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Classification Of Tropical Cyclones Observed By Satellites In The Southwest Indian Ocean Basin Using The 2D-CNN Model

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Abstract— The aim of this work was to model the images of tropical cyclones seen from the meteorological satellites using the 2D-CNN model. The work remained within the framework of the classification problem. More specifically, the experiment consisted of training, then testing and validating a 2D-CNN model that predicts the class of the cyclone image using a set of images of tropical cyclones obtained by satellites. The model only took into account 2 classes. The first (respectively the second) class contains images of cyclones with a wind force less than 34Kt (respectively greater than or equal to 34Kt). In fact, the cyclone begins to be named as soon as the force of the wind that accompanies it is greater than or equal to 34Kt. The simulations were done for each value of the batch size corresponding to the power of 2, namely 2, 4, 8, 16, 32, 64, 128 and 254. For each of these batch size values, the simulations were evaluated using the evolution of the mean curve between training and test data as a function of the epoch. The best classification model was obtained by running the simulation with a batch size of 64 at the 25th epoch with a model reliability rate of 97%.

Keywords—Batch size, Southwest Indian Ocean Basin , Image classification, Tropical cyclone, 2D-CNN, Epoch.

I. INTRODUCTION

Tropical cyclones can cause enormous damage to both property and people [1] [2] [3]. The existence of a disturbed area therefore requires a permanent monitoring [4] [5]. If a cloud cluster is present on satellite imagery available in real time to the general public via the Internet, the question is whether or not this cluster has already reached the stage of a tropical cyclone. In other words, is the system baptized or not? In the Southwest Indian Ocean basin, a convective cloud cluster reaches the cyclone stage as soon as the force of the accompanying wind is greater than or equal to 34Kt [6]. The problem is therefore to determine whether or not an image of a convective cloud cluster reaches the cyclone stage.

Recently, artificial intelligence techniques such as Deep Learning have focused on image classification. This work consisted of experimenting with the 2D-CNN model [7] using images of tropical cyclones in the Southwest Indian Ocean basin.

II. MATERIALS AND METHODS

A. EXPERIMENTAL DATA

The experimental data were images of tropical cyclones obtained from meteorological satellites. The data were taken between the 2005-2006 cyclone season and the 2022-2023 cyclone season. Note that the cyclone season begins in November of year Y until April 30th of year Y+1 [8].

The image archive was available on:

http://www.meteo.fr/temps/domtom/La_Reunion/webcmrs9.0/francais/index.html

The datasets were classified into two classes:

- Class 1 contained images of unbaptized convective clusters;
- Class 2 included images of tropical cyclones already named (corresponding to a wind force greater than or equal to 34 knots).

To be more objective in evaluating the performance of the 2D-CNN model, the datasets were separated into training and testing data:

- 227 images of class 1 and 227 images of class 2 intended for training the 2D-CNN model;
- 35 images of class 1 and 35 images of class 2 to test the model.

B. Methodology

The *batch size* is the number of data samples used to calculate a gradient estimate and update the model parameters during training pass [9].

An epoch is a complete iteration through the entire training dataset, used once to update the model parameters. It means that each example in the dataset has been seen exactly once by the model during that epoch [9].

For each value of the batch size corresponding to the power of 2 ranging from 2 to 256, the established approach for modeling was as follows:

Step 1: Data preprocessing;

Step 2: Training the 2D-CNN model with the 227 images of class 1 and 227 images of class 2;

Step 3: Testing the model with the 35 images of class 1 and the 35 images of class 2;

Step 4: Evaluating the overall performance of the 2D-CNN model.

a) Step 1 : Data preprocessing

The data preprocessing consisted of separating images of tropical cyclones in the Southwest Indian Ocean basin obtained from meteorological satellites into training and test data, and into images of class 1 (image of cyclones with a corresponding wind force less than 34 knots) and of class 2 (image of cyclones with a wind force greater than or equal to 34 knots).

b) Step 2 : 2D-CNN model training

The training of the 2D-CNN model was done with the 227 images of class 1 and 227 images of class 2. During the training process, for each value of the batch size corresponding to the power of 2 (ranging from 2 to 256), the recording of the trained 2D-CNN model was done every 5 epochs from 1 to 60 epochs.

The mapping of the 2D-CNN model [7] that was exploited consisted of:

- *A first convolution layer* [7] with 32 filters and 3x3 kernels, ReLU activation function. The padding step resulted in a loss of 2 pixels. This layer took as input the color image of tropical cyclones of dimensions 150x150x3. The output of this layer was a tensor of size 148x148x32.
- *A first layer of 2D-MaxPooling* [7] of size 2x2. This layer applied the maxpooling operation [7] to the output of the previous layer. This reduced the size of feature maps. So, after this layer, a tensor of dimensions 74x74x32 was obtained.
- *A second convolution layer* [7] with 64 filters, 3x3 kernels and ReLU activation function with 64 filters. After this layer, the tensor had a dimension of 72x72x64.

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- *A second layer of 2D-MaxPooling* [7] of size 2x2. After this layer, a tensor of dimensions 36x36x64 was obtained.
- *A third convolution layer* with 128 filters, 3x3 kernels and ReLU activation function. After this layer, the tensor had a dimension of 34x34x128.
- *A third layer of 2D-MaxPooling* [7] of size 2x2. After this layer, we had a tensor of dimensions 17x17x128.
- *A fourth convolution layer* [7] with 128 filters, 3x3 kernels, and ReLU activation function. After this layer, the tensor had a dimension of 15x15x128.
- *A fourth layer of 2D-MaxPooling* [7] of size 2x2. After this layer, we had a tensor of dimensions 7x7x128.
- *A layer of flatten* [7] which flattened the previous 3D output into a 1D vector for the next fully connected layer. After this layer, we had a 1D vector of dimension 6272.
- *A Dense layer* [7] with 512 neurons and ReLU activation function. This was a fully connected layer and output a 1D vector of dimension 512.
- *A layer of 50% Droupout* [7]. This layer allowed to randomly deactivate 50% of the neurons in the Dense layer to avoid over-fitting the model. In other words, it is a regularization layer. After this layer, we still had a 1D vector of dimension 512.
- *A last Dense layer* [7]. The number of neurons in this layer was equal to the number of classes. So in this study, there were two fully connected neurons. The values from these neurons corresponded to the probability of the image belonging to the class. The image was classified into the class with the highest probability.

Figure 1 summarizes the mapping of the 2D-CNN model [7] to classify images of tropical cyclones obtained from satellites.

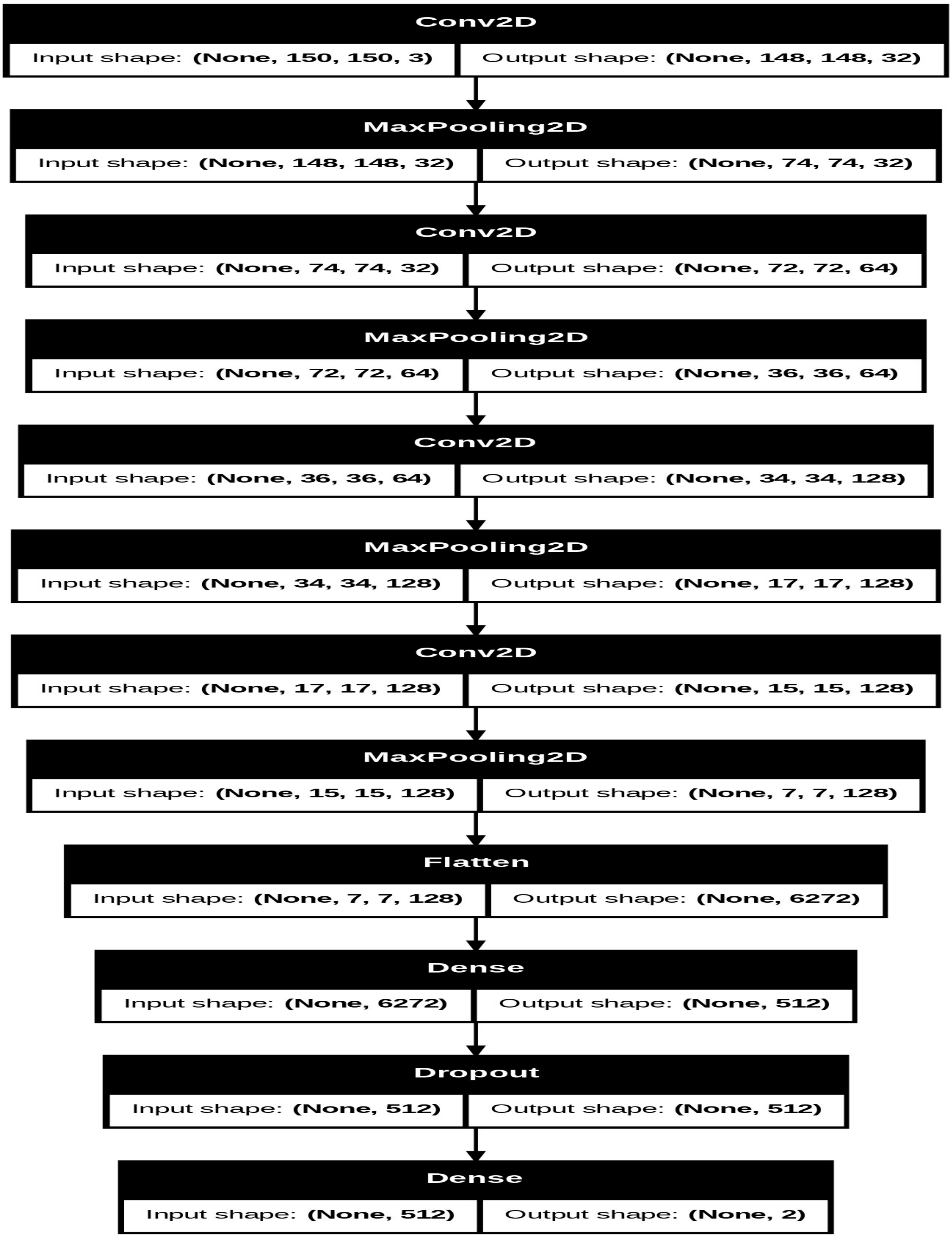

Fig. 1. Summary of the 2D-CNN model mapping used for the classification of images of tropical cyclones in the Southwest Indian Ocean basin obtained from meteorological satellites

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c) Step 3 : Testing the 2D-CNN model

For each value of batch size, the model was tested with images of tropical cyclones in the Southwest Indian Ocean basin that had not been used during model training. For each epoch multiple of 5 ranging from 1 to 60, the trained model was tested with 35 images of class 1 and 35 images of class 2. More precisely, for each possible pair of batch size and epoch, the trained model predicted the class of the 70 images. Thus, the number of correctly classified images was obtained and consequently the accuracy rate of the classification model.

d) Step 4 : Evaluation of the overall performance of the 2D-CNN model

For each value of batch size, the overall performance of the 2D-CNN model was evaluated using the mean accuracy curve between the training and testing curves of the model as a function of the epoch. Using these curves, the range of the epoch that corresponds to the maximum accuracy of the model could be known.

III. RESULTS AND INTERPRETATIONS

A. RESULT OF THE EVALUATION OF THE ACCURACY OF THE MODEL FOR A BATCH SIZE = 2

Figure 2 shows the accuracy curves for training and test data for a batch size of 2. The maximum accuracy rate is 66% at the 60th epoch.

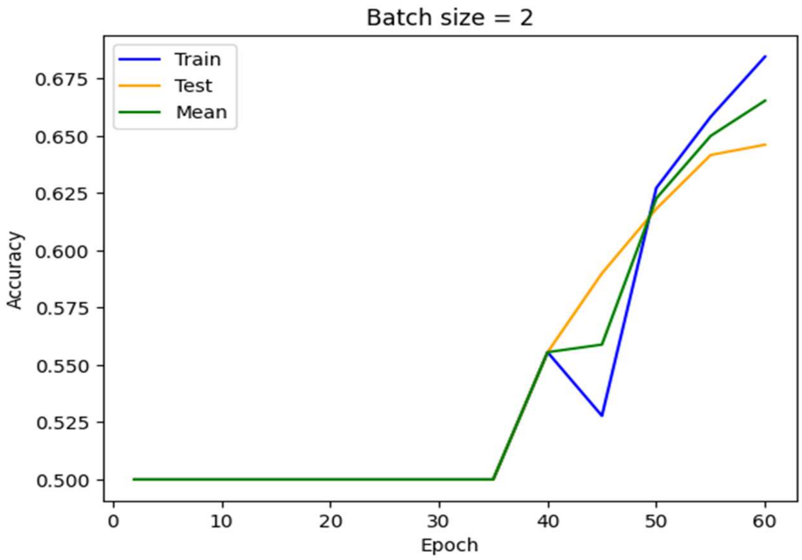

Fig. 2. Result of the classification model accuracy evaluation for a batch size = 2

B. RESULT OF THE EVALUATION OF THE ACCURACY OF THE MODEL FOR A BATCH SIZE = 4

Figure 3 shows the accuracy curves the training and test data for a batch size of 4. The maximum accuracy rate is 93% at the 20th epoch.

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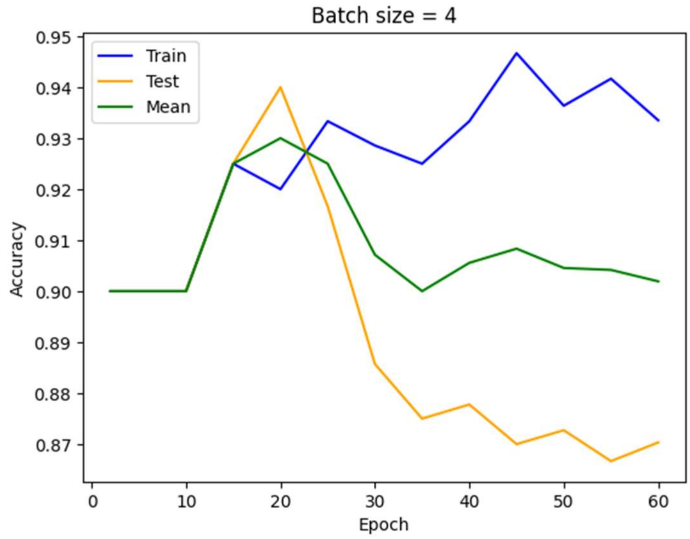

Fig. 3. Result of the classification model accuracy evaluation for a batch size = 4

C. RESULT OF THE EVALUATION OF THE ACCURACY OF THE MODEL FOR A BATCH SIZE = 8

Figure 4 shows the accuracy curves for training and test data for a batch size of 8. The maximum accuracy rate is 92% at the 50th epoch.

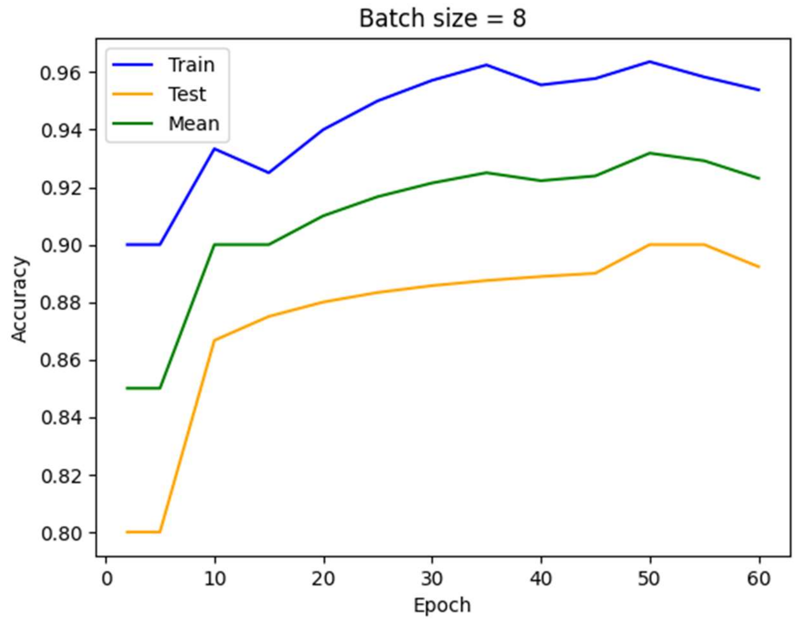

Fig. 4. Result of the classification model accuracy evaluation for a batch size = 8

D. RESULT OF THE EVALUATION OF THE ACCURACY OF THE MODEL FOR A BATCH SIZE = 16

Figure 5 shows the accuracy curves for training and test data for a batch size of 16. The maximum accuracy rate is 89% at the 60th epoch.

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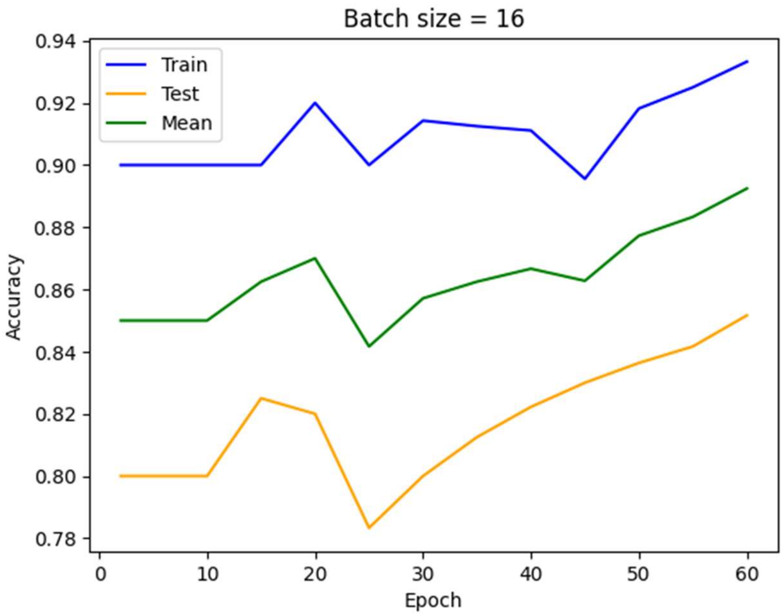

Fig. 5. Result of the classification model accuracy evaluation for a batch size = 16

E. RESULT OF THE EVALUATION OF THE ACCURACY OF THE MODEL FOR A BATCH SIZE = 32

Figure 6 shows the accuracy curves for training and test data for a batch size of 32. The maximum accuracy rate is 96% at the 60th epoch.

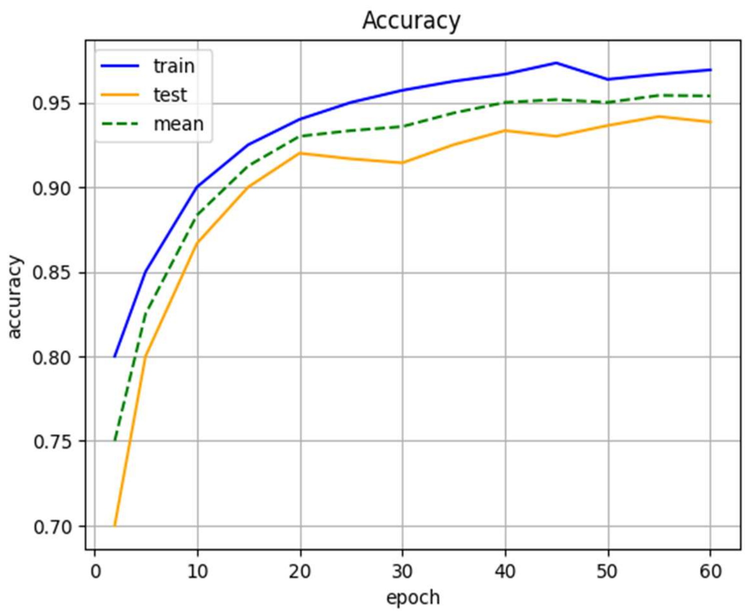

Fig. 6. Result of the classification model accuracy evaluation for a batch size = 32

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F. RESULT OF THE EVALUATION OF THE ACCURACY OF THE MODEL FOR A BATCH SIZE = 64

Figure 7 shows the accuracy curves for the training and test data for a batch size of 64. The maximum accuracy rate is 97% at the 25th epoch.

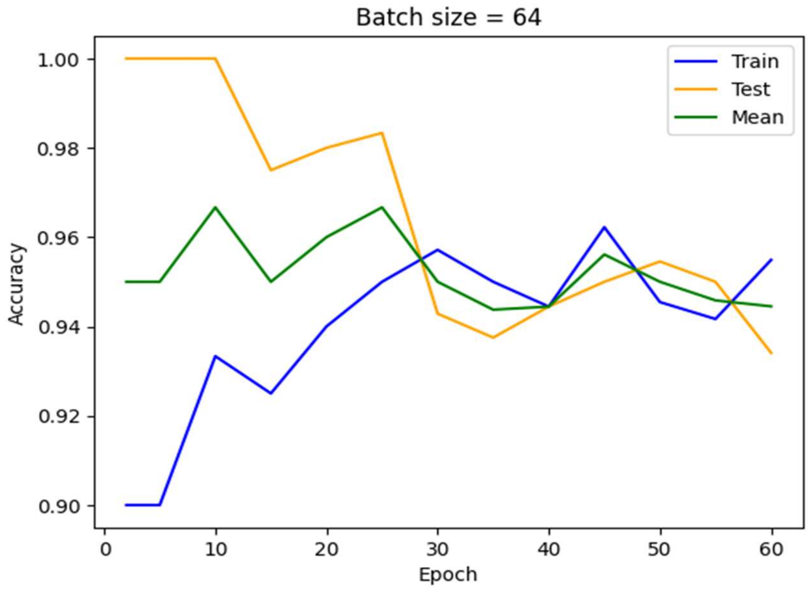

Fig. 7. Result of the classification model accuracy evaluation for a batch size = 64

G. RESULT OF THE EVALUATION OF THE ACCURACY OF THE MODEL FOR A BATCH SIZE = 128

Figure 8 shows the accuracy curves for training and test data for a batch size of 128. The maximum accuracy rate is 92% at the 40th epoch.

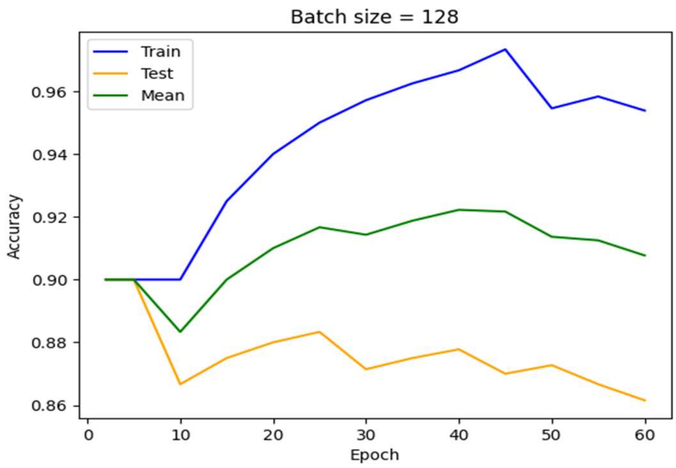

Fig. 8. Result of the classification model accuracy evaluation for a batch size = 128

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H. RESULT OF THE EVALUATION OF THE ACCURACY OF THE MODEL FOR A BATCH SIZE = 256

Figure 9 shows the accuracy curves for training and test data for a batch size of 256. The maximum accuracy rate is 82% at the 60th epoch.

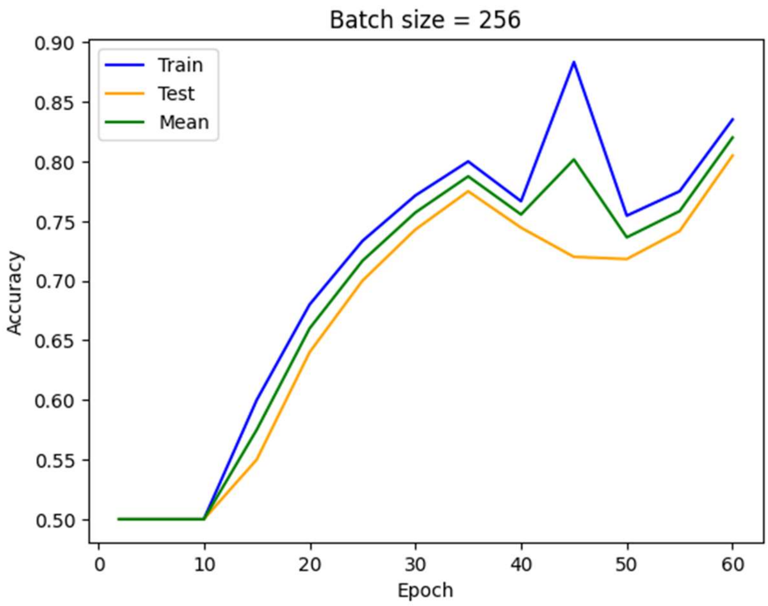
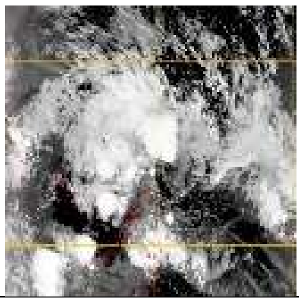


Fig. 9. Result of the classification model accuracy evaluation for a batch size = 256

I. EXAMPLE OF CLASSIFICATION WITH THE OPTIMAL MODEL

Table I shows an example of a cyclone and a tropical disturbance image seen from the meteorological satellite that was used to test the 2D-CNN model with the optimal epoch parameter. Thus, the optimal model was able to classify the image given to it into a named or unnamed system. The details of the system in question are also shown in table I.

TABLE I. EXAMPLE OF CLASSIFICATION WITH THE OPTIMAL MODEL

Image of the disturbance	Image details	Disturbance class	Forecasted class
	Image taken on March 5, 2001 at 0130 UTC during the 2000-2001 cyclone season. At that precise moment, the system had not yet been named. After a few days, the system evolved and was given the name Cyclone DERA.	Class 1 (Corresponding wind force less than 34 knots)	Class 1 (Unnamed system)

	Cyclone ELINE, 1999-2000 cyclone season, image taken on February 22, 2000 at 0455 UTC	Class 2 (Corresponding wind force greater than 34 knots)	Classe 2 (Named system)

IV. DISCUSSION

The experimental results highlighted the importance of a judicious choice of the number of epochs and the batch size to maximize the reliability of the model. Works of other researchers in the field exploit other regulation techniques such as early stopping [10], weight decay (or L2 Regularization) [11] or label smoothing [12] to further refine the training process.

This current work consisted of the classifying of images of tropical cyclones obtained from the meteorological satellites. After training and testing, the model was able to classify a cyclone image according to the whether the system is named or not. Other research such as [13] uses recent algorithms such as YOLOv5 to detect and classify tropical cyclones from satellite images. Other similar work includes, the detection of tropical and extra tropical cyclones with U-Net, which consists of detecting tropical cyclones regions of interest from satellite images, using water vapor and precipitation data [14]. Other work related to the classification of cyclones is done with binary local patterns. The application of these patterns and a histogram analysis makes it possible to classify tropical cyclones from satellite images [15].

Note that this current work was limited to the epoch value of 60.

V. CONCLUSION

In conclusion, this experiment highlights the sensitivity of the 2D-CNN model to the training parameters "epoch" and "batch size", while validating its potential for the automatic classification of tropical cyclones in a regional context (Southwest Indian Ocean basin). The reliability of the 2D-CNN model does not always increase indefinitely with the epoch. The optimal model classifies tropical cyclone images at 97% for a batch size of 64 at the 25th epoch.

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