Journal of Engineering and Technology for Industrial Applications

ISSN ONLINE: 2447-0228

ITEGAM-JETIA

Manaus, v.10 n.46, p. 15-21. Mar/Apr, 2024

DOI: https://doi.org/10.5935/jetia.v10i46.1109

RESEARCH ARTICLE OPEN ACCESS

DETECTION OF TRAFFIC ACCIDENTS USING ARTIFICIAL INTELLIGENCE

Jesus Gerardo Ávila Sánchez[1], Francisco Eneldo López Monteagudo*[2], Francisco Javier Martinez Ruiz[3] and Leticia del Carmen Ríos Rodríguez[4]

[1, 2, 3, 4] Autonomous University of Zacatecas, Av. López Velarde No. 801 CP 98060 Zacatecas, México.

[1] http://orcid.org/0000-0001-8518-2023, [2] http://orcid.org/0000-0001-6082-1546, [3] http://orcid.org/0000-0002-8842-7556, [4] http://orcid.org/0000-0002-1005-020X

Email: jesusw12@gmail.com, *eneldolm@yahoo.com, javier.martinezruiz@uaz.edu.mx, leticia.rios@uaz.edu.mx

ARTICLE INFO

Article History

Received: February 07th, 2024

Revised: March 19th, 2024

Accepted: April 26th, 2024

Published: April 30th, 2024

Keywords:

Machine learning,

Database for training,

Grid neural,

Traffic accidents.

ABSTRACT

This article analyzes different architectures with which a neural network can be developed using computer vision with the objective of detecting traffic accidents. For the development of the software, the Java Script programming language was used, reaching the conclusion that the best architecture to use is a Convolutional Neural Network since it has the capabilities of detecting features within the images. At the same time, a database was developed with the necessary characteristics for the functioning of the neural network.

I. INTRODUCTION

The objective of this research is to propose a database to implement a convolutional neural network trained for the detection of car crashes with a certain degree of effectiveness and with the ability to communicate to emergency services to contribute to saving lives, since as the average speed of vehicle driving increases, it also increases the probability of accidents and the severity of their consequences. Timely access to emergency care after a traffic accident can save lives and reduce the risk of disability among the injured; the key to an effective emergency care system is the establishment of universal access numbers [1].

To build the categories within the database, the data provided by the Ministry of Health of the federal government of Mexico was taken into account; traffic accidents are divided into three large groups. The first of them is the run over, the rollover, leaving the road, the fire and the crash; The second classification is the type of crash within this classification: head-on, reach, side, against the movement and the third classification is directed towards the target of the vehicle in motion [2].

In Mexico, the authorities state that there is a daily average of 9.6 Mexicans killed in traffic accidents and 56.6 injured. They have also recorded that 72% of the reasons why an accident occurs are attributable to the human factor, being the most common causes. incompetence, fatigue and drowsiness, only 14.73% are attributable to vehicle failures, [3].

Currently, the use of unmanned aerial vehicles (UAVs) in civil tasks is common, although the first data known about UAVs dates back to the 1950s and was exclusively in military applications [4]. Currently, with the release of this technology and its low production costs, they are more accessible for scientific development and public safety [5].

In the field of Machine Learning, there are projects aimed at detecting emergencies in traffic accidents, having the capacity to: predict accidents [6], use drones to assist in accident response [7], manage swarms of drones to maintain security in cities [8], image analysis for rescues in places with little or no accessibility [9]. We see that, despite what has been developed, these projects are focused on the ability to directly observe human beings, leaving aside the capacity of networks to detect the objects involved in the accident, such as cars. On the other hand, in databases for training and emergency detection with neural networks, the importance of progress in specialized databases for object detection with computer vision tools such as the ml5 library has not been considered [10] built with JavaScript and which is built on TensorFlow [11].

II. METHODOLOGY

The structure of the network is defined by the number of layers, the number of neurons in each layer, the degree of connection and the type of connection between neurons. However, the topology of the network depends on the complexity of the problem to be solved.

To develop an artificial neural network, several algorithms are used, of which the majority are based on adjusting the parameters of the network (value of the weights between the connections of neurons) previously designed, therefore, the training process is directly influenced. due to the limitations imposed in the design of the architecture of an artificial neural network (ANN) [12].

In this research, the data to be analyzed (images) were collected from an internet search, divided into a series of categories described by the Secretary of Health of Mexico, which are shown in Table 1.

Table 1: Number of images to train neuron network.

Platform	Category	Number of Images
GOOGLE	Car	1000
	frontal crash	250
	Side crash	250
	rear crash	250
	rollover	250

Source: Authors, (2024).

The general scheme to create the database and to detect traffic accidents with cars involved is based on the random search for images that contain vehicles in good condition, random search for images that contain vehicles involved in accidents, classification of the images collected in training and prediction classes and tests. The images selected to be part of the database must not be processed in advance. Table 2 contains the statistics of the database (set of images) proposed in this article.

Table 2: Database statistics.

Amount	Medium resolution	Maximum resolution	Minimum resolution	Standard deviation	Minimum resolution images	Medium resolution images	Maximum resolution images
2000	257x195p	800x1333p	300x168p	28x39p	458	879	46

Source: Authors, (2024).

The classification and labeling of the set of images, in which there are cars involved in an accident, were classified as follows: the class (accident), and a series of images of cars without apparent error such as the class (car), where the accidents were classified based on apparent external blows to the vehicles and/or situations where the accident is apparently unequivocal, such as an impact, so it must be taken into account that human experience can generate failures in the implementation in an ANN.

In the experiment, the covolutional neural network architecture was used, which is the best option for prediction using this type of data. Likewise, the weights of each neuron will initially be assigned randomly. Tables 3 describe the types of models developed for the experiment.

Table 3: Model configuration.

<table>
<tr><th colspan="2">Model</th><th>Dense</th><th colspan="3">Simple Convolutional</th><th colspan="3">Drop-out Convolutional</th></tr>
<tr><td rowspan="2">Neurons</td><td>Entrance</td><td>10000</td><td colspan="3">10000</td><td colspan="3"></td></tr>
<tr><td>Exit</td><td>2</td><td colspan="3">2</td><td colspan="3"></td></tr>
<tr><td colspan="2">Hidden Layers</td><td>3</td><td colspan="3">3</td><td colspan="3"></td></tr>
<tr><td colspan="2">Convolutional Layers</td><td>0</td><td colspan="3">3</td><td colspan="3"></td></tr>
<tr><td colspan="2">Filters</td><td>0</td><td>32</td><td>64</td><td>128</td><td>32</td><td>64</td><td>128</td></tr>
</table>

Source: Authors, (2024).

The algorithms must have a number of input neurons (10,000) that correspond to each of the 100 x 100 image pixels, and 2 output layers, which belong to the car and accident categories.

The pixel values are within the values 0 to 255 and multiplied by 3 these data are not within the activation threshold of the transfer function, therefore, it is necessary to normalize the data, so that each of The pixels have to go from the aforementioned range to values between 0 and 1.

The experimental configuration was carried out in two phases, in phase 1 three ANN architectures were used, dense, convolutional and drop-out convolutional, in the same way a variation in the dense and CNN2 topologies was used when performing data augmentation, the configuration It is presented in Table 4. In phase 2, prediction tests are carried out (laboratory simulation) as presented in Table 5.

Table 4: Experimental configuration by architecture.

Architecture type	Eras	Supervision in %
Dense	10	100
	50	100
	100	100
CNN	10	100
	50	100
	100	100
CNN Drop-out	10	100
	50	100
	100	100
Dense with Data Augmentation	10	100
	50	100
	100	100
CNN Drop-out with Data Augmentation	10	100
	50	100
	100	100

Source: Authors: (2024).

Table 5: Experimental setup for prediction through laboratory simulation.

Type of incident	Amount of C	Supervision in %
No accident	10	100
	20	100
	30	100
Frontal	10	100
	20	100
	30	100
Side	10	100
	20	100
	30	100
Rear	10	100
	20	100
	30	100
rollover	10	100
	20	100
	30	100

Source: Authors, (2024).

III. RESULTS AND DISCUSSION

To choose the best network architecture, a series of training experiments were carried out with the database using the Google Colab platform [13], TensorBoard [14] was used for graph visualization and data analysis. Microsoft Excel [15] was used. Table 6 shows the experimental results with the different architectures and Table 7 shows the experimental results for different types of classes.

Table 6: Experimental results with different architectures.

Dense architecture					
	Amount	Half	Maximum	Minimum	Deviation Standard
Precision	100	68.25	76.08	57.37	4.786
Loss	100	59.04	67.61	50.29	4.771
Precision Assessment	100	58.51	61.00	55.36	1.225
Loss Assessment	100	72.20	86.86	65.93	5.314
Simple convolutional architecture					
Precision	100	98.56	99.99	67.37	4.45
Loss	100	3.44	56.19	0.72	9.04
Precision Assessment	100	84.14	85.64	77.45	1.19
Loss Assessment	100	122.90	182.16	33.78	37.14
Drop-out convolutional architecture					
Precision	100	97.92	99.72	76.5	4.16
Loss	100	5.31	48.63	0.94	9.04
Precision Assessment	100	84.30	86.48	76.53	1.45

Loss Assessment	100	79.82	130.69	35.33	22.39
Drop-out convolutional architecture with data augmentation					
Precision	100	76.65	81.76	54.18	5.29
Loss	100	47.79	68.68	40.00	6.79
Precision Assessment	100	79.82	86.24	55.64	5.95
Loss Assessment	100	42.63	68.45	31.42	8.54

Source: Authors, (2024).

As seen in Table 6, among the different architectures analyzed, the Drop-out convolutional neural network architecture with data augmentation is the one that presents the best results in prediction.

Table 7: Experiment results for different types of classes.

Experiment	Class	Time (sec)	Total Time (sec))	Average	Maximum	Minimum	Deviation Standard
1	Nothing	30	90	83.8117	93.9335	50.2577	9.2268
	Car	30					
	Accident	30					
2	Car	30	90	88.6343	96.9580	50.1106	8.0948
	Accident	30					
	Nothing	30					
3	Accident	30	90	88.6573	95.9763	52.1264	8.2450
	Nothing	30					
	Car	30					
4	Nothing	30	60	89.0279	97.7199	50.7856	8.5295
	Car	30					
5	Nothing	30	60	89.0732	96.4942	53.3304	7.6006
	Accident	30					
6	Car	30	60	85.5743	94.9029	50.2936	9.1175
	Accident	30					
7	Nothing	30	30	89.5539	97.6704	60.8352	7.6981
8	Car	30	30	86.3457	95.7900	50.0037	10.6814
9	Accident	30	30	86.4051	95.3482	52.5358	8.8555

Source: Authors, (2024).

.

III.1 EXPERIMENT 1. NOTHING/CAR/ACCIDENT CLASS

In an experiment with the CLASS NOTHING/CAR/ACCIDENT, the system that contains the neural network was allowed to operate, detecting a series of objects or surfaces that are neither cars nor accidents, immediately afterwards it was allowed to predict cars and ended up detecting accidents, each class was operated for the amount of 60 prediction cycles, the results are shown in the Figure 1.

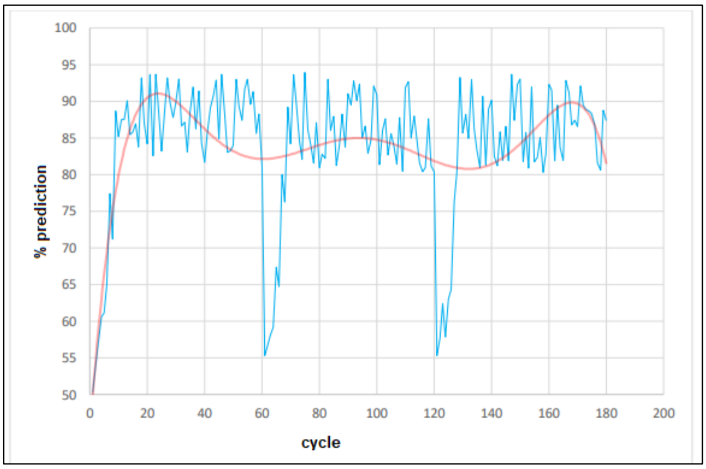

Figure 1: Experiment 1 results.
Source: Authors, (2024).

III.2 EXPERIMENT 2. AUTO/ACCIDENT/NOTHING CLASS

In the experiment with the AUTO/ACCIDENT/NOTHING CLASS, the system was allowed to operate with different cases that included the types of classes in an orderly manner for 60 cycles each and the results shown in Figure 2 were obtained.

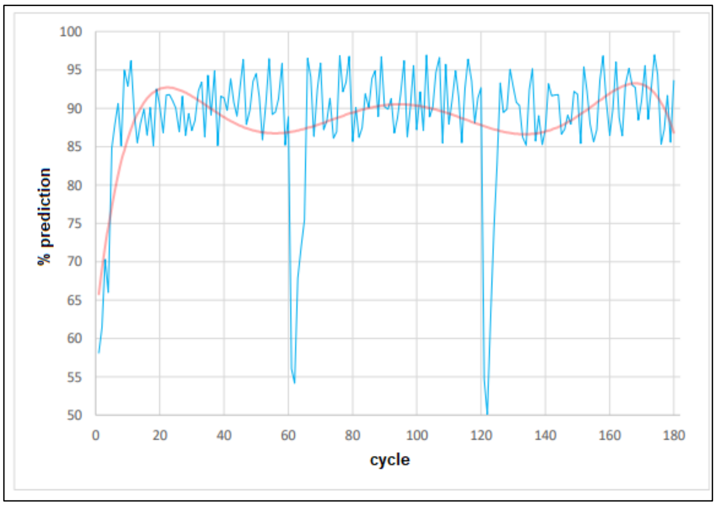

Figure 2: Experiment 2 results.
Source: Authors, (2024).

III.3 EXPERIMENT 3. ACCIDENT/NOTHING/CAR CLASS

In this experiment Class ACCIDENT/NOTHING/AUTO, the system was allowed to operate with 60 cycles per class and the results shown in Figure 3 were obtained.

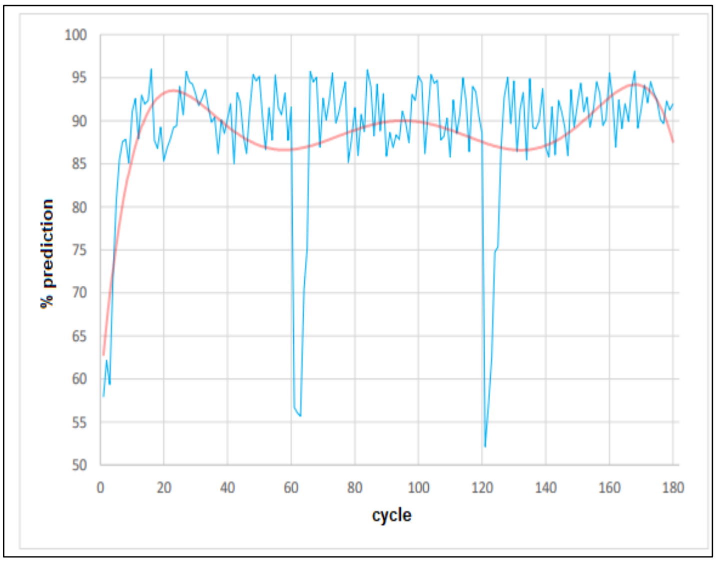

Figure 3: Experiment 3 results.
Source: Authors, (2024).

III.4 EXPERIMENT 4. NOTHING/ACCIDENT CLASS

From this experiment it begins with the combination of classes, in the specific case of this the system was configured for the detection of NOTHING (different objects) and ACCIDENTS for a number of 120 cycles divided into two, 60 cycles for each class. The results are shown in Figure 4.

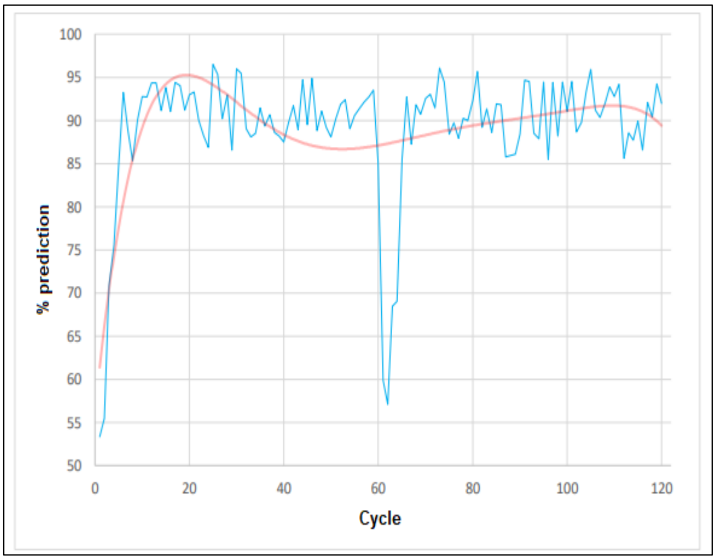

Figure 4: Experiment 4 results.
Source: Authors, (2024).

III.5 EXPERIMENT 5. NADA/AUTO CLASS

In this experiment, the prediction of the NADA and AUTO class is carried out through the system, which was programmed for the number of 120 cycles, divided into two of 60 each, the results are shown in Figure 5.

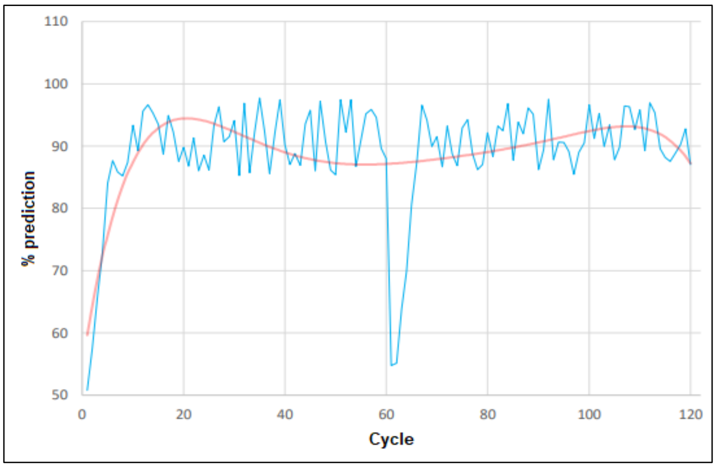

Figure 5: Experiment 5 results.
Source: Authors, (2024).

III.6 EXPERIMENT 6. AUTO/ACCIDENT CLASS

In this experiment, the results obtained by the system are presented after programming them to analyze the AUTO and ACCIDENT classes obtained in a series of 120 cycles divided into 2, 60 for each class, the results are shown in Figure 6.

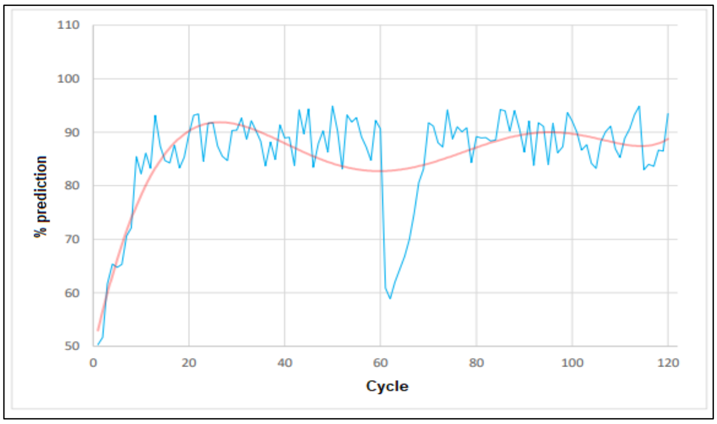

Figure 6: Experiment 6 results.
Source: Authors, (2024).

III.7 EXPERIMENT 7. NOTHING CLASS

In this experiment, a 60-cycle programming was carried out where the network tries to predict the class NOTHING, which includes everything that does not fall into the car and accident classes, the results are shown in Figure 7.

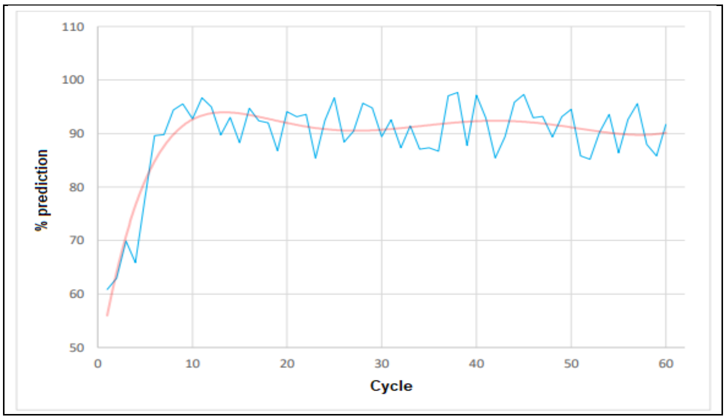

Figure 7: Experiment 7 results.
Source: Authors, (2024).

III.8 EXPERIMENT 8. AUTO CLASS

In this experiment, a series of data is introduced to the network where cars without apparent accident are found, for 60 cycles, obtaining the results shown in Figure 8.

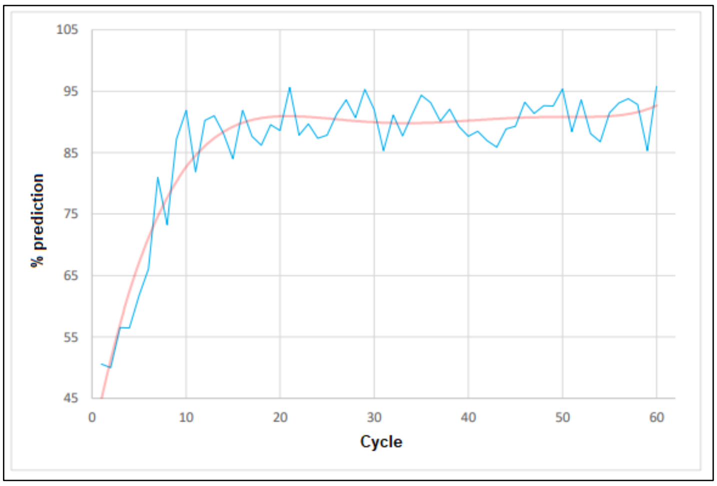

Figure 8: Experiment 8 results.
Source: Authors, (2024).

EXPERIMENT 9. NOTHING CLASS

In this experiment, the results obtained by letting the system analyze a series of data are presented where images of cars involved in apparent accidents are found. The results are shown in Figure 9.

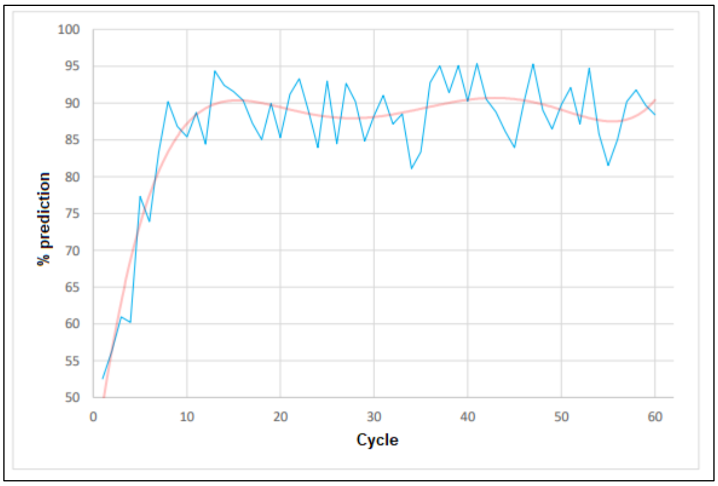

Figure 9: Experiment 9 results.
Source: Authors, (2024).

In the network training stage, a series of open source libraries were used, especially tensorflow [11] specially designed for object detection through computer vision; the neural network was trained for a set of 60 epochs.

In the prediction tests carried out on a number of 100 images divided into 5 categories, the neural network trained with the set of images proposed in contrast to human experience was found, the results are shown in Table 8.

Table 8: Database statistics and prediction average.

Category	Prediction	human experience	Detection Average	Prediction Security
Car	20	20	100%	98.56%
Car and accident	11	20	55%	97.32%
accident	18	20	90%	87.54%
Multiple Accident	5	20	25%	81.42%
Neither Car, nor Sinister	20	20	100%	100%

Source: Authors, (2024).

Using the database, 2000 images were processed using neural networks to detect car accidents. The stopping average represents the number of images detected by the network and the reliability in predicting damaged cars.

IV. CONCLUSIONS

The architecture with which the best results were obtained with an average of 98.56 in the prediction is the simple convolutional, so we selected this architecture, but in it we found overfitting of the data, simply going from a real prediction to the simple learning of the data from the network, this means that when making a simple change in one of the images or the situation where a car or an accident is located, this architecture does not fulfill its purpose. To repair this type of errors, the architecture was modified by going from a simple convolutional neural network to one with drop-out with which the data overfitting error is corrected, sacrificing the prediction average, going from 97.91% to only 76.74%. Overfitting error is eliminated and the accident prediction results correspond to reality within the technological capabilities with which the network training was developed. Likewise, it is observed that the network increases its detection capacity the more cycles it is. trained, observing that at the end of the training, it obtains a capacity of around 86%, which allows us to conclude that with more training cycles the capacity of the network to detect the classes with which it was trained increases. Taking into account the above, a series of experiments was developed with the drop-out convolutional neural network architecture and with data augmentation, which were developed with a simulation in several of the scenarios that could exist in the event of an accident on a road. , from which it was concluded that on a general average the network has the capacity to detect traffic accidents with an average certainty of 87.45% in correspondence with the hypothesis that artificial intelligence is capable of reducing the time for an accident to be attended to.

V. AUTHOR'S CONTRIBUTION

Conceptualization: Francisco Eneldo López Monteagudo, Jesus Gerardo Ávila Sánchez, Francisco Javier Martinez Ruiz, Leticia del Carmen Ríos Rodríguez.
Methodology: Francisco Eneldo López Monteagudo, Jesus Gerardo Ávila Sánchez, Francisco Javier Martinez Ruiz, Leticia del Carmen Ríos Rodríguez.

Discussion of results: Francisco Eneldo López Monteagudo, Jesus Gerardo Ávila Sánchez, Francisco Javier Martinez Ruiz, Leticia del Carmen Ríos Rodríguez.
Writing – Original Draft: Francisco Eneldo López Monteagudo, Jesus Gerardo Ávila Sánchez, Francisco Javier Martinez Ruiz, Leticia del Carmen Ríos Rodríguez.
Writing – Review and Editing: Francisco Eneldo López Monteagudo, Jesus Gerardo Ávila Sánchez, Francisco Javier Martinez Ruiz, Leticia del Carmen Ríos Rodríguez.
Resources: Francisco Eneldo López Monteagudo, Jesus Gerardo Ávila Sánchez, Francisco Javier Martinez Ruiz, Leticia del Carmen Ríos Rodríguez.
Supervision: Francisco Eneldo López Monteagudo, Jesus Gerardo Ávila Sánchez, Francisco Javier Martinez Ruiz, Leticia del Carmen Ríos Rodríguez.
Approval of the final text: Francisco Eneldo López Monteagudo, Jesus Gerardo Ávila Sánchez, Francisco Javier Martinez Ruiz, Leticia del Carmen Ríos Rodríguez.

VI. ACKNOWLEDGMENTS

We thank the Autonomous University of Zacatecas and the Zacatecano council of science and technology for the support for the realization of this article.

VII. REFERENCES

[1] Y. Campos Villalta, P. R. Suasnavas Bermudez, A. R. Gomez Garcia, and M. R. Hernandez Aragon, "System of morbidity and mortality indicators for traffic accidents: a systematic review". Rev. salud pública [online], vol.21, n.6, e301. Publicado Septiembre 14, 2021, pp. 1–10. ISSN 01240064. https://doi.org/10.15446/rsap.v21n6.

[2] H. S. Sánchez Restrepo, L. Chias Becerril, H. Reséndiz López, "Evolución de los accidentes de tránsito en las zonas urbanas y suburbanas de México en el periodo 1997-2016: mayor exposición al riesgo y menor letalidad". Revista Gerencia y Políticas de Salud, vol.18, n.37, Julio-Diciembre 2019, pp. 1–16. https://doi.org/10.11144/Javeriana.rgps18-37.eatz

[3] C. F. Alastruey, "The Impact of Advances in Artificial Intelligence, Autonomous Learning Systems, and Science". Revista Sociología y Tecnociencia, vol. 11, n. 2, published: 12/11/2021, pp. 182–195. ISSN 19898487. DOI: https://doi.org/10.24197/st.Extra_2.2021

[4] A. G. Howard, M. Zhu, B. Chen, D. Kalenichenko, W. Wang, T. Weyand, and H. Adam. "Mobilenets: Efficient convolutional neural networks for mobile vision applications". Revista arXiv preprint arXiv:1704.04861, publicado abr. 2017, Disponible en: http://arxiv.org/abs/1704.04861

[5] S. Kharuf-Gutierrez, L. Hernández Santana, R. Orozco Morales, O. de la C. Aday Díaz, and I. Delgado Mora, "Análisis de imágenes multiespectrales adquiridas con vehículos aéreos no tripulados", Revista EAC, La Habana, v. 39, n. 2, p. 79-91, agosto 2018. Disponible en: http://scielo.sld.cu/

[6] A. J. Díaz Ortíz, J. M. Martínez Zaragoza, J. N. García Matías, " Propuesta de Entrenamiento de Red Neuronal Artificial Para la Prevención de Accidentes Carretero " European Scientific Journal July 2019 edition Vol.15, No.21 ISSN: 18577881 (Print) e - ISSN 18577431. http://dx.doi.org/10.19044/esj.2019.v15n21p18

[7] A. S. Kristensen, D. Ahsan, S. Mehmood, y S. Ahmed, "Rescue Emergency Drone for Fast Response to Medical Emergencies Due to Traffic Accidents". World Academy of Science, Engineering and Technology, Open Science Index 131, International Journal of Health and Medical Engineering, vol. 11, n. 11, p. 637 - 641, publicado 2017. http://dx.doi.org/10.19044/esj.2019.v15n21p18

[8] J. E. Márquez Díaz "Seguridad metropolitana mediante el uso coordinado de Drones", Rev. Ing. USBMed, vol. 9, n.1, pp. 39-48, publicado en 2018, ISSN-e 2027-5846.

[9] C. Pérez Bernal, "Creación de un simulador y una IA sobre drones para la ayuda al rescate de montaña", sep. 2018, Accedido: abr. 23, 2020. https://riunet.upv.es/handle/10251/107279

[10] G. L. Hart, T. Mueller, C. Toher, "Machine learning for alloys", p. 730–755. https://doi.org/10.1038/s41578-021-00340-w, Published 20 July 2021.

[11] A. Martín, A Ashish, B. Paul, B. Eugene, C. Zhifeng, C. Craig, Z. Xiaoqiang. " TensorFlow: Large-Scale Machine Learning on Heterogeneous Distributed Systems". Revista arXiv preprint arXiv: 1603.04467, publicado marzo. 2016, Accedido: junio 18, 2021. Disponible en: https://arxiv.org/abs/1603.04467. https://doi.org/10.48550/arXiv.1603.04467

[12] K. P. Carpio Peláez, F. Oñate Valdivieso. "Redes neuronales artificiales aplicadas en sistemas de predicción para la seguridad vial", v. 17, n. 2. pagina 1-16. publicado en el 2020. https://doi.org/10.18041/1794-4953/avances.2.6632

[13] E. Bodero, M. P. López, A. E. Congacha, E. Cajamarca and C. H. Morales. "Google Colaboratory como alternativa para el procesamiento de una red neuronal convolucional". Vol. 41, Nº 7. Pág. 1-22. ISSN 0798 1015. Publicado en la revista espacios 05/03/2020.

[14] W.Q.Yan "Deep Learning Platforms. In: Computational Methods for Deep Learning. Texts in Computer Science". Publisher in Springer 2021, Cham. https://doi.org/10.1007/978-3-030-61081-4_2, Print ISBN 978-3-030-61080-7 Online ISBN 978-3-030-61081-4.

[15] C. V. Niño Rondón, D. A. Castellano Carvajal, S. A. Castro Casadiego, B. Medina Delgado, and D. Guevara Ibarra. "Detección de placas vehiculares mediante modelo de clasificador en cascada basado en lenguaje Python", Publisher in Eco Matemático Scientific Journal of mathematics, enero 2021. v.12, n.1. ISSN:17948231, https://doi.org/10.22463/17948231.3068