrices and chromatic treatments.
5. **Test run. Once the model is trained, it is possible to identify the degree of reliability in the identification of events.** Once the program has been run with the images to be detected, reliability tests can be performed in different scenarios.
6. **Performance assessment.** Result study to improve predictability, elimination of false positives and robustness of the system. From the statistical reliability data of the systems, different techniques can be applied to debug the results and filter out false positives, thus increasing the degree of reliability of the system.

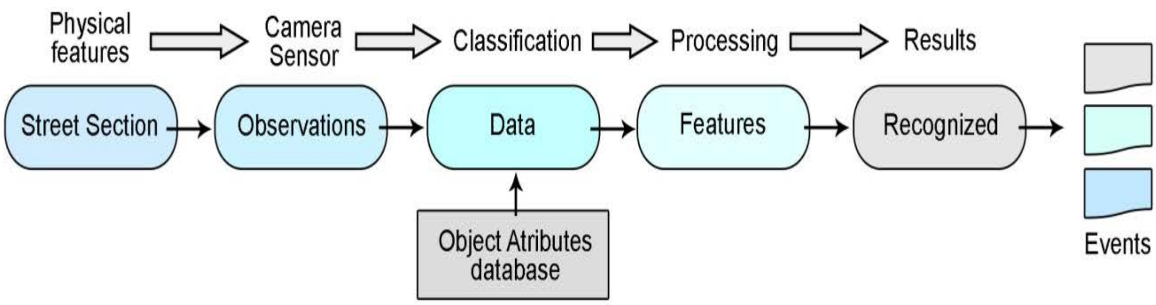

Figure 2. Process scheme of the built-in procedure from the data collection system to the handling of the data and the identifying stages.

5.2 Initial approach to vehicle presence identification.

A first exploratory experiment has been carried out, consisting of analyzing photographs from different sources related to stretches of roads. The purpose of the exercise was to assess the feasibility of assessing the presence of vehicles on different stretches of roads regardless of the origin of the information collected, so that if the experiment proved to be satisfactory, we should be able to have a generalist tool for assessing the detection of the presence of vehicles on stretches of traffic sections.

In this experiment the first level was carried out in the following way: Initially we proceeded to capture images of the Google Street View application with the intention of having a sufficiently large bank of images to start testing with the AI software. A total of 2,097 photos were captured, which were classified manually on the one hand, depending on whether vehicles were observed or not; and on the other hand, depending on whether they were in an urban or interurban environment.

The classification of the images was carried out to evaluate the degree of success of the application, being able to compare the results obtained from the analysis of the images by the analysis application with those observed by a person.

Figure 3. Sample of images used in the performance of the experiment to identify the presence of vehicles and the type of road section.

Two different experiments were carried out on two scopes of information contained in the pictures: One experiment tested whether or not vehicles were detected on the section and the second experiment tested whether the section was an urban street or an interurban road. The analysis was carried out by performing binomial tests in which two sections were performed: a first phase of model training and a second level of testing on the presence or absence of the event.

The results were found to be poor and unreliable. Therefore, it became obvious that the kind of images used did not lead to results that could be suitable as a basis for the development of any kind of application.

It was found that there are different factors causing the poor results, among others the different sizes, lighting, exposure, orientation, quality and accuracy of the images. These considerations lead to the conclusion that in order to conduct this type of experiments it is necessary to consider initially the use of images taken by the same camera, focus, ambient, exposure, orientation and zooming.

6. EXPERIMENT

6.1 Design of the experiment.

In this section, we described in detail the experiment carried out about how to detect vehicles on an urban street section from images and the usage of the technology.

The poor results of the initial approach using external images and explained in the previous section led us to the perspective that in order to have a better control of the experimentation it is relevant to generate one's own images. That is why we conducted this new experiment using raw images captured by our own devices and which are explained as follows.

The experiment consisted of selecting a section of urban section to initially analyze the phenomenon of the presence of vehicles on the stretch. Once a high reliability in the detection of the presence of vehicles is achieved, it is possible to advance in the generation of variables for monitoring the use of parking spaces by vehicles.

An ideal environment was sought in Barcelona that met the requirements: continuous presence of vehicles, among which: cars, taxis, motorcycles, bicycles, as well as the presence of pedestrians.

The photos had to be taken from a certain height in order to obtain a clear image of several lanes of traffic and thus control vehicle traffic. All these requirements were met, in the centre of the town of Barcelona, which supports a high rate of circulation compared to other parts of the city.

The place chosen was the Carrer de Provença, from a floor where the circulation of the vehicles was observed properly by the two existing lanes, as well as a two-way bike lane is observed and a pedestrian alley is available. It implies the continuous transit of pedestrians which cross the Carrer de Provença.

Figure 4 shows the elements of the set. Image capture was conducted with a Canon camera (model EOS 50D DS126211 and Canon zoom lens EF-S 17-85mm F 4-5.6 IS USM) and the storage of the images was downloaded into a DELL laptop. OpenCV, a computer-vision library was used for automatic image processing.

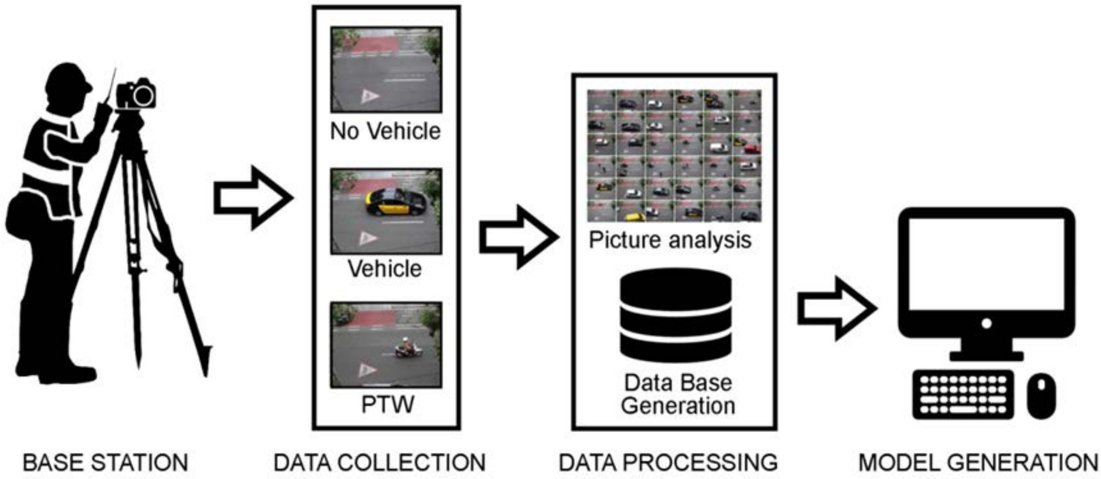

Figure 4. System Set. Design of the images capture system from a base station and data processing for the preliminary pretreatment of the data.

Once the location was chosen, several tests were taken to evaluate the chances to collect the images in the adequate environment conditions. The frame of action has been a stretch of road considering the width and the set of lanes that make up the section.

The location had adequate visibility conditions so that data collection could be performed in an automated manner without the continuous assistance of operators.

A camera was pointed at the road and pictures were taken over a period of time. The camera was connected via cable to the DELL laptop. The first realized were made from the time-lapse of the camera while was connected to the laptop, it was programmed so that every five seconds it took a picture. Once this step was done, they began to classify the photos.

For the management of the photographs, it was used as a photographic assistant the software of the Canon Reflex camera used to perform image capture. The computer used for data processing has an Intel I5-9400 processor running at 2.9 GHZ, with a RAM memory of 19 GB, and the graphics card used is a Radeon RX-580 graphics card.

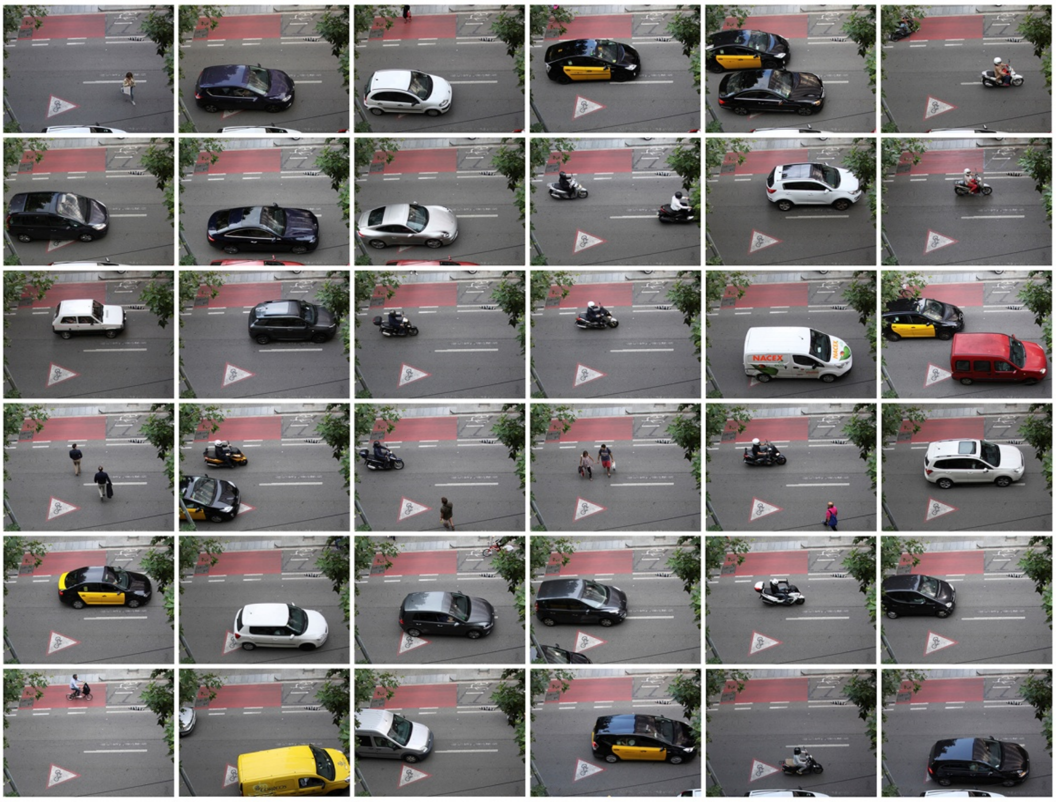

Figure 5. Sample of different pictures taken for the performance of the experiment.

Each photo was analyzed by a specialist and a database was created in which the numeration of the photograph was collected and the following fields were filled in with binary data (0: negative; 1: positive): presence of vehicle, the vehicle is a car, the vehicle is a PTW, the vehicle is a heavy vehicle, the vehicle is a cab. (LIM, G.H. et al.).

Picture #	Vehicle presence	Car	PTW	heavy	Cab
#00001	0	0	0	0	0
#00002	0	0	0	0	0
#00003	1	1	0	0	0
#00004	1	0	1	0	0
#00005	0	1	0	0	0

Table 2. Fields of the dataset

The use of deep learning allows detecting an object with certain accuracy. Open source AI libraries and data flow graphs were used to develop the neural network. To create neural networks with different layers, TensorFlow and Keras (an end-to-end open source platform for machine learning by Google) as a R modules was used, which allows building a neural network based on the requirements of the model with Keras deep learning API.

Once pre-processing data was done, before training the sequential model, values for hyper parameters were chosen. Batch size (number of training examples present in a single batch), epoch's number (number of iterations passing the full dataset by the network) and learning rate (amount that the weights are updated during training) have to be fixed.

The used hyper parameters are shown in the following table:

Hyper parameter	Value
BATCH-SIZE	128
NUM_EPOCHS	100
LEARNING RATE	0.01

Table 3. List of the selected values for the hyper parameters selected for sequential training.

The API requires other general parameters to compile the Keras model that in this case are fixed as the following table summarizes:

Parameter	Value
Number of layers	3
Activation functions	Rectified linear unit activation function Softmax (converting real vector to a vector of categorical probabilities
Metric	Accuracy
Optimizer	RMSprop
Loss function	Categorical crossentropy

Table 4. Summary table of additional general parameters applied in the compilation procedure of Keras model.

About 2100 images were prepared to train. In our research, the primary target output is whether or not there was a vehicle on the section of road.

Two experiments were performed: the first one was to identify the presence of the vehicle on the stretch and the second one was to try to identify the type of vehicle.

The first experiment consisted in identifying or not the presence of a vehicle on the section. From the training phase images with and without vehicles on the section where used and then went on to a second phase to perform the testing of the training carried out previously. Once the algorithm is selected, we proceed to split the pre-processed data. A percentage of the data, typically 80% of the total, will be used as training data and the rest 20% to evaluate the model performance.

Once the model is fitted, the next step is the model evaluation phase. This will be done with the remaining data, that which was not used for the training phase, which will be referred to as model evaluation data. In other words, it will be the data to which will be applied the fitted model. On this data will be used to achieve the initial objective and evaluate it.

The metric for assessing the results of the experiments is accuracy (simply a ratio of correctly predicted observation to the total observations) and precision (ratio of correctly predicted positive observations to the total predicted positive observations), which are calculated as shown below:

	Predicted class		
Actual Class		Class = Yes	Class = No
	Class = Yes	True Positive	False Negative
	Class = No	False Positive	True Negative

Table 5. Relation of the parameters applied in the classification of the classes and results of the events.

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \quad (1)$$

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

Where TP= correctly predicted positive values, TN= correctly predicted negative values, FP= incorrectly predicted positive values and FN= incorrectly predicted negative values.

The experiment of identification vehicles on the section was performed and a level of 64 % was matched.

The results have a level of significance that allows us to propose in the advance of performing calculations to count vehicles in a street section.

The second experiment that was carried out was to try to identify the type of vehicle. It must be taken into account that it is already part of a high determining factor and that is that the system has an accuracy level of 64% to detect or not vehicles in the section, so there is already a level of lack of precision to pass to the second experiment.

After the training phase (machine learning) and testing of the second experiment it was found that the results were not representative and therefore that the type of vehicle that circulated on the section could not be reliably identified.
Once the two initial experiments have been carried out, the conclusion is reached that for the

time being we discontinue advancing in an identification model of the typology of vehicles that are on a section of road and we focus on a model of identification of the presence/absence of vehicles in a section of urban road.

The next steps to be carried out in the following sections are the implementation of image processing adjustments and the use of augmented reality techniques, in order to improve the reliability of the model and the reduction of the volume of information to be managed.

Some adjustments were made to the images to reduce their size, decrease their resolution and switch them to black and white, so that more pictures could be taken in order to develop an experiment and obtain the most detailed results possible.

The following sections show different image debugging procedures and the application of data optimization methods to evaluate possible variations in the results obtained.

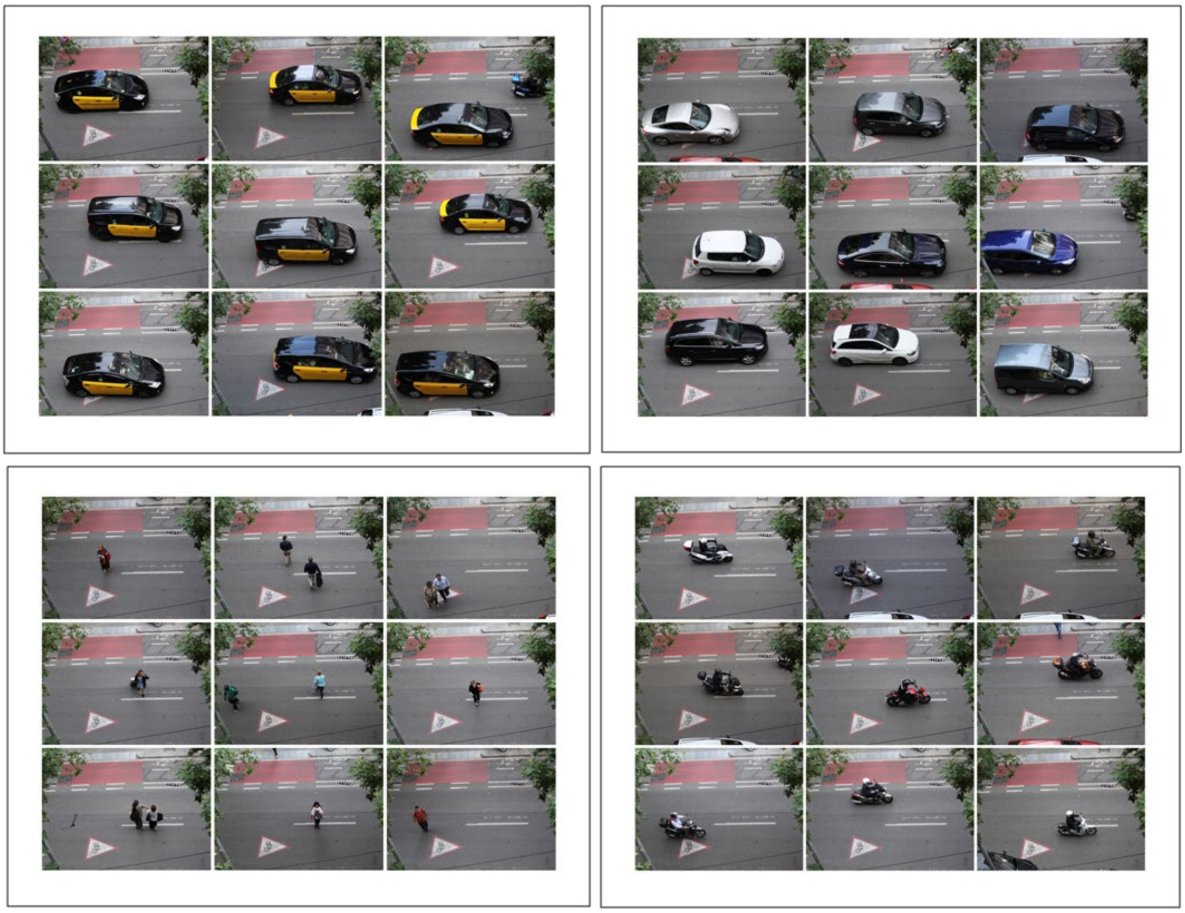

Figure 6. Different types of entities that can be identified in the information capture and analysis environment.

6.2 Reduction of image size by pixel processing.

One of the problems of working with photographs is that the more information they contain, the more accurate they are, but there is a significant increase in the size of the files, which makes them difficult to manipulate and process in the analysis and elaboration of results. (DEY, V., et al. 2010). Image pixelation allows the clustering of spectral information and enables the matrix comparison of a smaller quantity of data, which increases the processing rate of the information.

In this stage, we proceeded to apply techniques to reduce the size of the photographs by increasing the pixel size. The size of the photos has been reduced by enlarging the pixels. This is intended to manage the photos, improve the processing speed and even the data transfer if smaller photographs are available to keep the results high, the system experiences several improvements. First of all, a smaller volume of information is required, which increases the speed of data processing, analysis and transport.

It can be seen how by means of image pixelation techniques it is possible to significantly reduce the size of the images. The training phases (machine learning) and testing of the results are carried out and a reliability of 51% is found. Therefore, a significant reduction in the accuracy of the results is observed.

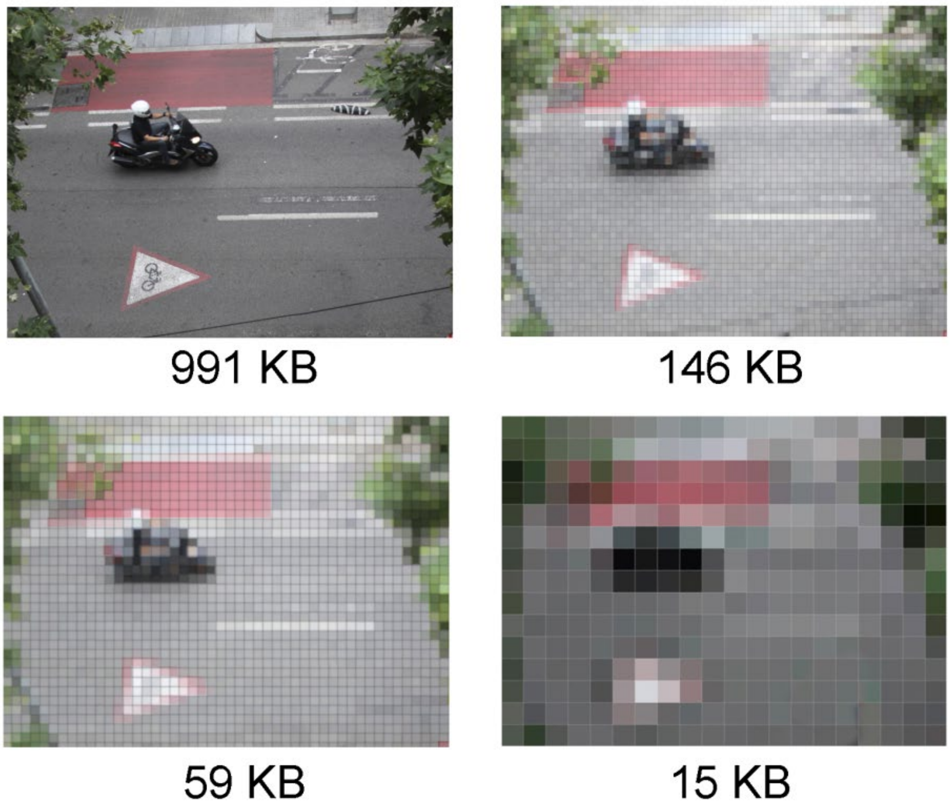

Figure 7. It can see the pixel processing with the output grid for size reduction in a ratio 65 times smaller.

6.3 Transformation of black and white photos.

We proceeded to process the images in black and white. Working with black and white images also helps to mitigate problems such as errors associated with shade and mitigates problems with bright light. The processing of the images goes through a phase of change to grayscale and then to black and white. It should be noted that the focus cannot cope with gradual illumination changes in the scene.

Vehicle detection is hampered by bright sunny conditions combined with shaded areas. Using black and white images can diminish the influence of excessive brightness and shadows "noise" in the frame. If the shadow contour is not clearly detached from the objects, the possibility of detecting moving targets is enhanced. Different algorithms for moving object detection work on detaching vehicles from their shadows to achieve better results (KILGER, M. 1992).

It is stated that the processing of the images to black and white allows reducing the size of the frames in the order of 7 times lighter in weight and thus simplifies data processing and transmission.

Once the images have been processed and rendered to black and white, the training process (machine learning) and testing of the results is carried out and a reliability of 48% is found. A significant reduction in the accuracy of the results is noticed.

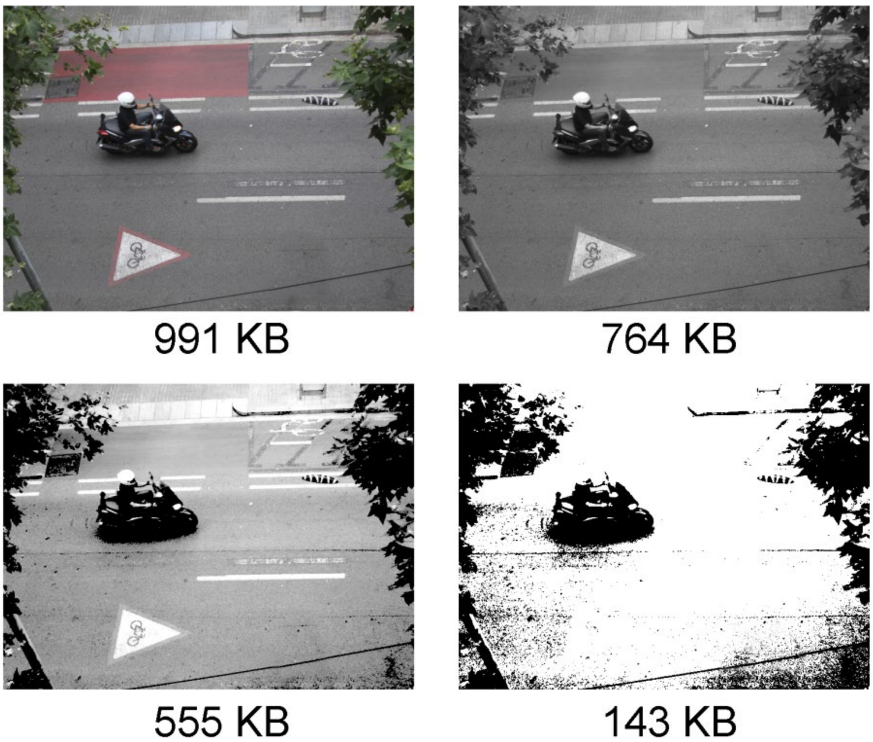

Figure 8. Sequence of frames of the processing of the color picture to grayscale, and subsequently to black and white with fading of the shadows and shines effect. It is evident a reduction in the size of the image of almost seven times the weight of the photograph.

6.4 Use of augmented reality techniques.

One technique that can be employed is to focus the analysis on the areas of the photograph where changes can occur. When working with a vehicle detection algorithm, one of the problems faced is that of redundant features not associated with the object to be detected. That is why in order to reduce the risk of presence of redundant elements it is useful to narrow down the plane of possible relevant events.

The subtraction or reduction of study areas involves analyzing a reference image shrinking the analysis area in each frame and scaring the result threshold. This is achieved by reducing the information and adjusting the binary segmentation of what is to be examined in the image, especially the detection of non-stationary objects. A photo processing technique can be applied in order to select attributes that can be mobile entities within the image and therefore, if their presence is detected in the picture, it means that there is a vehicle in the scene.

First of all, a reduction in the size of the images of more than 9 times the size was verified. After the training process (machine learning) and testing of the results, a reliability of 42% is checked. Therefore, a remarkable reduction in the accuracy of the results is registered.

The following is a sequence of images treated in order to identify features with volumetric attributes that could be related to a vehicle.

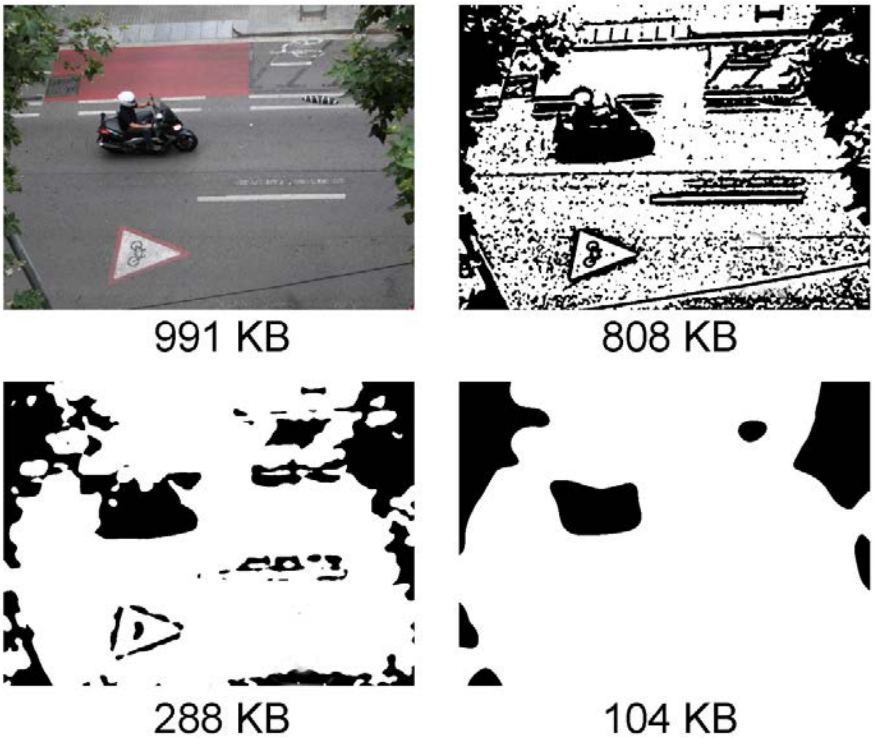

Figure 9. Transformation process of an image by reducing the information to volumes that could be identified as vehicles, and based on their presence or absence, test the detection model.

7. FUTURE SCOPE

7.1 Debugging of information by eliminating redundancies through the identification of changes.

SHANNON, C.E. (1951) emphasized how "redundancy" can be something like an opposite of information. BARLOW, H. (1961) developed an idea about redundancy reduction and pattern recognition, whose ramifications have influenced the debugging of Artificial Intelligence models, vindicating the need for interpreting the goals of the system to avoid heaps of irrelevant data that may result in crucial observations being overlooked. According to information theory, this can be achieved by eliminating redundancy through inhibition and adaptation. BARLOW, H. (1961) and ATTNEAVE, F. (1954) proposed the reduction of redundancies as a response through systems of transmission inhibition of non-relevant information. Barlow, H. suggested that at the level of the biological systems of sensory perception there are mechanisms adjusted to eliminate massive redundancy in order to avoid constantly informing about the state, so the relevant information to be reported to the system is changed in state, leaving the system to assume that everything not reported remains the same. In this way, the system reports information only when there is a change. This achieves a significantly reduction of the amount of information and it ensures that practically all the information that is managed is relevant, since by avoiding repetitions (redundancy).

If most of the data to be analyzed by the system come from events of possible changes, great savings in management and greater efficiency in interpretation are achieved. These methods have some problems and involve a training period with no objects in the plane under analysis. The movement of background objects after the training period and foreground objects without movement during the training period would be regarded as permanent foreground objects. (CHANGALASETTY, S. B. et al. 2014).

An intuitive method is to apply a Kalman filter to track changes in the background of each pixel in the image (KALMAN, R.E.1960). That tool attempts to assist in predicting future states of the system by taking the series of previous records. It's an algorithm for identifying states of a dynamical system that relies on the known information of the previous states of the given system by comparing with the previous ones.

An additional starting stage can be performed using a customized version of the moving segregating objects. An adaptive filter-based Kalman model could implement in future steps, to analyze the changing background conditions. The foreground is refreshed at each frame using the following update equation:

$$B_{t+1} = B_t + (\alpha_1(1 - M_t) + \alpha_2 M_t)D_t \quad (3)$$

7.2 Assessment of use of logistic regression to improve machine learning and binomial event classification.

In order to work with a dichotomous outcome predictor variable, Logistic Regression algorithms allows assigning the probability between 0 and 1. In this way a binary classification is obtained, with only two possible outcomes. The regression algorithm is one of the most prevalent and common classification algorithms found valuable in machine learning. The binary options allows to plot the coordinates of the set of features with their values and then attempts the most accurate function possible that can predict the output values of the input features.

The logistic regression model has two dependent and independent variables, while the dependent variable with two values is represented by proxy variables shown in the following equation.

$$P(x) = \frac{e^{(\beta_0+\beta_1 x_1 \cdots\cdots \beta_n x_n)}}{e^{(\beta_0+\beta_1 x_1 \cdots\cdots \beta_n x_n)}+1} = \frac{1}{e^{-(\beta_0+\beta_1 x_1 \cdots\cdots \beta_n x_n)}+1} \in [0,1] \quad (4)$$

7.3 Use of other software or analysis procedures.

In the field of study there is a continuous great amount of innovations and applications that can be implemented on the basis of images already available. In this case study it is relevant to have generated the images themselves, so that we can have our own base material. This material has been applied to carry out the present study, but as there are continuous innovations in the procedures, it is feasible to continue advancing in the improvement of the results already obtained from the use of other protocols and programs such as Wolfram, MatLab...

Advances are increasingly being made in computing power at a significantly higher level than ever before, benefiting from built-in computational intelligence based on a great depth of algorithms and knowledge that can substantially improve the results already obtained.

Futures line of research are the identification of possible innovations that may appear and the wide range of already available programs and methods that can test different domains of mathematical modeling, statistical applications, information management and data processing.

8. CONCLUSIONS

Several experiments have been carried out in order to develop tools to identify vehicles in urban areas using different technologies of Big Data, Artificial Intelligence (AI) and Augmented Reality (AR).

A first attempt has been made to identify vehicles in a stretch of road using images from different sources and it has been found that it was not an adequate approach. Subsequently It has been performed an experiment based on the shooting of our own images by locating an observation station and collecting pictures pointing to a specific segment of road.

After applying image training techniques, it was found that the most reliable results were obtained with the least treated frames, which retain the greatest amount of raw information. By applying artificial intelligence techniques on the unprocessed images, a result of 64% identification of the presence of vehicles on the section was achieved.

The subsequent experimentation carried out consisted of image processing refinements, the application of augmented reality techniques, in order to improve the reliability of the model and the reduction of the volume of data to be handled. To this end, the black and white photos were processed, the images were pixelated to reduce the information and size, and an attempt was made to identify the volumetry of moving objects. The summary of the results obtained is as follows:

Picture treatment	Recognition Accuracy
Raw	64
Pixel processing	51
Black & White	48
Edging	42

Table 6. Comparison table recognition accuracy (%).

It should be noted that there has been significant advances in the use of images own collected in a controlled environment, because it allows to work with data that are easier to be treated and adjusting the parameters to improve the result. The tests of different treatments of the images were carried out, obtaining mixed results. There were satisfactory results for the detection of the vehicle's presence, but in the application for the determination of the type of vehicle, the results were not reliable.

In global terms we must validate as adequate the concept of the experiment, the location and the methodology adopted. We can also consider the results as satisfactory and encouraging as a starting point for further progress in improving reliability.

Next challenges of using these technologies in the transportation sector will be to expand the fields of analysis to different areas such as pollution reduction, road safety, improved accessibility and seamless mobility.

Future lines of progress in the research could be considered such as the application of techniques for filtering the information by eliminating redundancies through the detection of modifications in the images; exploring the implementation of mathematical models to increase machine learning and binomial events, as well as examining the application of other software or analysis protocols.

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