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Smart X-Ray Scanners Using Artificial Neural Networks

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Abstract **- Object detection and classification in Artificial Neural Networks (ANN) can play an important part in finding solutions for various tasks that are considered critical or time consuming if executed by humans. Also, object detection can be used in several applications and domains. One of which is physical security, where many illegal items, that should not pass through checkpoints, exist. In this sense, smart X-ray scanners can help in detecting any restricted object like weapons, knives or even drugs within a bag or held by an individual. This paper aims to provide a first step towards smart scanners where the MultiLayer Perceptron (MLP) is used to classify and detect two different types of illegal objects. Moreover, training of the network is performed using the Back Propagation algorithm, one of the most widely used algorithms in the MLP.**

Keywords – Smart Scanners; X-Ray; Artificial Neural Networks

I. INTRODUCTION

X-ray scanners are used in various security checkpoints especially in airports. They constitute a key figure in the detection of illegal objects and help insuring the general security. Nevertheless, all detections still use the supervision of an employee that may miss or fail to recognize an item due to many reasons and inadvertence error. Replacing the traditional scanners with new innovative smart x-ray scanners which can detect untrusted or illegal items, can remarkably improve the security sector and decrease the probability of errors. This solution can be used in many sensitive sites, like airports, governmental sectors, prisons or even in public places. The main purpose of this work is to create innovative solutions to improve detection and recognition of illegal and unauthorized items held by an individual using a smart scanning methodology for recognizing prohibited items. The created system tackles the problem of X-Ray capturing and classifying specific items using the MLP in an ANN [1], [2], [3], [4]. For most images with a reasonable resolution, pixels have spatial constraints, which should be enforced during the classification [5]. The aim of image classification is to automatically categorize an image, after being trained on a set of different categories. Supervised machine learning techniques are usually used for this task using sample images of each category, called the training data. Such algorithms categorize an unknown image depending on the samples that are most similar to it [6].

II. THE NEURAL NETWORK

ANNs became well known and frequently used in many applications. They are inspired by the human brain and by its training on distinguishing between several items by classifying them. A powerful tool used in a neural network is the MLP. It is considered to be a powerful mechanism due to its ability to solve difficult classification problems, where a single perceptron fails to do so. MLPs can use a powerful algorithm known as the “Back Propagation Algorithm” [7]. In the latter, two passages exist. A direct one, known as the forward calculation path, and a backward passage known as the backward path.

In the forward path, the output of the network is computed by multiplying the weight vector by the input vector. While the backward path consists of a reverse calculation from the output layer to the input layer in order to adjust the weight vector.

Furthermore, the MLP has three major characteristics (see figure 1):

- The neuron model in the network has a nonlinear output, i.e. the activation functions can be sigmoidal functions:

$$y\,(j) = \frac{1}{1-e^{av_j}} \tag{1}$$

- The network contains one or more Hidden Layers (HL); these HLs are used for complex systems and causes.
- The network has a large number of connections.

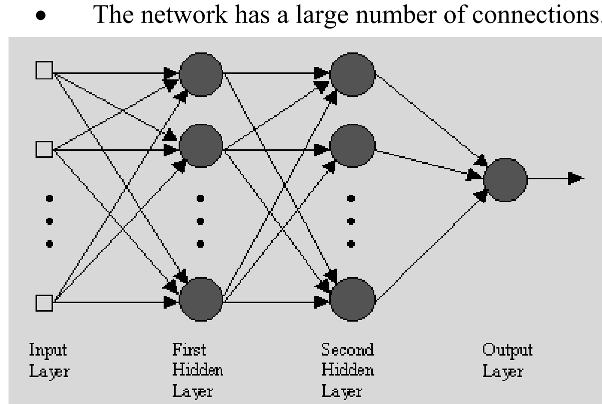

Figure 1.Network Architecture.

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The combination of these major characteristics, together with the ability of learning from experience through training, give the MLP its computing power. These same characteristics are also responsible for the deficiencies in our present state of knowledge on the behavior of the network [8],[9],[10].

III. TRAINING

In order to reach a final solution of a smart x-ray system, it needs to undergo several steps and processes to learn what to detect and alert in case of detecting an illegal item. The learning process uses a training technique where a set of images of specified objects are fed to the system in order to treat them and collect data for every item [1]. This process is done by the backpropagation algorithm where the forward and backward paths are performed. This learning process, normally called as epoch, is maintained until obtaining the final result.

During training, the weights are fixed in the forward path, and adjusted in the backward one. The backpropagation algorithm will persist until minimizing the errors and meeting the desired outputs.

In our architecture, the dimension of the input pattern set was chosen to be reliable to the number of pixels of the images supplied to the network. Each input node is connected to each neuron of the hidden layer, where the number of neurons in the hidden layer is equal to the input pattern set divided by two. Performing this scenario on two items, a gun and a knife, produces an output layer with two neurons in order to obtain the desired outputs of {0, 1} and {1, 0}. Then each neuron in the hidden layer is connected to the output neurons with a weight value of this connection. Figure 2 illustrates the training window of our ANN.

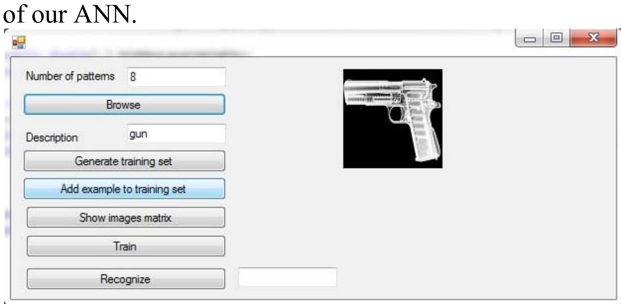

Figure 2.Training Images.

As a first step, the system needs to be trained with items that are to be scanned and detected. Therefore, a training data set needs should be prepared and used as the database of the objects that the network needs to identify. Images containing a gun and a knife, to be recognized later, are fed to the system in order to be added to the training sequence. In our case, 8 images per object are used. The system starts loading the images and converts them to a set of array fitting the input nodes.

During the training process, after calculating the output of each pattern, the system starts computing the error function which is the difference between the desired and obtained outputs. Afterwards, it starts the back propagation technique to minimize this error and to compute the local gradient needed to adjust the weights reaching a final set of newly updated weights [7], [8]. These weights are then used to classify and distinguish objects. Moreover, these final weights can be reached when the total error of the system tends to zero or when the maximum number of iterations exceeds the configured one. Figure 3 shows this training process.

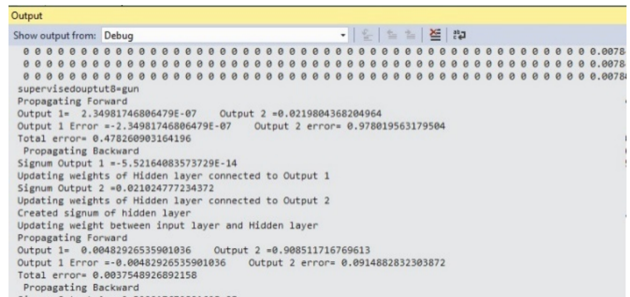

Figure 3.Training process.

IV. IDENTIFICATION OF RESTRICTED ITEMS

Once the training is finished, the system is supplied with an image of a restricted item which should be known. The image's pixels are converted to a set of data and inserted as an input. Afterwards, forward propagation begins using the new weights. And the output result should classify and detect the item.

Moreover, recognition based on matching, assigns each unknown pattern to the closest class in terms of a predefined metric. The minimum distance classifier computes the Euclidean distance between the output of the captured items and all the predefined patterns; the calculation resulting in the smallest distance is then flagged as the recognized object is classified.

V. RESULTS AND DISCUSSIONS

This paper aims to provide a blueprint for developing an autonomous device capable of identifying and classifying an object with a high success rate and least amount of time. It is merely a first step towards obtaining smart x-ray scanners.

After a lot of testing and variable adjusting, an average of around 75% of correct classifications was reached. Figure 4 shows one of these results.

Figure 4.Showing Results and Classification.

This 75% success rate is based on statistics collected after trying to classify 8 images. These results are considered good as a first step, but nevertheless, the system can be optimized for better classification and identification.

The main constraints of this work were the compromise between the number of examples to be used and the number of epochs to be done, also the learning parameters to be used while making sure to avoid local minima and not bypass the global minima. All of these parameters and constraints can only be resolved by trial and error. And the system should become more stable, after many trials using several examples of each picture. Also, the learning parameter is taken 0.5 while the initial weights are randomly selected between -1 and 1.

VI. CONCLUSIONS AND FUTURE WORK

This paper presented the detection and classification of items using ANNs. The backpropagation algorithm is used to differentiate between items and the MLP is used to automatically detect and classify the items. The performance of the system is fair, but can still be optimized in many ways for better performance. The initial weights can be amended, and the learning parameter can be changed. Also, more examples should be added and the number of epochs should be increased to minimize the error.

Furthermore, this system was trained only on two types of examples, and it can be extended to hold more examples and more complex items.

This work is a step forward towards smart scanners. And, as a future work, the system can be upgraded to recognize more items and to obtain a higher success rate which might eventually lead to a complete smart x-ray scanner.

REFERENCES

[1] S. Haykin, Neural Networks - A Comprehensive Foundation, 2nd ed., India: Prentice Hall, 1998.

[2] G. Nasr, R. Achkar, and F. Fayad, Stereo-Vision Calibration by Multi-Layer Perceptrons of an Artificial Neural Network, IEEE 7th International Symposium on Image and Signal Processing and Analysis, ISPA 2011, Dubrovnik Croatia, September 4-6, pp. 621-626.

[3] R. Achkar, M. Owayjan, and C. Mrad, Landmine Detection and Classification Using MLP, IEEE Third International Conference on Computational Intelligence Modeling and Simulation, CIM Sim 2011, Langkawi Malaysia, September 20- 22, pp 1-6.

[4] R. Achkar and M. Owayjan, Implementation of a Vision System for a Landmine Detecting Robot Using Artificial Neural Network, International Journal of Artificial Intelligence & Applications (IJAIA), September 2012, Volume 3, Number 5, pp73-92.

[5] J. G. Rocha, S. Lanceros-Mendez, X-ray imaging matrix with light guides and intelligent pixel sensors radiation or high energy particle detector devices that contain its fabrication process and its use, Google Patents, 2007.

[6] Jean-Michel Morel, Guoshen Yu, ASIFT: A New Framework for Fully Affine Invariant Image Comparison, SIAM Journal on Imaging Sciences, 2(2), 438–469, 2009

[7] R. Hecht-Nielsen, Theory of the backpropagation neural network, International joint conference on Neural Networks, Washington, DC, USA, 1989

[8] Roger Achkar, Mustafa El-Halabi, Elie Bassil, Rayan Fakhro, and Marny Khalil. Voice identity finder using the back propagation algorithm of an artificial neural network. Procedia Computer Science, 95:245–252, 2016.

[9] Youssef Harkouss, Souhad Mcheik, and Roger Achkar. Accurate wavelet neural network for efficient controlling of an active magnetic bearing system. 2010.

[10] Chafic Saide, R´egis Lengelle, Paul Honeine, Cedric Richard, and Roger Achkar. Nonlinear adaptive filtering using kernel-based algorithms with dictionary adaptation. International Journal of Adaptive Control and Signal Processing, 29(11):1391–1410, 2015.