CollabNet - Collaborative Deep Learning Network

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Abstract: The goal is an improvement on learning of deep neural networks. This improvement is here called the CollabNet network, which consists of a new method of insertion of new layers hidden in deep feedforward neural networks, changing the traditional way of stacking autoencoders. The new form of insertion is considered collaborative and seeks to improve the training against approaches based on stacked autoencoders. In this new approach, the addition of a new layer is carried out in a coordinated and gradual way, keeping under the control of the designer the influence of this new layer in training and no longer in a random and stochastic way as in the traditional stacking. The collaboration proposed in this work consists of making the learning of newly inserted layer continuing the learning obtained from previous layers, without prejudice to the global learning of the network. In this way, the freshly added layer collaborates with the previous layers and the set works in a way more aligned to the learning. CollabNet has been tested in the Wisconsin Breast Cancer Dataset database, obtaining a satisfactory and promising result.

1 INTRODUCTION

The use of machine learning techniques is becoming more frequent in the most varied tasks of everyday life, and the growth of this area of knowledge continues at a fast pace. This growth is due to many factors, including the growing volume and variety of data available, computational processing and data storage, both increasingly cheaper. Thus, it is possible to cite some examples of its applicability, such as the filtering of content in social networks, recommendations of sites, identification of objects present in images and videos, transcription of voice in text, diagnosis of diseases, etc.

Although the studies of machine learning techniques began in the 1960s, it was only by means of the use of deep learning techniques that this area of knowledge started to present similar performance to humans in complex problems, and some cases even surpassed. The performance of deep algorithms can be attested in several machine learning competitions scattered around the world (Bengio et al., 2006)

Deep learning brought significant advances in solving problems that until they were a barrier, even for the best machine learning techniques known to the scientific community. The deep learning technique is very efficient in the discovery of complex structures in high dimensional data and is therefore applicable to many fields of science, business, and government (Lecun et al., 2015). This technique has produced promising results for various tasks of natural language processing, feeling analysis, classification, chatbot and language translation (Schmidhuber, 2014).

Most deep network architectures use stochastic methods in initializing and adding new hidden layers (Huang et al., 2016; Arjovsky et al., 2017; Goodfellow et al., 2014). The use of stochastic methods slows learning because as a result of their randomness and the natural tendency is that there is a disturbance in error. In an attempt to optimize learning by increasing the depth of a neural network at runtime, minimally disturbing the network error emerged at CollabNet. In this way, the present work is to present a proposal of insertion of new layers in a feedforward type neural network, so that you work collaboratively without learning of the neural network as a whole.

The organization of this work is given as follows, the first section introduced the research theme. The following chapter presents the main concepts of deep learning, describing a set of works that propose new architectures of deep learning networks and

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training methods. The third section presents the proposed methodology, explaining details of the structure and training of the CollabNet network, as well as the change made in the sigmoid activation function, called $sigmoid_A$. Section 4 presents the experiences of CollabNet in the task of pattern recognition with the base Wisconsin Breast Cancer Dataset (Wolberg et al., 2011). From these tests, the results are presented and attest the efficiency of the method, demonstrating that it has a promising future in the resolution of classification problems and pattern recognition. The last section shows the observed conclusions as well as the contributions obtained.

2 RELATED WORK

The algorithms that implement deep learning generally seek the identification of abstractions from the data, starting from the identification of the lowest levels and arriving at the highest levels, so that, through the composition of the lower level characteristics, the higher-level features and, consequently, new representations (Larochelle et al., 2009). In this way, the learning of characteristics in multiple levels of abstraction allows the computational system to learn complex functions of mapping the data from input to output, independently of features created manually. That is, this technique can be considered as a way to automate the generation of characteristics that are more representative of a given pattern recognition problem (Bengio, 2009; Lecun et al., 2015). In this way, the number of algorithms, strategies, and architectures implementing this technique is increasing. This section presents some approaches that somehow brought innovation to the area and served as a conceptual basis for the present work.

A strategy for building deep networks based on stacking layers of denoising autoencoders is presented in (Vincent and Larochelle, 2010), where autoencoders are trained individually to restore the corrupted versions of their entries. This approach is a variant of traditional self-encryption, where an element called denoising autoencoder added, which is trained to reconstruct a repaired entry of a corrupted version of the x vector using a stochastic input mapping $\tilde{x} \sim q_D(\tilde{x}|x)$.

In (Netanyahu, 2016), a new activation function is proposed, which implements nonlinear orthogonal mappings based on permutations using deep convolutional autoencoders. The OPLU, thus named, was tested in feedforward and recurrent networks, performing similarly to other already-recognized activation functions, such as Tanh and ReLU. The OPLU activation function has a fundamental characteristic to preserve the norm of the backpropagation gradients.

3 METHODOLOGY

The present work focuses on the implementation of a new strategy of insertion of hidden layers in a deep feedforward network, to avoid instabilities in the error of exit, during training, from a new layer inserted by traditional methods. The integration between the new layers must be carefully observed so that the network output error always converges. This continuous convergence must be such that a new layer always improves the result of the previous layers and with this ends up still having a collaboration of the new layer. Hence, this work presents an efficient way to increase the depth of the network, by adding layers collaboratively in the execution time.

3.1 Materials

For training and testing of the network, the database was divided into two parts. A part containing 75 % of the database was used for training and the remainder for testing. At the end of the tests, the cross-validation of the data was promoted to verify the independence of the result concerning the data. After several tests with different configurations, better performance was obtained in the selected base, with the use of 16 neurons in all the hidden layers, a rate of learning to vary between $\eta = 10^{-3}$ a $\eta = 10^{-5}$. The variable c started at 0 with a jump ranging from 10^{-2} e 10^{-3} every 20 times, ΔD varying at the same rate as c, the activation function $sigmoide_A$ in the intermediate layers and the linear function in the output layer.

With this configuration above, CollabNet obtained a decay of the Mean Square Error (MSE) more efficiently, with the decay of the permanent error, when compared to the MLP training without the method proposed by this work, as shown in Figure 1. The hit rate for this setup was 95.7%.

3.2 Method

This approach assumes that each new layer must begin its training precisely from the point at which the immediately preceding layer has stopped. In other words, it is sought to decrease the error gradually, even when another layer is inserted into the neural network, as shown in Figure 2. Thus, this scheme can provide increasing learning, avoiding traps of local minimums or plateaus.

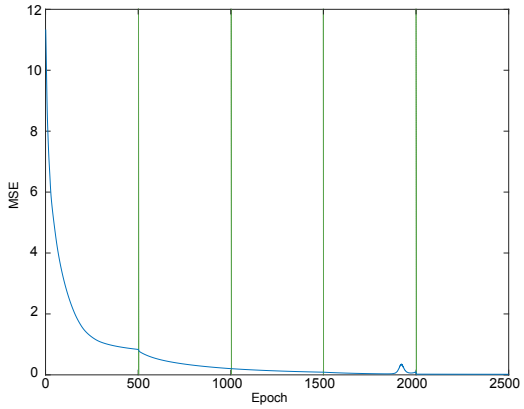


Figure 1: Decay of the MSE.

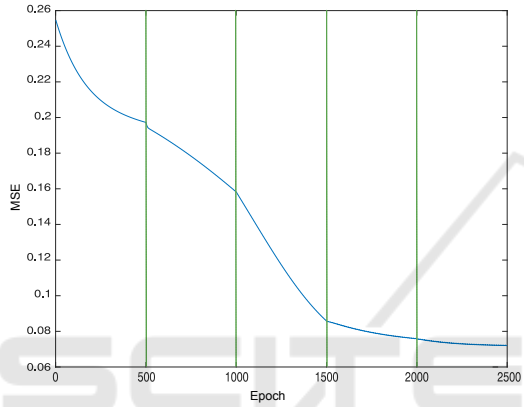


Figure 2: Expected error behavior.

However, to succeed in this task, the integration of the new layer must be properly performed, otherwise the further layer may negatively affect the learning already achieved, causing a worsening in learning. Therefore, the main idea of this proposal is to develop a technique to incorporate the learning of the previous layers in the training of the new layer, in order to provide knowledge about the learning already obtained to a new layer.

The CollabNet structure is given according to equation $f(x) = w \cdot f^{(3)}(w \cdot f^{(2)}(w \cdot f^{(1)}(x)))$. In this case, w represents the training weights of the layers, $f^{(1)}$ is the activation function of the neurons of the first layer, $f^{(2)}$ of the second one and $f^{(3)}$ represents the function of the third layer. The last layer is called the output layer, and the network depth is given by the total length of the layered chain.

3.2.1 Training

The training strategy proposed in this work starts analogously to the traditional method of an MLP network, with only one hidden layer and the use of the backpropagation algorithm (Glorot and Bengio, 2010). After this first stage of training, when the network exit error does not decrease further, then a new layer can be inserted into the training network. This inclusion must necessarily be done one by one, since after the insertion of a new layer it is necessary to carry out several procedures, commented below, aiming at the harmonious inclusion of the new hidden layers.

The proposed approach presents an innovative way of inserting new layers. This method is intended to ensure that new layers do not corrupt the network exit error. For this, it is necessary that the output of each neuron of the newly inserted layer is the same value of the output of the corresponding neuron of the previous layer considering all the input data (Figure 3).

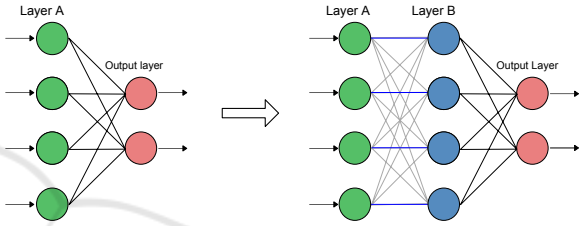


Figure 3: Insertion of a new layer.

In this proposal, the initialization of weights between layers A and B is performed randomly. This initialization disturbs the network output error after the inclusion of a new layer. Therefore, in order to provide output of layer B equal to output of layer A, that is, the output error is not disturbed at the insertion of a new layer, it is necessary to provide treatment at the output of the layer A. Otherwise there is no guarantee that the output of layer B is the same of layer A, since the output of layer B will be altered by the newly initialized weights and by the activation function of layer B neurons.

This work proposes to perform the data treatment between layers A and B to compensate for the change given by the newly created weights. This treatment consists of a kind of mask, here called D, as shown in Figure 4. The mask D modifies the values that arrive in the neurons of layer B, allowing that the output of each neuron is exactly equal to the output of the corresponding neuron in layer A.

The D mask ensures that each neuron in the new layer receives only the influence of its corresponding neuron from the previous layer. The operation of the mask D is shown in Figure 4 and occurs as follows: the connections represented by a colored line indicate that the mask does not change the value, that is, the neurons of the new layer B) receive exactly the output value of the corresponding neuron in the anterior layer (A). The connections represented by a gray line have

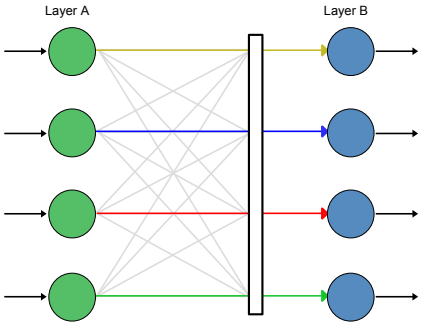


Figure 4: Mask D between an old layer and the newly inserted layer.

their value overridden by the mask, so the value received from the adjacent neurons is null. In this way, the input value of each neuron of the new layer is the same value that leaves the neuron in layer A.

For the mask D to perform the filter as mentioned earlier, there must be multiplication by the inverse of the corresponding weight value, such that the value effectively processed by the layer B neuron is exactly the output value of the corresponding neuron of the layer A. In this way, it is guaranteed that the training of layer B will start exactly from the point where the previous layer stopped. It is also ensured that new insertions do not hinder the learning of the network as a whole.

After the inclusion of layer B, it is then taken to calculate the input of this layer, given by equation 1, where W_hi are the weights between layers A and B, D is the mask and Y is the output of layer A. The $.*$ operator means an element-by-element multiplication and not a standard matrix multiplication.

$$net_h = (W_{hi}.*D)*Y \tag{1}$$

In addition to the mask D, another modification proposed in this work consists in altering the activation function of the B layer neurons to, instead of sigmoid, to be the identity function. In this way, what enters the neurons of layer B becomes the output of this layer. Thus, one has the guarantee that the output of each neuron from layer B is exactly the output of the corresponding neuron in layer A.

However, the innovations proposed in this work, as they are, do not allow the new layer to acquire an apprenticeship since the output of layer B will always equal the output of layer A; therefore, there is no reduction of the network output error by modification of the new weights created. Thus, after insertion of layer B, when the network training algorithm is executed, both the mask D and the activation function of the neurons of layer B must change, to allow an influence on the output from the Web.

However, abrupt withdrawal of the D mask and/or the swapping of the sigmoid identity-activation function promote, on the one hand, the possibility of learning acquisition by layer B, but on the other hand, provide a sudden rise in error network. Thus, it is necessary that there is a smooth and gradual transition of mask removal D and the conversion of the identity function to sigmoid.

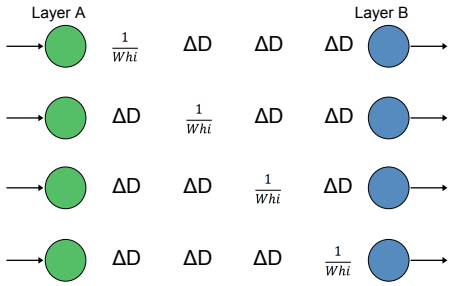


Figure 5: Change mask values D through ΔD.

The transition expressed in the previous paragraph must occur during the execution of the training. Thus, after a certain number of iterations (in this work it was around 300), the weights between layers A and B should promote the reduction of the output error of the network, without prejudice to the decay of the error promoted by the previous layers. This transformation is performed through a ΔD ranging from $0 to 1$, with speed defined via parameterization of the initialization of the new layer, as shown in Figure 5. In this way, it is intended to ensure that the disturbance caused by the insertion of a new layer hidden in the network is the smallest possible.

While all the elements of the mask D varied uniformly, the elements of its main diagonal would vary according to the random weights generated at the initialization of the new layer depending on the initial values of those weights, the values of the main diagonal converge faster to one.

For this approach a sigmoid activation function was used; however, its use is only performed when the network is only a hidden layer. Thus, from the inclusion of the second hidden layer, it was necessary to make a small adaptation in the sigmoid function, with the intention of precisely controlling the influence of the new layer in learning the network. This adaptation is presented in Eq. 2.

$$\phi_A(n) = \frac{1}{1+e^{-n}} * c + n * (1-c) \tag{2}$$

where $\phi_A(n)$ is the output of the neuron with the $sigmoide_A$, c is the weighting factor of the activation function and n is the weighted sum of all the synaptic inputs of the neurons.

The adaptation performed in Eq. 2 was implemented by the need for the activation function to be the identity function at the beginning of training of a new layer. Throughout the training of this layer, the activation function must be gradually converted into the sigmoid function, which is promoted by the c variable, so that after a certain amount of iterations, the activation function returns to be only the sigmoid function traditional. Thus, the variable c acts by weighting the identity and sigmoid functions, transforming an activation function of identity at the beginning of the training of the new layer, to a sigmoid function at the end.

The inclusion of the c variable in the sigmoid activation function (ϕ) gives the designer the power to control the influence of a layer in learning, in which the closer to 1 is the value of the variable c, the greater its influence and the closer to 0, the less will be such influence. The use of the variable c in training is of great importance for the method of inclusion of new layers, because, with this artifice, it is possible to guarantee that the influence of the new layer is gradual, as the weights of the new layer adjust to the problem, since, by default, these are generated randomly for each new layer inserted.

Due to the change in the sigmoid activation function mentioned above, it was necessary to use the derivative of the altered function in the backpropagation algorithm (Eq. 3).

$$\frac{\mathrm{d}\phi_A}{\mathrm{d}n} = c \cdot (y) \cdot (1-y) + (1-c) \tag{3}$$

where y is a traditional sigmoid function and c is the weighting factor.

Using the D mask and the activation function changed with the use of the variable c, the insertion of a new layer did not interfere negatively in the learning, as it can be seen in the following chapter with the presentation of the results obtained in the experiments.

4 RESULTS AND DISCUSSION

CollabNet application was performed in a pattern recognition task. The base used was the Wisconsin Breast Cancer Dataset, withdrawn from the Machine Learning Repository of the University of California at Irvine (UCI). This database has information on 669 breast tumor registries, having two classes identified as malignant (M) and benign (B) tumors, each with ten calculated real characteristics for each cell nucleus: radius, texture, perimeter, area, softness (local variation in radius length), compactness ($\frac{perimetro^2}{area-1.0}$), concavity (concave portions of the contour), concave points, symmetry, and fractal dimension.

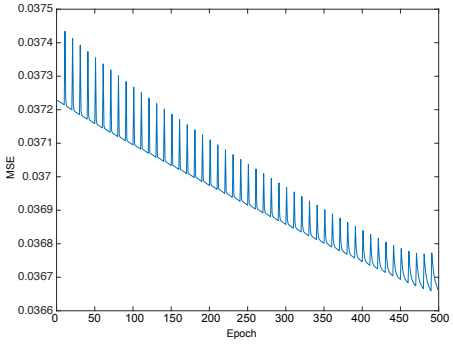
For this database, several configurations of the proposed network were tested, varying several initialization parameters, for both network and new layers: number of neurons and epochs, learning rate, value and moment of increment of variable c e of the mask D (ΔD) and the behavior of the weights in the training. However, the amount of neurons in the hidden layers is a primary parameter that relates to the structure of the network. This parameter is defined at the moment of creation of the network, being immutable from the insertion of the second hidden layer, ensuring that each new layer hidden changes only the depth of the network and not its width.

4.1 Parameterization

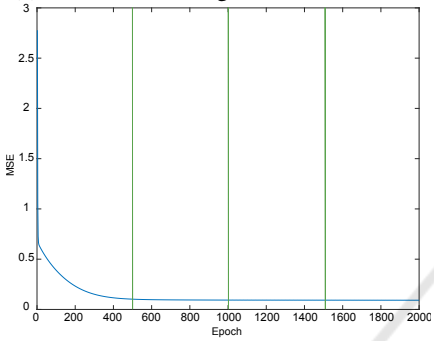
The training parameters were estimated empirically and always with the inclusion of a new layer. The learning rate, the number of times, the behavior of the weights of the new layer in relation to its initialization are essential parameters of the insertion of a new layer. Finally, we have the parameters related to the behavior of the variable c and the mask D, defining information regarding the velocities of variation of these variables in training.

Given the various parameters of the network, the variable c deserves a more comprehensive explanation, which in this project plays a special role. This variable is directly related to the inclusion of a new layer, as well as its transition, so that a newly inserted layer, not useful for learning the network, can become an element of importance to this learning, as presented in the Section 3. The variable c has the responsibility to control the influence of a new layer in training, being that influence is a quantity directly proportional to the value of c, that is, the closer the c is of its value (1), the higher the influence of the new layer in training. Therefore, the control of c is the great challenge of this proposal and the way that the value of this variable increases during the training of the new layer needs to be parameterized individually. The parameterization occurred empirically, with values between 0.001 and 0.003 being chosen.

The designer must carefully observe the adjustment of the increment of c since its correct parameterization has a direct influence on the behavior of the MSE. Figure 6(a) presents an enlarged view of the last training layer shown in Figure 6(b), wherein this inclusion an increment of the variable c relatively high was defined, approximately 0.3 at each iteration. In each iteration of c, it is possible to perceive the perturbations in the MSE. This phenomenon is explained by



(a) Variable c with high incremental value



(b) Variable c with low incremental value

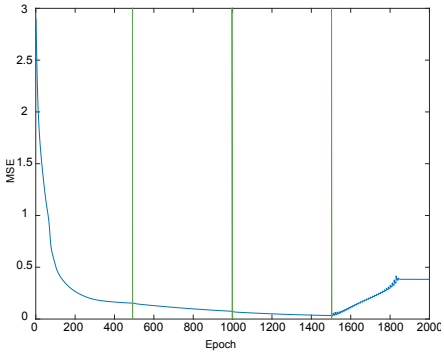
Figure 6: The behavior of MSE variations of c.

a high variation of the variable c and by the weights that are not yet close to the convergence of the final value.

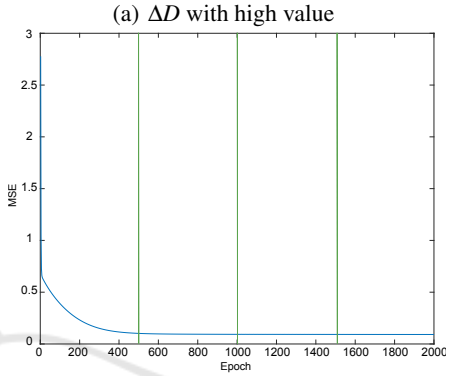
In Figure 6(b), the MSE is presented shortly after the inclusion of a new layer with an increment of the variable c relatively low. In this case, the influence of the new layer is low and this new layer increases the training time.

Also the variable c, the mask variation D also plays a vital role in the inclusion and control of new layers, necessitating that it be observed in the act of inserting new layers, considering that ΔD has its variation intrinsic to the incremental value of c and is directly related to the mask transformation D. The correct parameterization of ΔD is essential for training since this parameter together with the variable c controls the influence of the new layer in the global training. The mask D must be started with 0, the exception of the main diagonal and its update is carried out simultaneously with the variable c by the value ΔD.

A non-harmonious configuration of these parameters results in the undesirable behavior of the MSE, and consequently impairs training. As an example of such undesirable behavior, cases are shown wherein ΔD is high 1 and low 2, respectively. This parameter refers to the speed that mask D is invisible to the training, that is, the process of inclusion of the new layer has been completed.



(a) ΔD with high value



(b) ΔD with low value

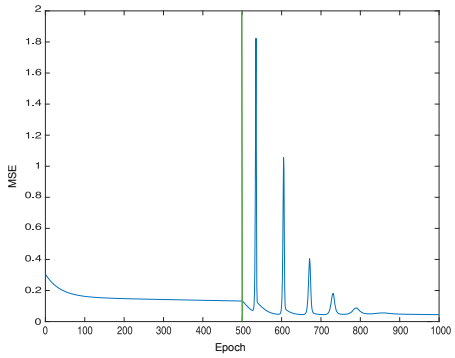
Figure 7: The behavior of MSE variations of ΔD.

Figure 7(a) shows an undesired behavior in the last layer, caused by the convergence velocity of the mask D. In Figure 7(b), another unwanted behavior is presented, where the influence of the new layer is practically null because the updating rate of ΔD was relatively small.

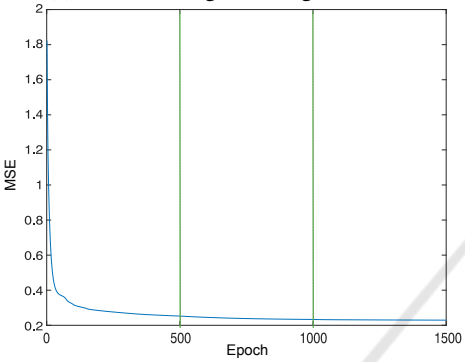
Another major challenge in CollabNet's parameterization, as in any MLP-based approach, is the definition of the learning rate. This parameter is directly related to the learning speed of the network. At CollabNet, the learning rate may be different for each layer. In this way, it is necessary that the designer has the sensitivity and the ability to define the value of the learning rate for each layer. Figure 8(b) illustrates the CollabNet output, with three hidden layers and the relatively low learning rate value ($5x10^{-5}$).

In this example, the output MSE behavior is displayed with a low learning rate. Thus, the MSE tends to continue the output of the network in previous layers, without promoting any improvement in the decay of the output error.

In Figure 8(a), the error behavior is presented with the inclusion of a new layer, now with learning rate having a relatively high value (0.1). It is possible to observe that the tendency of the error, in this case, is to initially lower and soon after increasing sharply with each increment of c. This behavior is explained



(a) MSE with high learning rate value



(b) MSE with low learning rate value

Figure 8: MSE for variations of learning rate.

by the fact that with the high learning rate at a time where the weights of the new layer still do not conform to the weights already trained in previous layers, thus generating a greater disturbance in the MSE. This fact can be still perceived, observing in the final graphics part, where the weights are already more adequate for the rest of the training, so the perturbation of the NDE with each new increment of c is smaller.

4.2 Validation Metrics

In this work, the confusion matrix and receiver operating characteristic (ROC) were used as evaluation metrics. With the confusion matrix, one can check the network performance in the task of sorting patterns, regardless of the class. Figure 9 presents the confusion matrix obtained from the experiment quoted in this section, finalized with five hidden layers. In this figure, class 1 represents benign cases, and class 2 represents malignant cases, the first two diagonal cells show the number and percentage of correct classifications by CollabNet, that is, 448 biopsies were correctly classified as benign (True Negative - TN) and 221 cases were correctly classified as malignant (True Positive - TP), corresponding respectively to 64.1% and 31.6% of the 699 biopsies. 20 samples (2.9% of total) of the malignant biopsies were incorrectly classified as benign (False Positive - FP). Similarly, ten biopsies (1.7 % of the data) were improperly classified as malignant (False Negative - FN).

Of the 468 benign predictions, 95.7% were correct and 4.3%, erroneous. Of the 231 malignant predictions, coincidentally, 95.7% were accurate and 4.3 %, incorrect. Of the 458 benign cases, 97.8% of the cases were correctly predicted to be benign, and 2.2% were predicted to be malignant. Of the 241 malignant cases, 91.7% were correctly classified as malignant and 8.3% as benign.

Overall, 95.7% of predictions were correct, and 4.3% were wrong classifications.

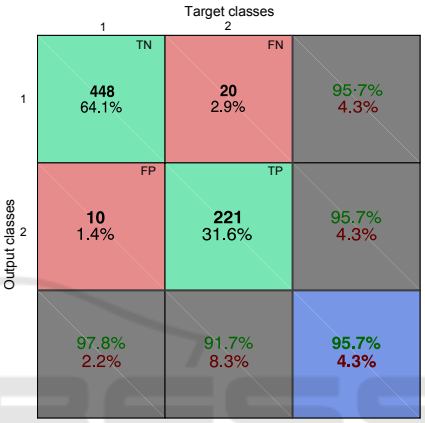


Figure 9: Matrix of confusion at the end of training.

Another metric used in the evaluation of CollabNet is the ROC, or ROC curve, where for each class of this classifier, there are values in the interval of [0,1] for each output. For each class, two values are calculated, the TP Rate or sensitivity and the FP Rate or specificity. Therefore, sensitivity is the ability of the system to correctly predict the condition for cases that have it, whereas uniqueness is the ability of the system to predict cases that do not have a certain condition precisely.

Figure 10 illustrates the ROC plot for the CollabNet configuration presented in this section, where the closer to the top left is the graph lines, the better the ranking.

In this graph it is possible to see that both classes, malignant (blue) and benign (red) tumors, have their curves near the upper left corner, demonstrating the efficiency of the method in the classification of the selected database. However, a greater approximation of the curves at the point of interest of the ROC curve must be object of constant search in any machine learning algorithm. In this way, parameter adjustments and more validation tests are essential in the search for better classifier results.

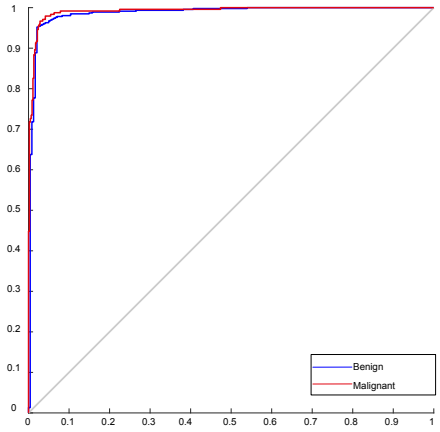


Figure 10: ROC plot.

5 CONCLUSIONS

This work proposes a training architecture inspired by layered stacking techniques; however, this approach goes hand in hand with the classic stacking since there is no need to corrupt data entry for each new layer. In this way, greater training control is achieved, starting the training of a new layer always from the point where the network stopped. For that, a change was performed in sigmoid function allowing to control the influence of the new layer in the global training of the network.

The results obtained in the experiments of this work demonstrate that this approach has a promising future regarding a new RNA concept, where good results were obtained even with some training disciplines. The way how to process variable *c* and the use of an intelligent algorithm to identify the ideal time for the inclusion of a new layer are possible outcomes of this work.

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