A Drone System with an Object Identification Algorithm for Tracking Dengue Disease

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***Abstract*—In recent decades, it has been shown that epidemiological surveillance is one of the most valuable tool that public health has, since it allows us to have an overview of the population general health, thus allowing to anticipate outbreaks of epidemics by helping in timely interventions. Currently there is an increase in cases of dengue disease in several regions of Peru. Therefore, to control this outbreak and to help population centers and human settlements that are far from the city this work puts forward a drone system with an object recognition algorithm. Drones are very efficient in terms of surveillance, allowing easy access to places that are difficult for humans. In this way, drones can carry out the field work that is required in epidemiological surveillance, carrying out photography or video work in real time, and thus identifying infectious foci of diverse diseases. In this work, an object detection algorithm that uses convolutional neural networks and a stable detection model is designed, this allows the detection of water reservoirs that are possible infectious sources of dengue. In addition the efficiency of the algorithm is evaluated through the statistical curves of precision and sensitivity that result of the training of the neural network. To validate the efficiency obtained, the model was applied to test images related to dengue, achieving an efficiency of 99.2%.**

***Keywords*—Epidemiological surveillance; drones, neural networks; recognition algorithms**

I. Introduction

Currently there is an increase in dengue cases in several areas of Peru, and for this does not exist a rapid surveillance system to detect areas where there is possibly dengue. At the moment Peru carries out traditional surveillance of going from house to house to carry out the detections of cases of dengue, through blood tests, filling out symptom files, etc.

The large increase in dengue cases in Peru occurs because the epidemiological focus of dengue is not being taken into account as before the pandemic, given that during the pandemic health personnel have focused mainly on COVID-19 leaving aside this disease that has afflicted Peru for approximately 30 years. Therefore, the most affected are the population centers and human settlements that have roads or accesses far from the city and with narrow main roads. Faced with this, there are various solutions through prevention campaigns against dengue, but in terms of the use of algorithms for the detection of dengue, they are very unusual and at the same time efficient.

Currently, the National Center for Epidemiology, Disease Prevention and Control (CDC - MINSA), shows in its epidemiological bulletin that there is currently a considerable increase in dengue cases in several regions of our country. Therefore, there is a way to support the surveillance carried out by the prevention system, using drones, since these devices can carry out aerial surveillance in areas of difficult access that detect dengue infectious foci.

II. Related Works

Regarding the technology of drones currently used, in [1] they provide in their article a complete review of current and future drones applied in medicine. For example, in 2013, drones were used in the aftermath of Typhoon Haiyon in the Philippines to assess initial storm damage and prioritize relief efforts. Another example mentions a study conducted in southern Italy, they used drones equipped with high-resolution photogrammetry software to accurately access and predict cancer risk from high-level copper concentrations in agricultural areas. And like other studies mentioned in the article, it highlights the advantage of using the drone as an aerial surveillance tool to assess biological risk areas and natural disaster areas. In addition, in [2], they carried out a project in which the design and construction of a drone with optimal characteristics to carry out photogrammetric plans to later be used in telecommunication networks, such as work in fiber optic networks, is proposed, because these they are found in places of difficult access such as high forests and steep mountains, for the design of both the chassis and the electronic part, easily accessible materials were used, which helps to design the drone according to the calculations made to take advantage of its resources and dimensions, since they were evaluated with commercial devices.

Regarding the drones used in epidemiological surveillance, in [3] the "IRIS PX4" drone was used as an identifier of violations of social distancing rules for an intelligent surveillance system against COVID-19, which the device uses two cameras, a frontal one for the detection of obstacles and another ventral one for the detection of people, in addition that it has an integrated GPS that locates the area observed by the drone. On the other hand, in [4] drones were used to transport blood samples, medicines, supplies in cases of disasters such as humanitarian aid and even as a portable laboratory. To carry out these tasks, Quadcopter drones (4 rotors, 20km range, 36km/h speed and with a maximum payload of 2kg) were used, most of DJI brands, for example, the DJI Phantom 4 Pro drone. It is mentioned that the models of medical drones made by the Zipline company, which are fixed-wing drones capable of flying at a speed of 128km/h with a range of 160km (round trip) while carrying a payload of 1.75 kg, are efficient in terms of transporting medicines, laboratory samples, blood donations, etc. Also in [5], drones are used to review assigned areas infected with malaria, which are sent by GPS to only capture images within the assigned geographic space, in this way they compare the progress of malaria in that area with respect to previous years such as the of 2013 and 2014.

In reference to its application in image and video acquisition, a study was carried out in [6] that aims to produce accurate geospatial 3D data by acquiring images captured by the drone or unmanned aerial vehicle. For this reason, an image of an area of the Najran University campus in Saudi Arabia was captured using a DJI Mavic Pro Platinum drone. Similarly in [7] , they mention that the use of unmanned aerial vehicles (UAV) provides the option of collecting detailed spatial information in real-time at a relatively low cost and thus avoids limitations associated with satellite data (such as cloud pollution, low resolution, bad camera angle and shooting time for taking pictures). Therefore, in their inspection of breeding habitats through drone surveillance, they used a low-cost Phantom 4 Pro DJI model drone, which integrates a 20-megapixel camera with a focal length of 35 mm and a theoretical resolution of 1 cm , which has a battery for a flight of 12 to 15 minutes, which allowed them to take photos of 15 to 20 houses per day.

Regarding the use of convolutional neural networks, in [8] they propose an efficient surveillance based on radiofrequency to detect and classify drones, for which they used the RF-UAVNet network, said network is characterized by having grouped convolutional layers because reduce the size of the network and the computational cost, these were tested in drones of the Phantom and Bebop brands. In addition, in [9] , they propose to identify weapons through surveillance applications based on Convolutional Neural Networks (CNNs) and Convolutional Long-Short-Term Memory (ConvLSTM). Simulation tests are performed on the data set using Python 3.5, Tensor Flow and Keras, which will be captured by wireless sensors distributed in networks for military applications.

Since the system has object detection and recognition techniques in the algorithm, in [10] they designed a deep YOLO-v3 model to detect small objects. The project consists of training the YOLO-v3 model previously trained with drone images, 106 convolution layers with several feature maps were designed to learn the small objects of the drones. The proposed deep YOLO-v3 revealed 99.99% accuracy because it used multi-scale predictions and backbone classifiers to better classify them. Likewise, in [11] they propose to use the YOLOv4 program to differentiate drones from birds through images captured by a digital camera which will have a visible sensor that has a resolution between 96 dpi and 300 dpi, the images will be captured in different environments and with different illumination. Similarly, in [12] they perform a vehicle detection using deep learning in UAV, which is proposed to record videos using the DJI drone, where the results show that the use of HSV for transformation data can enrich the set of samples. Thus, improving the detection accuracy, likewise, the SSD model can act on multiple feature layers, and its detection effect is better.

Finally, in relation to the current situation of dengue, in [13] studies related to coinfections of Dengue and COVID-19 were found. Most of the studies were case reports with a detailed description of clinical and co-infection features. Common symptoms were fever, dyspnea, headache, and cough. The cases were found in Brazil, Indonesia, India, France, Argentina, Pakistan, Thailand, among others. Because both diseases are present in several places, the study is necessary to verify the differences between both infections. On the other hand, in [14], he presents two cases of patients with dengue and coronavirus coinfection, due to severe acute respiratory syndrome. This research found that severe dengue infection is common in young adults, while coronavirus disease is generally asymptomatic. They also comment that, in older people, the severity of this disease will depend on their comorbidities or the infectious serotype, but contagion by coronavirus is consistently more serious.

In this work, it is proposed to carry out a drone system with an algorithm that detects and recognizes pools of water that are possible foci of dengue. To check its efficiency, a database that contains images of objects that store water will be used.

III. Methodology

For the development of the methodology, the efficiency of the design of the detection algorithm for epidemiological surveillance of dengue will be evaluated using drones, for which the research will be developed based on the following strategy shown in Fig. 1; a database, which will have images of the objects to be detected, the selection of a suitable drone, the software, which will carry out the programming, and the model of the algorithm that will be used for the detection and recognition of objects.

Therefore, for its procedure, as shown in Fig. 2, the drone will perform an acquisition of images and/or videos of the area for its evaluation, the use of a database containing images of objects that store water, in addition to the model of the object detection and recognition algorithm, which is one of the applications of convolutional neural networks. All this will be programmed in software that the computer will have, which will process the images to identify the pools of water in the photos or videos that the drone captured. In this way, the possible transmitting sources of dengue will be detected.

A. Database

To carry out this procedure, there will be a database of the objects to be detected, for example: buckets, pots, bottles, tires, tubs and vases.

B. Dron Selection

To select a suitable drone for the field of epidemiology, you must be able to take good resolution images and/or video in places or areas of difficult access that are affected by some type of disease. Therefore, the following technical specifications will be analyzed as indicated in Fig. 3, to select a suitable drone for this field.

Considering the main points necessary for the selection of an optimal drone in the investigation, they are the following: the camera must have a maximum of 12MP, because the smaller the image size, the shorter the processing time; Regarding the operating range, a range of [4 – 10] km of maximum transmission distance will be chosen. As a last point,

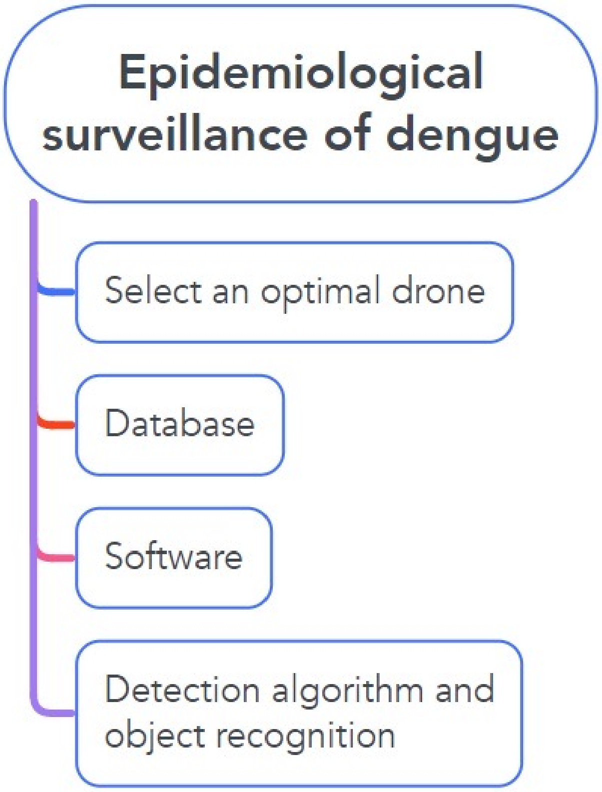

Fig. 1. Diagram of the Strategy of Research.

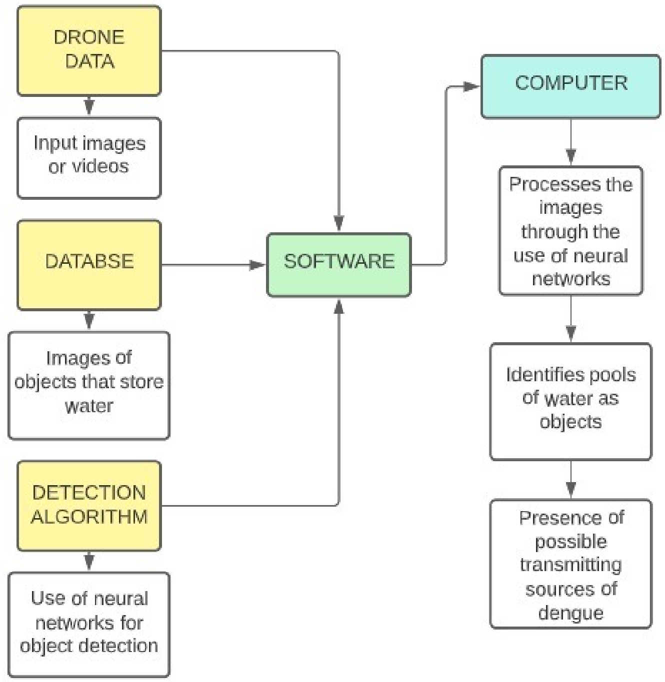

Fig. 2. Diagram of the Design of the System.

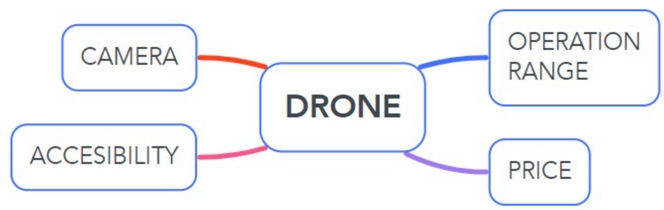

Fig. 3. Characteristics Considered to Select the Drone.

cost and accessibility will be taken into account, since most drones are acquired by import, therefore, the search for brands available for our country was carried out, obtaining DJI drones as a result.

Taking into account the importance of a drone with an affordable cost, as well as the criteria of the main technical specifications of the drone, DJI MINI 2 is chosen as the first option, since it has a maximum operating range of 10km, in comparison to the DJI MAVIC Mini drone, as a second option, which has only 4km.

C. Software

Since the object detection algorithm needs software that contains libraries on neural networks for its training, it is decided to choose the free software "Google Collaborate", which is compatible with the Yolo algorithm, and its environment is developed using the language of Python programming. Its environment is very friendly to users, it does not require configuration, it gives free access to GPUs for fast code execution.

D. Detection Algorithm

In the case of the algorithm required for object detection, some main detection techniques were found: SORT, YOLO and SDD.

In the case of YOLO, compared to other detection techniques, it makes predictions with a single network evaluation through the use of CNN. In addition to having continuous updates or versions to improve its efficiency in terms of detection in both images and videos in real time. For this reason, the Yolo algorithm will be applied in its version 3 "Yolov3", due to its stability and precision for object detection, as shown in Fig. 4, the Yolov3 algorithm in the Google Colab environment.

This algorithm requires "labels" of the images found in the database, which will be obtained through "Makesense", a tool to label photos and thus organize the images into classes, as shown in Fig. 5, an example of classifying images of the "buckets" type.

In addition, Makesense allows you to export the labels in a ".txt" file for the operation of the YOLO algorithm. This will allow pre-training of the neural network for image classification.

YOLOv3 ALGORITHM FOR OBJECT DETECTION AND RECOGNITION

```
[ ]  !git clone https://github.com/ultralytics/yolov3  # clone
     %cd yolov3
     %pip install -qr requirements.txt  # install

     import torch
     from yolov3 import utils
     display = utils.notebook_init()  # checks
```

Fig. 4. Algorithm YOLOv3.

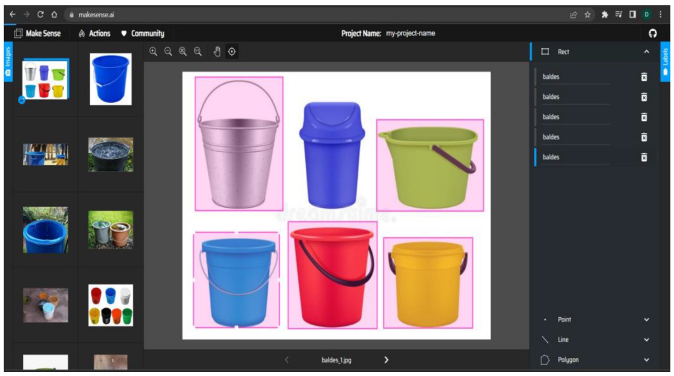

Fig. 5. Images Classification using Makesense.

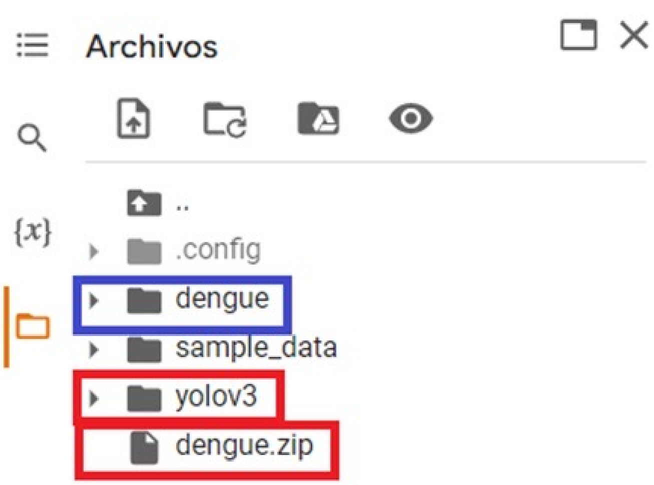

Fig. 6. Adding YOLOv3 Folder to the Database dengue.zip.

E. Programming

Given that at this stage the necessary elements are already available to carry out the recognition of dengue, the programming part will be developed, which will carry out the identification of the possible infectious foci of said disease.

As a first step, the database will be added in .zip format to extract it in the section and in turn compile the "Add Yolov3 algorithm" cell, as shown in Fig. 6 in the Files section, the yolov3 folder and the dengue.zip database highlighted in red.

```
# YOLOv3

train: ../dengue/images/train
val: ../dengue/images/val

# Classes
nc: 6  # number of classes
names: ['buckets', 'bottle', 'vases', 'pots', 'tire', 'tubs']  # class names
```

Fig. 7. File dengue.yaml for Training and Network Validation.

TRAINING OF THE CONVOLUTIONAL NEURAL NETWORK THROUGH YOLO

```
[ ]  !python train.py --img 640 --batch 16 --epochs 100 --data dengue.yaml --weights yolov3.pt --cache
```

Fig. 8. Training Expression for the Neural Network with 100 Epochs.

TRAINING OF THE CONVOLUTIONAL NEURAL NETWORK THROUGH YOLO

```
[ ]  !python train.py --img 640 --batch 16 --epochs 20 --data dengue.yaml --weights yolov3.pt --cache
```

VALIDATION OF TRAINING USING IMAGES OR VIDEO FOR OBJECT DETECTION

```
[ ]  # python detect.py --source 0  # webcam
     #                           img.jpg  # image
     #                           vid.mp4  # video
     #                           path/  # directory
     #                           path/*.jpg  # glob
     #                          'https://youtu.be/Zgi9g1ksQHc'  # YouTube
     #                          'rtsp://example.com/media.mp4'  # RTSP, RTMP, HTTP stream
```

VALIDATION CODE

```
[ ]  !python detect.py --weights yolov3.pt --img 640 --conf 0.25 --source data/images
```

EXAMPLE

```
[ ]  # !python detect.py --weights 'PLACE TRAINING WEIGHTS' --img 700 --conf 0.25 --source 'PLACE IMAGE OR VIDEO'
     # !python detect.py --weights /content/yolov3/runs/train/exp6/weights/last.pt --img 700 --conf 0.25 --source ../Imagen_1.jpg
```

Fig. 9. Training Expression using an Image or Video.

As a second step, the ".yaml" file is created, in which the classes and locations of the images that will be trained and validated by the neural network are declared. As can be seen in Fig. 7, the training variables "train" and "val", followed by the classes associated with the objects to be detected in the images.

As a third step, the convolutional neural network training command will be executed, which is made up of the size of the image, the number of epochs, the data and the weights provided by the yolov3 algorithm, as can be seen in Fig. 8.

Finally, Fig. 9 presents the command for the validation of the Yolo algorithm through an image or video, for the detection of water pools, using the weights of the trained network.

IV. Results and Discussion

Regarding the technical characteristics that a drone must have to adapt an epidemiological surveillance system, the drone selected in the methodology is evaluated, the DJI MINI 2 drone, which offers greater stability despite being very light (250gr), it has an acceptable wind resistance (29 – 38 km/h), however in [4] it mentions a study that used the DJI Phantom 4 Pro drone for epidemiological surveillance of malaria in the Peruvian Amazon, identifying breeding sites through multispectral images captured by the drone, said drone has an autonomy greater than 30 minutes, in the same way in [7] they used the same drone to capture images in an endemic city of Tapachula in Mexico. Likewise, in [6] the use of the DJI Mavic Pro Platinum drone is mentioned to obtain images of a test area, which has a flight time of 30 minutes, considered

Fig. 10. Drone DJI MINI 2 and its Remote Control.

very high, it also has GPS, a 12.35 MP camera, among other features. Taking into account the mentioned specifications, both studies considered autonomy or flight time as the main characteristic. In Fig. 10, the DJI MINI 2 drone is shown.

Regarding the development of the database, in [7] a database acquired by the drone of a total of 2579 images of various house roofs was used to identify Aedes Aegypti breeding sites, divided into 10 categories. On the other hand, in [15] they use Microsoft's COCO data set, which contains a base of 330,000 images, divided into 91 categories that can be freely used by any user. Instead, [11] mentions the use of a database of 3,000 images, including 1,000 of birds, 1,000 of helicopter-type drones, and 1,000 of multi-rotor drones. Therefore, it is recommended to use a greater number of possible images to carry out an optimal detection. Since a total of 86 images were used in the investigation for six classes or types of objects, which are buckets, bottles, vases, pots, tires and tubs.

With respect to the simulation, images containing the objects to be detected were used, for example buckets, tubs, bottles, pots, vases, tires, etc., which were extracted from the internet. Similarly in [7], for the detection of dengue it is recommended to identify these objects.

From the training carried out in Fig. 11, it is visualized that 60 images were used for the validation of the training, the different classes used, the number of labels of each class, the "P" value of total precision and of each class, the value "R" for recall (Sensitivity) total and of each class and the Accuracy value "mAP" total and of each class. Similarly, in [11] and [12], the use of these variables is highlighted to evaluate the accuracy and sensitivity of the proposed model. Furthermore, in [11], they obtained a 90% accuracy "P" to identify drones and birds in test images. On the other hand, the proposed model has an accuracy value "P" of 98.6% to identify water reservoirs.

Fig. 12 shows the graphs of the curves F1, P, R and PR that indicate the combination of P and R in a single measure, the quality of prediction, the quantity that can be identified and the performance of the predictive model, respectively.

Of the curves, the most important is the P-R curve that generally indicates the efficiency of the Yolov3 model applied to the detection of dengue, whose value is 99.2%, this indicates that the use of the algorithm for the detection of dengue is efficient. and that the simulation helps in part to validate its efficiency.

```
100 epochs completed in 0.232 hours.
Optimizer stripped from runs/train/exp/weights/last.pt, 123.6MB
Optimizer stripped from runs/train/exp/weights/best.pt, 123.6MB

Validating runs/train/exp/weights/best.pt...
Fusing layers...
Model Summary: 261 layers, 61524355 parameters, 0 gradients, 154.6 GFLOPs
               Class     Images     Labels          P          R     mAP@.5 mAP@.5:.95: 100% 2/2 [00:01<00:00,  1.39it/s]
                 all         60        118      0.986      0.979      0.992      0.842
               balde         60         39      0.985      0.923      0.993      0.874
             botella         60         14          1      0.949      0.995      0.805
             florero         60         17      0.992          1      0.995      0.813
              maceta         60         22      0.997          1      0.995       0.85
              llanta         60         19      0.942          1       0.98      0.828
                tina         60          7          1          1      0.995      0.881
Results saved to runs/train/exp
```

Fig. 11. Training Results using 100 Epochs.

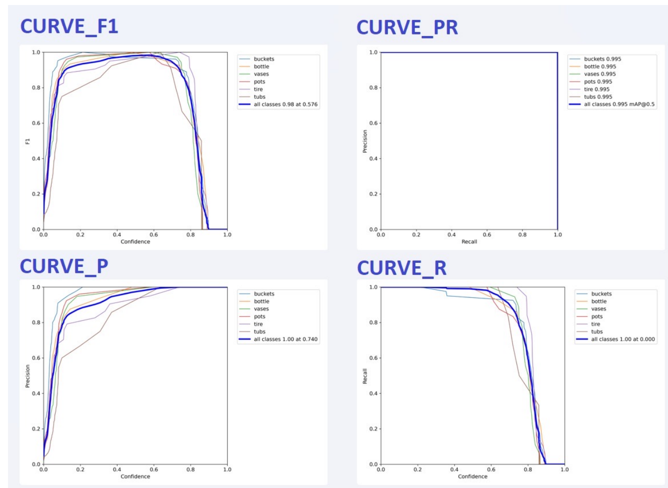

Fig. 12. Curves F1, P, R and PR from de Neural Network.

In Fig. 13 it can be seen that each class is detected in reference to the image of the database, in addition to showing a number between 0 and 1, which means the value of precision that it has when recognizing the object, said value will be higher if the number of epochs increases.

The design of the detection algorithm proposed for dengue surveillance using drones allowed the recognition of objects or containers that store water to identify the infectious foci of the disease through the precision and sensitivity value which are the result of training the neural network. In addition, through test images, which contain figures of buckets, bottles, vases, pots, tires and tubs, it was possible to identify these objects with a total efficiency value of 99.2%. This design is an important contribution, since, in terms of disease surveillance in the country, this type of technology is not available, due to the fact that there is little research regarding drones dedicated to epidemiological surveillance.

The information on the technical specifications of the drones is important for their selection in cases of epidemiological surveillance, since, according to the authors, they consider the MP of the camera for the images, the flight time or its autonomy, and the cost of the device. Therefore, taking into account these considerations, it is concluded that the DJI MINI 2 drone is optimal to perform the image acquisitions required for the development of the proposed detection algorithm.

Fig. 13. Validation of the Neural Network with the Test Images.

V. CONCLUSIONS

The test simulation was optimal for the evaluation of the detection algorithm, using some input images to detect the pools of water that are possible infectious foci of the disease. Resulting in the value of 99.2% total efficiency of the detection algorithm.

The design of the detection algorithm uses the Yolov3 model, since it is more stable, but the following versions such as Yolov4 and Yolov5 could be used to improve its efficiency, precision and sensitivity. As for drones, the recommendations for their selection vary according to the field, since most of these devices cover the military field, agriculture, archeology, medicine, home deliveries, etc.

Regarding the simulation of the evaluation of the algorithm, it is recommended to use software that runs without the need for an internet connection, for example, Octave, Visual Studio, among others, that have libraries applied to the detection and recognition of objects.

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