

# Convolutional Neural Network applied for degradation criticality classification: The pump bearing vibration degradation case.

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**Abstract**— The Convolutional Neural Network (CNN) aims to perform image classification that enables to detect product failures, unsafe conditions as well as classify equipment degradation based on images. Such images classification enables detect equipment degradation based on images as result of predictive maintenance methods such as ultrasound, infrared radiograph or even on images that comes from online monitoring graphs images. This paper aims to demonstrate the application of CNN to classify equipment degradation as moderate and critical based on online monitoring vibration graphs images of pump bearing case.

**Keywords**—Convolutional Neural Network, convolutional layers, pooling layer, ReLu layer, Full Conexion Layer, Softmax.

## I. INTRODUCTION (HEADING I)

The Neural Network (NN) model mimics the human neurons, that pass relevant information for one each other. As already presented before, the Neural Network structure that encompasses input neurons in the first layer, hidden neurons and the output as shows figure 1. The neural network uses the input vector values and weight's as input to the output function in each hidden layer in the end produce a classification or a regression prediction.

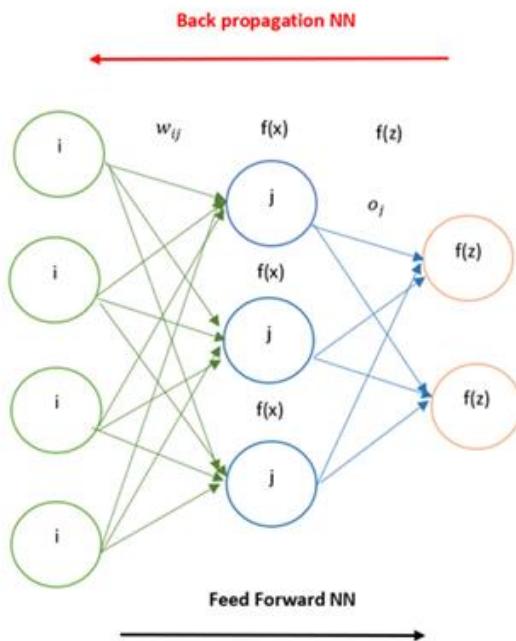


Fig. 1. Neural Network

The network elements are:

- $(x_i, y)$  =The input vector with x variables and y labels  
 $(W_{ij})$  = The weigh  
 $f(x_i)$  =The output functions.

The Deep Learning methods is a more sophisticated neural network with several hidden layers s shows the figure 2. The principles of Deep Neural network are the same on the Neural network presented before, but with the complexity to have several hidden networks that will give the final outputs based on the activation functions and weights distributed across the network.

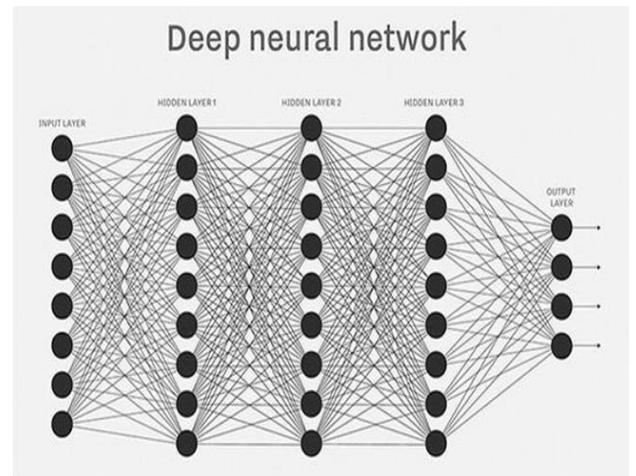


Fig. 2. Deep Neural Network

The advantages of Deep Neural network when compared with Neural network are the following:

- Deep learning models are capable of creating new features by themselves.
- Deep learning is able to work with unstructured data such as figures and text very well.
- Deep learning is precise and produce reliable results.

Some current application of deep learning in the real world is speech translation, object detection and identification application used by car in their safety functions. Despite of all

such advantages, the principle of neural network remains the same as discussed before. However, the evolution of Deep Neural Network is the so called “Convolutional Neural Network (CNN)”, which the main objective is to classify images.

## II. THE CONVOLUTIONAL NEURAL NETWORK

### A. The CNN concepts

The “Convolutional Neural Network (CNN)” is similar to the neural network in principle but has a more robust concept. Since the CNN aims to classify images, the structure of the CNN is quite complex with different types of layer as shown the figure 3.

- The elements of CNN are the following:
- Input Image;
- Convolution Layer;
- Pooling Layer;
- ReLu;
- Fully Connected;
- Softmax;
- Output Classification.

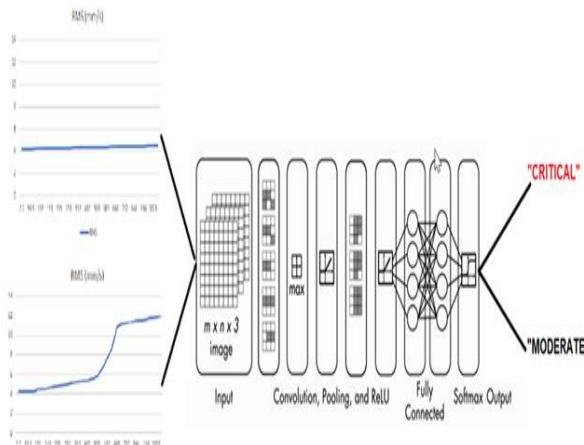


Fig. 3. CNN image classification

The CCN receive the input image and send the image throughout the different CNN layers to define an image classification in the end. The image is represented initially in pixels matrix and based on filter's matrixes, such input matrix is transformed in smaller matrix. The next step is to decode the smaller matrix and classify the image. This process is performed step by step by the different CNN layers listed above as shows the figure 4. The Input Image can be the figure of the equipment or product that we want to identify as defected or not or even figures that describe equipment degradation based on graphical representation of SoH or RUL. The picture is loaded and input in the CNN software solution and have its intrinsic characteristic concerning the number of pixels. There's a different of representation of black and white

picture, that is represented by a matrix  $n \times m$  or a colour matrix that is represented by  $m \times n \times 3$ . The number 3 means three basic colours such as Red, Blue and Green (RGB), that combined generate the colour of the picture.

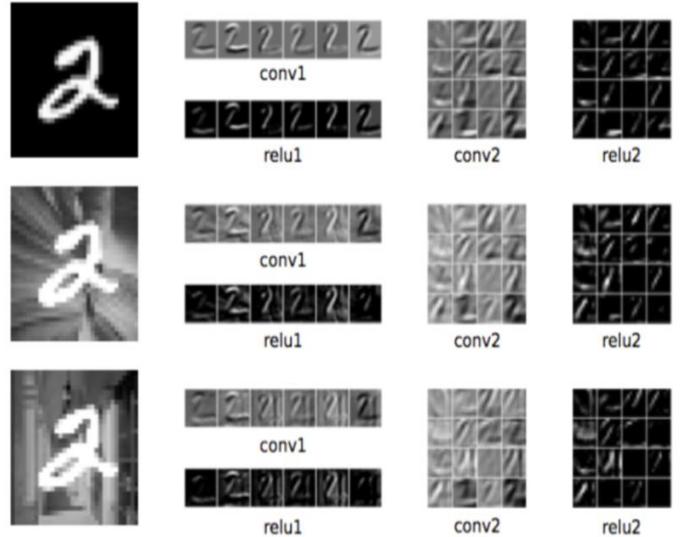


Fig. 4. Convolutional Neural Network Input image.

## III. THE CNN LAYERS

### A. Convolutional Layer

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable. The “Convolution Layer” aims to perform the reduction of the picture size represented by the input  $m \times n$  matrix by using filters that are also matrix. Each of these filters can be thought of a feature identifiers. That means, identify a part of the whole picture. The input matrix used to have a higher number of pixels, for example 272x272. However, let's assume a simple example for an easier understanding about the convolution layer process.

Let's consider that we have an input matrix 6x6 as shown on the left of the figure 9-5, then we use a filter 3x3 (in the middle of the figure 9-5) to produce a matrix 4x4 (on the bottom of figure 9-5). In order to do that, the input matrix is divided into regions 3x3 beginning of the first line and first columns (on the left of the figure 9-5). The procedure is to multiply each cell of the sub matrix 3x3, from the matrix 6x6, by the filter matrix 3x3. The result will be the cell 1x1 of the matrix 4x4 as described below.

$$x_{11} = (1x - 1) + (0x2) + (0x0) + (0x - 2) + (1x1) + (0x2) + (0x2) + (0x1) + (1x2) = 2 \text{ (cell } 1x1 \text{ of matrix } 4x4\text{)}$$

The next step is to produce the values of the cell 1x2 of the matrix 4x4. In order to do that, the regions 3x3 from the previous step shift one column to the right as showing the matrix 6x6 highlighted in red (on the top right side of the figure 5). The procedure is the same, beginning of the first line and the second column, we multiply each cell of the new sub

matrix  $3 \times 3$  (in red) by the same filter matrix  $3 \times 3$ . The result will be the cell  $1 \times 2$  of the matrix  $4 \times 4$  as described below.

$$x_{12} = (0x - 1) + (0x2) + (0x0) + (1x - 2) + (0x1) + (0x2) + (0x2) + (1x1) + (0x2) = -1 \text{ (cell } 1 \times 2 \text{ of matrix } 4 \times 4\text{)}$$

By shifting one column space to the right and after the to achieve the right side limit, one line space to the bottom, from the extreme left side of the first line and first columns, the new matrixes  $3 \times 3$  comes out and when multiplied by the filter matrix  $3 \times 3$  will produce the values of the matrix  $4 \times 4$  (cell  $2 \times 1$ ). By doing that, the matrix  $3 \times 3$  will shift to the right and down until complete the matrix  $4 \times 4$ . The final matrix  $4 \times 4$  is called an activation map.

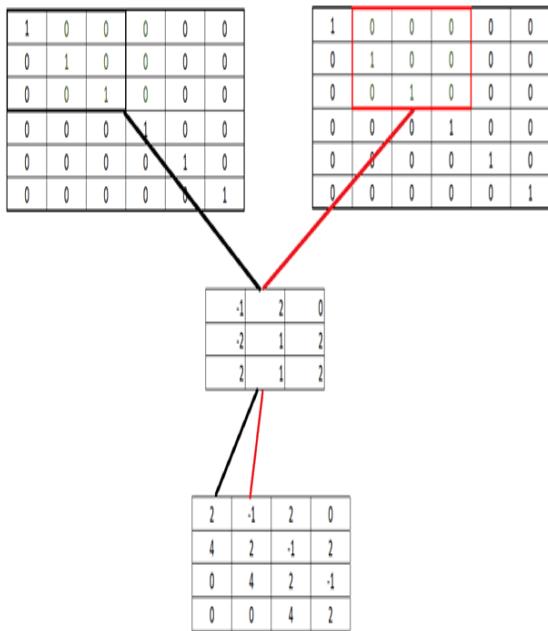


Fig. 5. Convolutional Layer procedure

#### B. Pooling Layer

The “Pooling Layer” is another filter process but uses the max or mean value of the subset matrix  $2 \times 2$  of the matrix  $4 \times 4$  that comes out the convolutional process. Therefore, considering the pooling filter a  $2 \times 2$  matrix, the matrix  $4 \times 4$  will be divided into subsets  $2 \times 2$  matrixes and each subset will give a value for the final  $2 \times 2$  matrix. In case of Max Pooling, the highest value will be taken and in the case of the mean pooling, the mean value will be taken. The figure 6 shows the pooling filter process. The subset matrix  $2 \times 2$  has the element  $x_{11}, x_{12}, x_{21}, x_{22}$  that is highlighted in black. In case of Max pooling, the highest value is 4. This value will take place the position in the final Max pooling matrix in the position  $x_{11}$ . However, if the mean Pooling is applied, the mean value is considered, that means, the values of 1.75 will take the position  $x_{11}$ .

The next step is to shift to the green position for a new matrix  $2 \times 2$  subset. The new matrix  $2 \times 2$  subset has the element  $x_{13}, x_{14}, x_{23}, x_{24}$ . In case of Max pooling, the highest value is 2. This value will take place the position in the final

Max pooling matrix in the position. If the Mean Pooling is considered as a filter, the mean value of 0.75 will take the position  $x_{12}$ . The same step goes on for the subset matrixes with elements  $x_{31}, x_{41}, x_{32}, x_{42}$  and  $x_{33}, x_{43}, x_{34}, x_{44}$ .

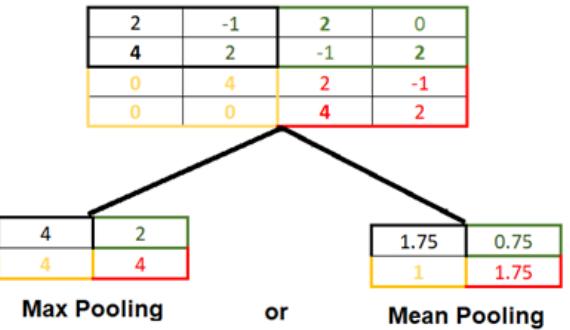


Fig. 6. Pooling Layer Procedure.

#### C. Rectified Linear Unit (Relu)

The “Rectified Linear Unit (Relu)” layer is a type of activation function that get the input of pooling layer and produce the output to the fully connected layers. The Relu is mathematically defined as:

$$y = \max(0, x)$$

The Relu graphic activation function shows the application of the function above by defining the values of  $y$  based on  $x$  is described by the figure 7.

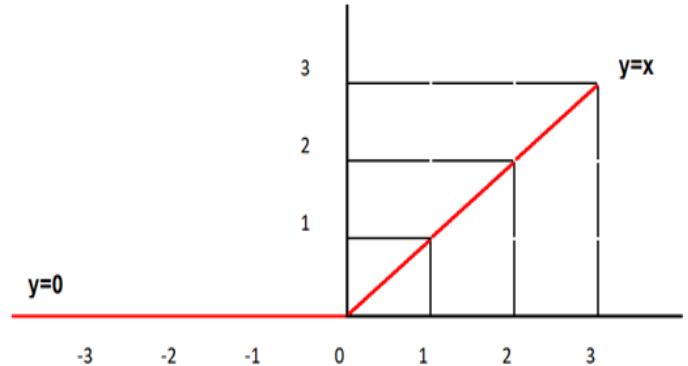


Fig. 7. ReLu function

By applying the Relu from the max Polling or mean Pooling values we have different results as shows figure 8.

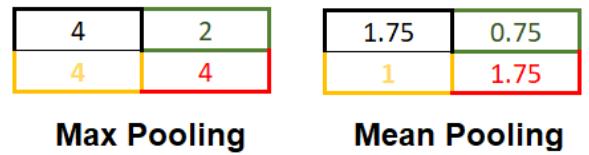


Fig. 8. ReLu fprocedure

(1)

#### D. Full Conexion Layer

The next step is to apply the Fully Connected layers, that connects every neuron in one layer to every neuron in another layer. This principle is the same applied to the traditional Neural Network as shows in figure 1. This layer basically gets the output of the pooling layer and produce an N dimensional vector where N is the number of classes.

Considering the Max Polling matrix 2x2, the vector will be. [1.75,1,0.75,1.75]. This vector will be the input to the first connected layer that applies the common procedures of the neural network with different weights for each neuron. Let's consider that the output of the last connected layer after pass for all neurons is the vector[0.5,1.7]. The final step is to pass the vector through the classification function Softmax.

#### E. SOFTMAX

The "Softmax" is used for predicting a K independent probability. The softmax function is defined by:

$$S(x_i) = \frac{e^{x_i}}{\sum_{i=1}^n e^{x_i}}$$

By applying the Softmax function to the vector we have:

$$S(0.5) = \frac{e^{0.5}}{e^{2.2}} = 20\% \text{ (probability to be moderate)}$$

$$S(1.7) = \frac{e^{1.7}}{e^{2.2}} = 80\% \text{ (probability to be critical)}$$

Therefore, the input image is classified as critical because the probability of Critical classification is 80% and the probability of moderate is 20%.

#### IV. THE CNN RUL GRAPH IMAGE CLASSIFICATION: THE PUMP BEARING CASE STUDY

Let's consider the application of the CNN to classify images of RUL of a compressor bearing, which the vibration degradation limits range from 4mm/s to 12 mm/s. Therefore, the application of the CNN aims to identify the degradation pattern whenever the vibration goes up to 6mm/s. In fact, the vibration can be detected in different levels by different sensors installed in the compressor and the RMS graph will be plotted based on a pre-defined interval of time. In this case study, we will limit the scope to the frame corner measurement as shown the figure 9.

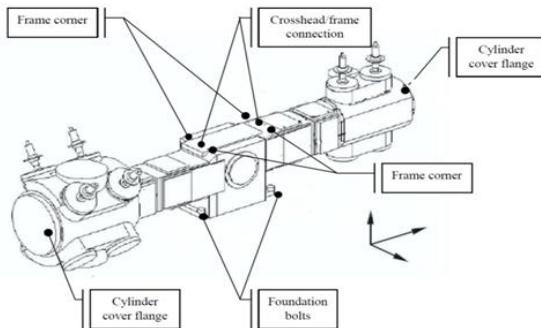


Fig. 9. Compressor Vibration Measurement: Frame corner. Source: EFRC, 2009

In order to train the CNN, the set of figures with different pattern of RUL were classified as "Critical" and "Moderate". The figures classified as moderate have the vibration between 4mm/s and 6mm/s. The figures classified as critical has the vibration measurement values between 4mm/s and 12mm/s as shows the figure 10 A and B respectively.

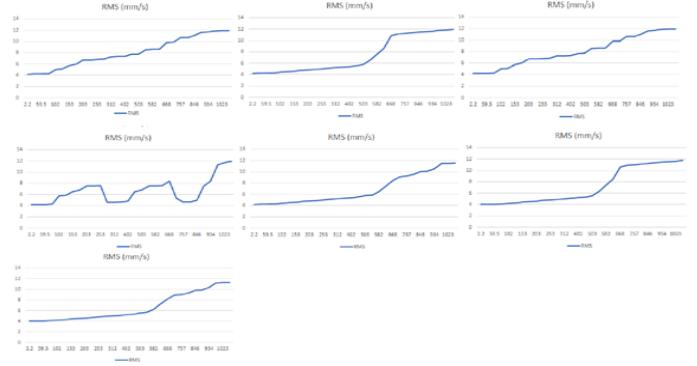


Fig. 10. Collected Vibration profile input data: Critical

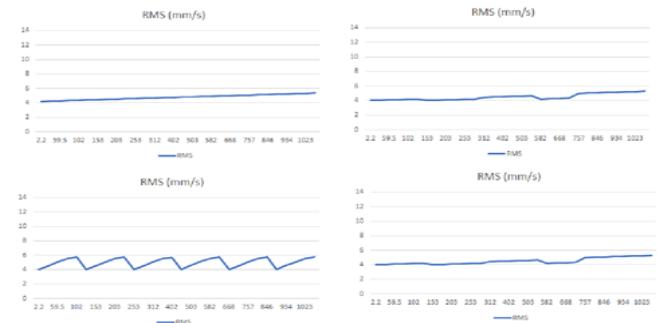


Fig. 11. Collected Vibration profile input data: Moderate

The figures 10 and 11 are organized in a file called RMS and it is the input in the CNN based on the MATLAB Software app. In addition, to the input the file RMS, the CNN need to be configured considering the convolutional layer, polling layer, as shows the figure 12.

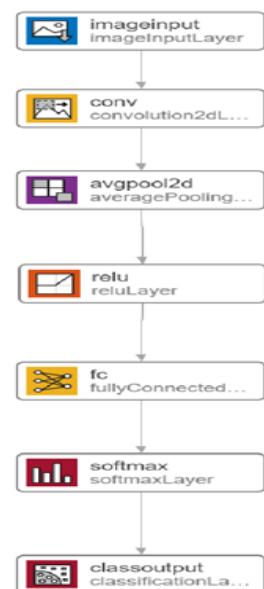


Fig. 12. CNN configuration

Since the dataset is small with only eleven figures, the dataset was not divided into training and test data sample. However, it's highly recommended to do that for the bigger dataset samples. The next step is to perform the CNN training in order to obtain the CNN model for classifying the RUL figures. The figure 13 shows the performance of the training that achieves 100% of performance and zero loss after five interactions.

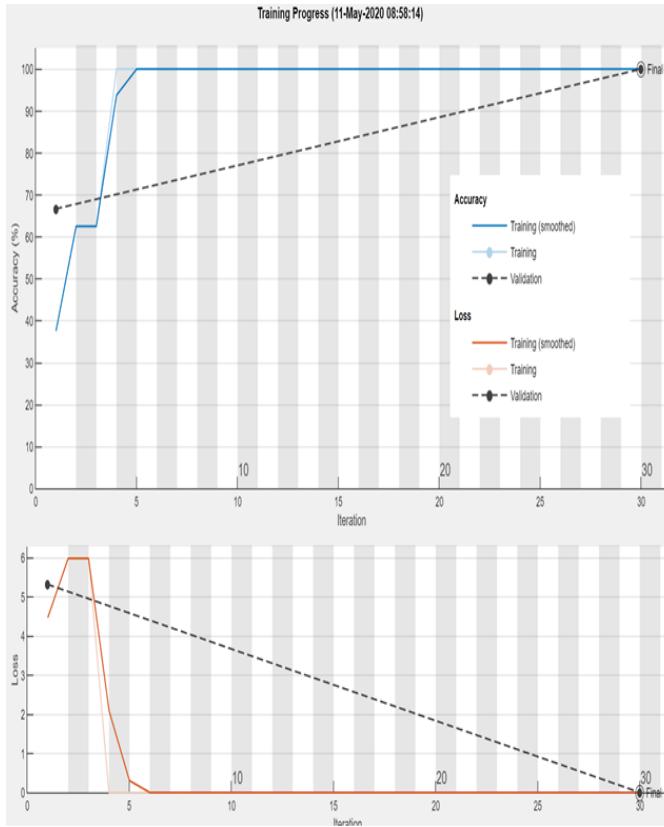


Fig. 13. CNN Training performance result

The final step is now validating the CNN model by using new input data figures such as new RUL profiles from different compressors bearing vibration measured in the frame. The figure 14 shows the input data applied for validation by using the model defined in the figure 12. Note that RUL figures have both classifications such as "Critical" and "Moderate" and we expect that the model performs a proper classification for each one of them. The Figure 14 (D) is a special case where the RUL profile is not complete and just begin to go over the vibration moderate limit point of 6mm/s. It's expected that the model also classifies such figure as "Critical". That will prove the applicability of such model for any degradation period when the vibration level rises from moderate to critical level.

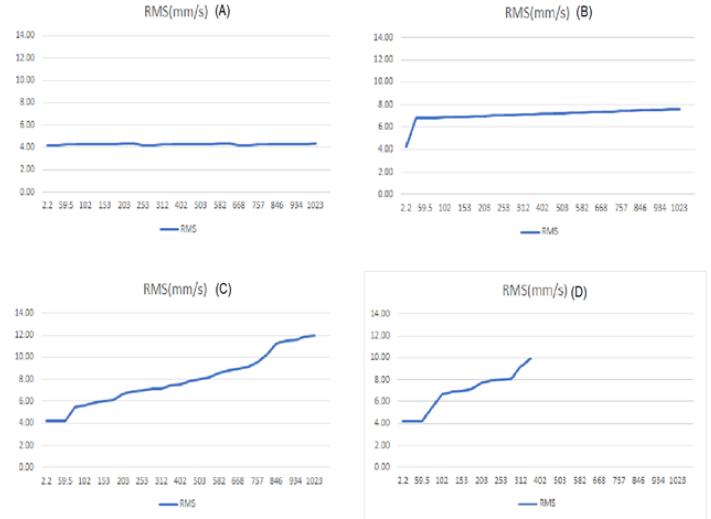


Fig. 14. Collected Vibration profile validation data: Moderate and Critical

The figure 15 shows the result of the classification performed by the MATLAB software by using the model defined in the figure 12.

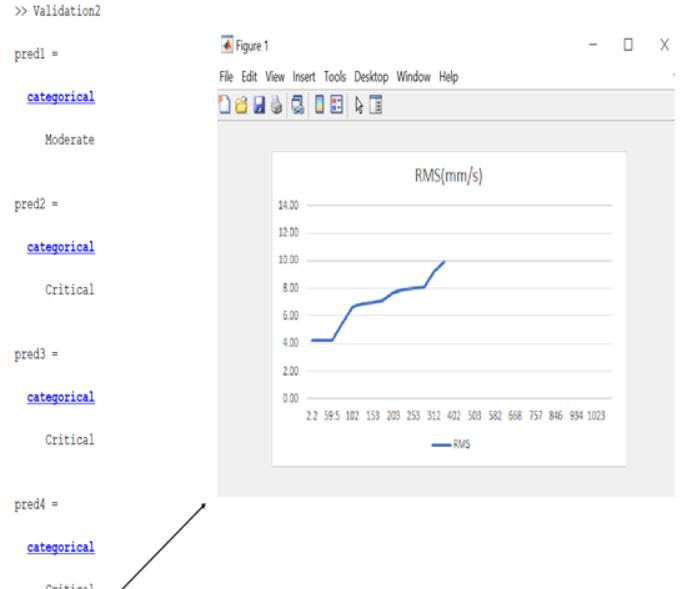


Fig. 14. Final validation data: Moderate and Critical classification

The validation result is demonstrated in the figure 14 that shows the proper classification of the RUL figures as described in figure 14. Therefore, Figures 14 A, B, C and D has been properly classified as Moderate (A) and Critical (B, C and D) respectively.

## V. CONCLUSION

The application of CNN method enables the automation of the Infrared Thermography test that will reduce drastically the effort of the maintenance team to go on the field and

perform such test in many electric motors and other equipment. By applying the CNN, the maintenance team will receive the information of each electric motor criticality level in their screen and the alert that indicate the one classified as critical. It will enable that such maintenance expert focusses their effort first in the critical equipment.

The CNN methodology is very promising and can be used as supported tool for the maintenance team in their daily based activities receiving alert of equipment/component under a critical state of degradation.

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The Convolutional Neural Network advantages:

- The ability to turn out image information in data classification
- Can be applied to alert levels of degradation detected by graph image or equipment defect and safety.

The Convolutional Neural Network drawbacks are:

- Requires a high level of A.I knowledge.
- Too complex model to be performed manually, it's necessary an algorithm.
- Depends on the problem, it will take a considerable time for the simulation.

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