Comparative Analysis on Algerian Forest Fires using MLP and BPN classification algorithms.

Jovita Maria James (1947227)[1], Kaushal Agarwal (1947229)[2] and Manish Bharti (1947235)[3]
Department of Computer Science, Christ (Deemed to be Universty).

Abstract—**Artificial Neural networks are at the forefront of machine learning. They are being trained to perform a variety of task imaginable. The paper focuses on Mulitlayer perceptron (MLP) and Backpropogation Neural Network (BPN) algorithms which is a part of Artificial Neural Network. The paper briefs about the classification algorithms and further details the merits and demerits of both the algorithms. The dataset that has been referred in this paper is Algerian Forest Fires which illustrates the real time prediction of forest fires in Algeria. A comparative analysis of accuracy obtained on both algorithms and their description is included at the end of the paper.**

***Keywords*—** Artificial Neural Network, Multilayer perceptron, Backpropogation.

I. INTRODUCTION

Artificial neural networks, or neural networks, are a subset of artificial intelligence.In several scientific disciplines, artificial neural networks are emerging as feasible alternatives to conventional statistical modelling techniques.The Multilayer Perceptron is an algorithm of the artificial neural network that is used extensively for the solution of a number of different problems, including pattern recognition and interpolation.It is a development of the Perceptron neural network model, that was originally developed in the early 1960s which were widely used in many applications.
Artificial neural networks also uses backpropagation as a learning algorithm to compute a gradient descent with respect to weights. Desired outputs are compared to achieved system outputs, and then the systems are tuned by adjusting connection weights to narrow the difference between the two as much as possible. The algorithm gets its name because the weights are updated backwards, from output towards input. Backpropagation requires a known, because of which the desired output for each input value in order to calculate the loss function gradient, it is usually classified as a type of supervised machine learning.

II. MULTILAYER PERCEPTRON

A multilayer perceptron (MLP) is a deep, artificial neural network. It is composed of more than one perceptron. They are composed of an input layer to receive the signal, an output layer that makes a decision or prediction about the input, and in between those two, an arbitrary number of hidden layers that are the true computational engine of the MLP. MLPs with one hidden layer are capable of approximating any continuous function.

The basic features of the multilayer perceptrons are described as follows:

1) Each neuron in the network includes a nonlinear activation function that is differentiable.
2) The network contains one or more layers that are hidden from both the input and output nodes.
3)The network exhibits a high degree of connectivity.

Multilayer perceptrons are often applied to supervised learning problems. They train on a set of input-output pairs and learn to model the correlation (or dependencies) between those inputs and outputs. Training involves adjusting the parameters, or the weights and biases, of the model in order to minimize error. Backpropagation is used to make those weigh and bias adjustments relative to the error, and the error itself can be measured in a variety of ways, including by root mean squared error (RMSE).

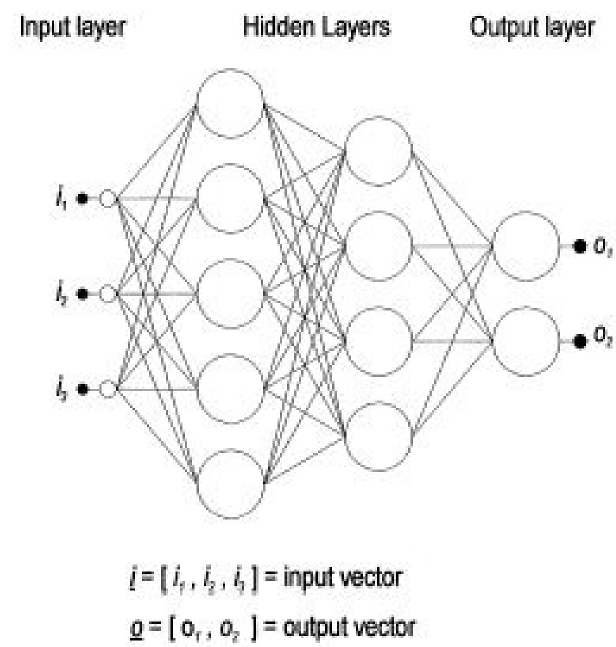

Fig. 1. Multilayer perceptron.

An MLP consists of at least three layers of nodes: an input layer, a hidden layer and an output layer. Except for the input nodes, each node is a neuron that uses a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training. Its multiple layers and non-linear activation distinguish MLP from a linear perceptron. It can distinguish data that is not linearly separable.The training algorithm multilayer networks requires differentiable, continuous nonlinear activation functions. Such a function is the sigmoid.

Feed forward networks such as MLPs are mainly involved in two motions, a constant back and forth.

In the forward pass, the signal flow moves from the input layer through the hidden layers to the output layer, and the decision of the output layer is measured against the ground truth labels.

In the backward pass, using backpropagation and the chain rule of calculus, partial derivatives of the error function w.r.t. the various weights and biases are back-propagated through the MLP. That act of differentiation gives us a gradient, or a landscape of error, along which the parameters may be adjusted as they move the MLP one step closer to the error minimum.

A. Advantages of Multilayer Perceptron

- They are often used to solve problems that are complex. They do, however, need considerable training time for the computation.
- MLP have an ability to learn how to do tasks based on the data given for training or initial experience.
- They are capable of generalisation, that is, they classify an unknown pattern with other known patterns that share the same distinguishing features. This means noisy or incomplete inputs will be classified because of their similarity with pure and complete inputs.
- MLP/Neural networks do not make any assumption regarding the underlying probability density functions or other probabilistic information about the pattern classes under consideration in comparison to other probability based models

B. Limitations of Multilayer Perceptron

The limitations of multilayer perceptron are as follows :

- The initial problem faced when using a multilayer perceptron is deciding on the network architecture—the number of layers and nodes in those layers.
- The optimum number of nodes required in the hidden layer is problem dependent, being related to the complexity of the input and output mapping, the amount of noise in the data and the amount of training data available. If the number of nodes in the hidden layer is too small the backpropagation algorithm will fail to converge to a minimum during training. Conversely, too many nodes will result in the network overfitting the training data resulting in poor generalisation performance.
- It is based on observations with a fixed amount of time. It necessitates a meaningful input-output mapping. There are static mapping functions as well as fixed inputs and outputs.
- In addition, the Multilayer Perceptron ignores spatial information. Its inputs are flattened vectors.

III. BACKPROPOGATION ALGORITHM

Back-propagation is the essence of neural network training. It is the method of fine-tuning the weights of a neural net based on the error rate obtained in the previous iteration. Proper tuning of the weights allows you to reduce error rates and to make the model reliable by increasing its generalization.

Backpropagation is a short form for "backward propagation of errors." It is a standard method of training artificial neural networks. This method helps to calculate the gradient of a loss function with respects to all the weights in the network.

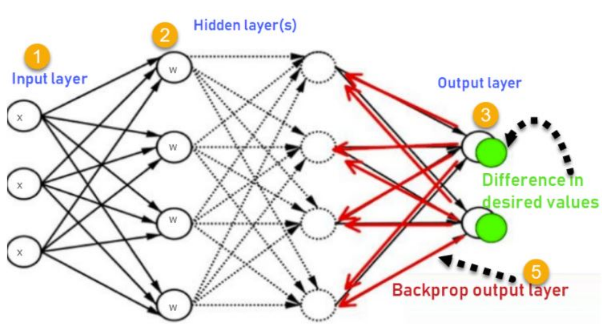

Fig. 2. Working of backpropogatoion.

The backpropogation algorithm works in the following way :

1) Inputs X, arrive through the pre-connected path
2) Input is modeled using real weights W. The weights are usually randomly selected.
3) Calculate the output for every neuron from the input layer, to the hidden layers, to the output layer.
4) Calculate the error in the outputs :

ErrorB = Actual Output – Desired Output

5) Travel back from the output layer to the hidden layer to adjust the weights such that the error is decreased.

Keep repeating the process until the desired output is achieved

Backpropogation simplifies the network structure by elements weighted links that have the least effect on the trained network.A group of input and activation values needs to be analyzed in order to develop the relationship between the input and hidden unit layers.It helps to assess the impact that a given input variable has on a network output. The knowledge gained from this analysis should be represented in rules.

A. Advantages of Backpropogation Algorithm

The advantages of backpropogation is as follows:

- Backpropagation is fast, simple and easy to program.
- It has no parameters to tune apart from the numbers of input.
- It is a flexible method as it does not require prior knowledge about the network.
- It is a standard method that generally works well.
- It does not need any special mention of the features of the function to be learned.

B. Limitations of Backpropogation Algorithm

The limitations of backpropogation is as follows:

- The actual performance of Backpropagation on a particular problem is clearly dependent on the input data.
- Backpropagation can be sensitive to noisy data and outliers.
- Fully matrix-based approach to backpropagation over a mini-batch .
- Backpropagation is that it can be sensitive for noisy data.

IV. DATASET DESCRIPTION

The dataset includes 122 instances that regroup a data of region of Algeria,namely the Bejaia region located in the northeast of Algeria.

122 instances for the region

The period from June 2012 to September 2012. The dataset includes 11 attributes and 1 output attribute (class) The 122 instances have been classified into "fire" (59 classes) and "not fire" (63 classes) classes.

Attribute Information:

- Date : (DD/MM/YYYY) Day, month ('june' to 'september'), year (2012) Weather data observations
- Temp : temperature noon (temperature max) in Celsius degrees: 22 to 42
- RH : Relative Humidity in
- Ws :Wind speed in km/h: 6 to 29
- Rain: total day in mm: 0 to 16.8 FWI Components
- Fine Fuel Moisture Code (FFMC) index from the FWI system: 28.6 to 92.5
- Duff Moisture Code (DMC) index from the FWI system: 1.1 to 65.9
- Drought Code (DC) index from the FWI system: 7 to 220.4
- Initial Spread Index (ISI) index from the FWI system: 0 to 18.5
- Buildup Index (BUI) index from the FWI system: 1.1 to 68
- Fire Weather Index (FWI) Index: 0 to 31.1
- Classes: two classes, namely "Fire" and "not Fire" where Fire is represented as 1 and not Fire as 0

V. Problem Statement

The following dataset "Algerian Forest Fire" gives an idea and view of about how the forest fire in Algeria gets affected by rain. Here the algorithm tries to use 14 attributes and predict how the rain affects the forest fire. Prediction is implemented by classifying each data item in the data set using a Multi-Layer Perceptron (MLP) and a Back Propagation Neural network (BPN) algorithm. The analysis compares the performance of the two algorithms to predict the target variables of the dataset by measuring accuracy, speed, robustness and interpretability.

VI. Results and Discussions

The dataset has been pre-processed to exclude any null values . Label Encoder is a tool for converting non-numerical labels numerical marks that are hashable and equivalent.The accuracy in predicting the data points in the dataset, as well as the accuracy of the data obtained, was discovered after applying both algorithms to the given dataset. BPN provides more accuracy and clarity about the data provided than the MLP algorithm. While the accuracy of the data using BPN was equal to 99.61904761904762

```
109  0.000000    0.0          0
110  0.000000    0.0          0
111  0.000000    0.0          0
Correct: 41 / 42 : 97.61904761904762 %
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
  import sys
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_gu
```

Fig. 3. BPN Results.

The accuracy of data using MLP algorithm was found to be equal to 84.0

Calculating the accuracy

```
def accuracy(confusion_matrix):
   diagonal_sum = confusion_matrix.trace()
   sum_of_all_elements = confusion_matrix.sum()
   return (diagonal_sum / sum_of_all_elements*100)
#Printing the accuracy
print("Accuracy of MLP Classifier : ", accuracy(res),"%")

Accuracy of MLP Classifier :  84.0 %
```

Fig. 4. MLP Results.

VII. CONCLUSIONS

The article carries a comparative study of Multi –Layer Perceptron and Back Propagation Neural Network on the Agerian forest fire which classifies the occurrence of forest fires the forest fires based on some parameters for a region specified in the dataset. The article represents the concepts of clasification algorithms work on the dataset to find the relevent product ID as our output. We can improve the model with actual use the reliability of the results presented by approving and comparing the results various data sources and forecast adjustments model.

References

[1] Gardner, M. W., Dorling, S. R. (1998). Artificial neural networks (the multilayer perceptron)—a review of applications in the atmospheric sciences. Atmospheric environment, 32(14-15), 2627-2636.

[2] Noriega, L. (2005). Multilayer perceptron tutorial. School of Computing. Staffordshire University.

[3] Alsmadi, M.S., Omar, K.B., Noah, S.A.: Back Propagation Algorithm: The Best Algorithm Among the Multi-layer Perceptron Algorithm. IJCSNS International Journal of Computer Science and Network Security 9(4) (2009)

[4] Hecht-Nielsen, R. (1992). Theory of the backpropagation neural network. In Neural networks for perception (pp. 65-93). Academic Press.

[5] Erb, R. J. (1993). Introduction to backpropagation neural network computation. Pharmaceutical research, 10(2), 165-170.

[6] Abid, F., Izeboudjen, N. (2019, July). Predicting Forest Fire in Algeria Using Data Mining Techniques: Case Study of the Decision Tree Algorithm. In International Conference on Advanced Intelligent Systems for Sustainable Development (pp. 363-370). Springer, Cham.

[7] Murtagh, F. (1991). Multilayer perceptrons for classification and regression. Neurocomputing, 2(5-6), 183-197.

[8] Khalil Alsmadi, M., Omar, K. B., Noah, S. A., Almarashdah, I. (2009, March). Performance comparison of multi-layer perceptron (Back Propagation, Delta Rule and Perceptron) algorithms in neural networks. In 2009 IEEE International Advance Computing Conference (pp. 296-299). IEEE.

[9] Lee, W.J., Wu, H., Yun, H., Kim, H., Jun, M.B., Sutherland, J.W.: Predictive maintenance of machine tool systems using artificial intelligence techniques applied to machine condition data. Procedia CIRP 80, 506–511 (2019). 26th CIRP Conference on Life Cycle Engineering (LCE) Purdue University, West Lafayette, IN, USA May 7–9, 2019.