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Artificial Neural Network for Mushroom Prediction

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***Abstract**: Predication is an application of Artificial Neural Network (ANN). It is a supervised learning due to predefined input and output attributes. Multi-Layer ANN model is used for training, validating, and testing of the dataset. In this paper, Multi-Layer ANN model was used to train and test the mushroom dataset to predict whether mushroom is edible or poisonous. The Mushrooms dataset was prepared for training, 8124 instances were used for the training. JNN tool was used for training and validating the dataset. The most important attributes of the dataset were identified, and the accuracy of the predication of whether Mushroom is edible or Poisonous was 100%.*

Keywords: artificial neural network, JNN, poisonous, mushroom, edible

1. INTRODUCTION

The standard "mushroom" is the cultivated white button mushroom, Agaricus bisporus; therefore the word "mushroom" is usually applied to those fungi (Basidiomycota, Agaricomycetes) that have a stem (stipe), a cap (pileus), and gills (lamellae, sing. lamella) on the bottom of the cap. "Mushroom" as well describes a variation of other gilled fungi, with or without stems; hence the term is used to describe the fleshy fruiting bodies of some Ascomycota. These gills produce microscopic spores that aid the fungus spread across the ground [1].

Mushrooms are used widely in cooking, in various cuisines (notably Chinese, Korean, European, and Japanese). Though neither meat nor vegetable, mushrooms are acknowledged as the "meat" of the vegetable world. Most mushrooms sold in supermarkets have been commercially produced on mushroom farms. The most common of these, Agaricus bisporus, is well-thought-out to be safe for utmost people to eat since it is grown in controlled, sterilized surroundings. Numerous varieties of A. bisporus are grown commercially, as well as whites, crimini, and portobello. Other cultivated species existing at many grocers include Hericium erinaceus, shiitake, maitake (henof-the-woods), Pleurotus, and enoki. Recently, increasing wealth in developing countries has directed to a substantial growth in attention in mushroom cultivation, which is now seen as a possibly significant economic activity for small farmers. The main edible mushroom producer is China [2].

The country produces about half of all cultivated mushrooms, and around 2.7 kg of mushrooms are consumed per person per year by over a billion people. In 2014, Poland was the world's largest mushroom exporter, reporting an estimated 194,000 tons annually. Distinguishing edible from poisonous mushroom species needs meticulous care to detail; there is no single trait by which all toxic mushrooms can be recognized, nor one by which all edible mushrooms can be recognized. People who gather mushrooms for eating are known as mycophagists and the act of gathering them for such is known as mushroom hunting, or simply "mushrooming". Even edible mushrooms may yield allergic reactions in susceptible individuals, from a mild asthmatic response to severe anaphylactic shock. Even the cultivated A. bisporus comprises small amounts of hydrazines, the most copious of which is agaritine (a mycotoxin and carcinogen) [3].

Nevertheless, the hydrazines are demolished by reasonable heat when cooking. A number of species of mushrooms are poisonous; even though some resemble sure edible species, consuming them could be deadly. Eating mushrooms collected in the wild is risky and should only be undertaken by individuals knowledgeable in mushroom recognition. Mutual best practice is for wild mushroom pickers to focus on gathering a small number of visually distinct, edible mushroom species that cannot be simply confused with poisonous varieties [4].

2. ARTIFICIAL NEURAL NETWORKS

Artificial neural networks (ANNs) are parallel computational models comprised of densely interconnected, adaptive processing units, characterized by an inherent propensity for learning from experience and also discovering new knowledge. Due to their excellent capability of selflearning and self-adapting, they have been extensively studied and have been successfully utilized to tackle difficult real-world problems and are often found to be more efficient and more accurate than other classification techniques. Classification with a neural network takes place in two distinct phases. First, the network is trained on a set of paired data to determine the input-output mapping [5].

The weights of the connections between neurons are then fixed and the network is used to determine the classifications of a new set of data [6]. Although many different models of ANNs have been proposed, the feedforward neural networks (FNNs) are the most common and widely used in a variety of applications [7].

Mathematically, the problem of training a FNN can be formulated as the minimization of an error function E; that is to find a minimizer [14-16] where E is the batch error measure defined by the sum of square differences over all examples of the training set, namely where yLj, p is the actual output of the j-th neuron that belongs to the L-th (output) layer, NL is the number of neurons of the output layer, t j , p is the desired response at the j-th neuron of the output layer at the input pattern p and P represents the total number of patterns used in the training set. A traditional way to solve this problem is by an iterative gradient-based training algorithm which generates a sequence of weights {w } starting from an ng the iterative formula Where k is the current iteration usually called epoch, nk > 0 is the learning rate and dk is a descent search direction[8].

Since the appearance of backpropagation a variety of approaches that use second order derivative related information was suggested for improving the efficiency of the minimization error process[9]. Here, we have utilized three well-known and widely used classical methods, namely the Broyden-FletcherGoldfarb-Shanno (BFGS), the Levenberg- Marquardt (LM) and the Resilient Backpropagation (Rprop). Moreover, we have also used a new efficient conjugate gradient algorithm, the modified spectral Perry (MSP). Due to space limitations, we are not in a position to briefly describe here the above methods. The interested reader is referred to [10-12].

The Biological Model (Neural Networks):

- Neural networks as a computing model possess the following properties[13-16]:
  - Operate in parallel Computing elements (neurons) work in parallel as opposed to the sequential action of Turing machines.
  - Hierarchical Multilayered Structure Information is transmitted not only to immediate neighbors, but also to more distant units, as opposed to CA.
  - No Program is handed over to the hardware The free parameters of the network have to be found adaptively - as opposed to conventional computers (which require pre-programmed algorithms to execute).

- Structure of the Neuron

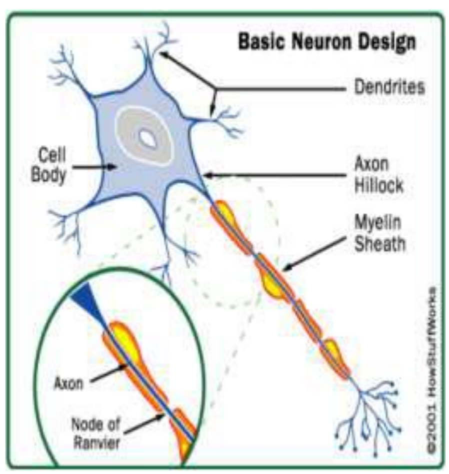

Figure 1: Cell

The cell body (soma) : "Processing" occurs here[27-30]:

- Dendrites: Protrude from soma. They conduct signals to the cell body
- Axon Hillock: Extends from cell body - initial portion of the axon.
- Axon: A long fiber - generally splits into smaller branches.
- Synapse: The axon-dendrite (axon-soma; axonaxon) contact between an endbulb and the cell it impinges upon is called a synapse [66-70]. (End bulbs can be seen at the bottom right corner of the above image.)

3. STUDY OBJECTIVES

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The objectives of this study are:

- to determine some suitable factors that affect predicting the Validity of Mushrooms
- to transform these factors into forms suitable for an adaptive system coding
- to model an Artificial neural network that can be used to predict the Validity of Mushrooms based some given input data for a given Mushrooms.

4. Literature Review

Artificial Neural Networks have been used many fields. In Education such as: Predicting Student Performance in the Faculty of Engineering and Information Technology using ANN, Prediction of the Academic Warning of Students in the Faculty of Engineering and Information Technology in Al-Azhar University-Gaza using ANN, Arabic Text Summarization Using AraBERT Model Using Extractive Text Summarization Approach[6].

In the field of Health such as: Parkinson's Disease Prediction, Classification Prediction of SBRCTs Cancers Using ANN [7], Predicting Medical Expenses Using ANN[8], Predicting Antibiotic Susceptibility Using Artificial Neural Network[10], Predicting Liver Patients using Artificial Neural Network[9], Blood Donation Prediction using Artificial Neural Network[11], Predicting DNA Lung Cancer using Artificial Neural Network[12], Diagnosis of Hepatitis Virus Using Artificial Neural Network[13], COVID-19 Detection using Artificial Intelligence[14].

In the field of Agriculture: Plant Seedlings Classification Using Deep Learning [14], Prediction of Whether Mushroom is Edible or Poisonous Using Back-propagation Neural Network[15], Analyzing Types of Cherry Using Deep Learning[15], Banana Classification Using Deep Learning[13], Mango Classification Using Deep Learning[16], Type of Grapefruit Classification Using Deep Learning[7], Grape Type Classification Using Deep Learning[30], Classifying Nuts Types Using Convolutional Neural Network[17], Potato Classification Using Deep Learning[18], Age and Gender Prediction and Validation Through Single User Images Using CNN[5].

In other fields such as : Predicting Software Analysis Process Risks Using Linear Stepwise Discriminant Analysis: Statistical Methods [13], Predicting Overall Car Performance Using Artificial Neural Network [8], Glass Classification Using Artificial Neural Network [9], Tic-Tac-Toe Learning Using Artificial Neural Networks[15], Energy Efficiency Predicting using Artificial Neural Network[14], Predicting Titanic Survivors using Artificial Neural Network[12], Classification of Software Risks with Discriminant Analysis Techniques in Software planning Development Process[13], Handwritten Signature Verification using Deep Learning[12], Email Classification Using Artificial Neural Network[14], Predicting Temperature and Humidity in the Surrounding Environment Using Artificial Neural Network[15], English Alphabet Prediction Using Artificial Neural Networks[18].

5. Methodology

After getting the Mushroom dataset from "the Center for Machine Learning and Intelligent Systems, University of California, Irvine"[19], we identified the input variables, output variables, upload the dataset, divided it to training and validating sets, determined the proper hidden layers. Then we trained and validated the sets to get the best accuracy.

5.1 The Input Variables

The input variables selected are those which can easily be obtained from Mushroom Database. The input variables are: cap-shape, cap-surface, cap-color, bruises?, odor, gillattachment, gill-spacing, gill-size, gill-color, stalk-shape, stalk-root, stalk-surface-above-ring, stalk-surface-belowring, stalk-color-above-ring, stalk-color-below-ring, veiltype, veil-color, ring-number, ring-type, spore-print-color, population, Habitat. These factors were transformed into a format suitable for neural network analysis. The domain of the input variables used in this study shown in Table1.

Table1: Input varaibles

#	Input Variable	Domain
1	cap-shape	bell=b , conical=c , convex=x , flat=f , knobbed=k , sunken=s
2	cap-surface:	fibrous=f , grooves=g ,scaly=y , smooth=s
3	cap-color:	brown=n, buff=b, cinnamon=c , gray=g , green=r , pink=p , purple=u , red=e white=w , yellow=y
4	bruises?:	bruises=t ,no=f
5	odor:	almond=a ,anise=l , creosote=c , fishy=y , foul=f , musty=m , none=n , pungent=p , spicy=s

6	gill-attachment:	attached=a ,descending=d ,free=f ,notched=n
7	gill-spacing	close=c ,crowded=w ,distant=d
8	gill-size:	broad=b ,narrow=n
9	gill-color:	black=k, brown=n, buff=b, chocolate=h, gray=g, green=r, orange=o, pink=p, purple=u, red=e, white=w, yellow=y
10	stalk-shape:	enlarging=e , tapering=t
11	stalk-root:	bulbous=b ,club=c, cup=u, equal=e, rhizomorphs=z, rooted=r, missing=?
12	stalk-surface-above-ring:	ibrous=f, scaly=y ,silky=k, smooth=s
13	stalk-surface-below-ring:	ibrous=f, scaly=y, silky=k, smooth=s
14	stalk-color-above-ring:	brown=n, buff=b, cinnamon=c, gray=g, orange=o, pink=p, red=e, white=w, yellow=y
15	stalk-color-below-ring:	brown=n,buff=b,cinnamon=c,gray=g,orange=o,pink=p,red=e,white=w,yellow=y
16	veil-type:	partial=p, universal=u
17	veil-color:	brown=n, orange=o, white=w, yellow=y
18	ring-number:	none=n, one=o, two=t
19	ring-type:	cobwebby=c, evanescent=e, flaring=f, large=l, none=n ,pendant=p, sheathing=s, zone=z
20	spore-print-color:	black=k, brown=n, buff=b, chocolate=h, green=r, orange=o, purple=u, white=w, yellow=y
21	population:	abundant=a, clustered=c, numerous=n, scattered=s, several=v, solitary=y
22	Habitat :	grasses=g, leaves=l, meadows=m, paths=p, urban=u, waste=w, woods=d

5.2 Output variable

The output variable is whether the mushroom edible or poisonous.

5.3 Neural Network

Topologies After the data classification, the neural network topology was built based on the Multilayer Perceptron with one input layer, two hidden layers (3x1) and one output layer as shown in Figure 5.

5.4 Evaluation of the study

First of all, for the evaluation our study, we used a sample of 8124 mushrooms representing edible and non-edible mushrooms. Most of the mushrooms are Poisonous in order to examine whether the Mushroom is edible or not edible, we develop a model able to differentiate between editable and poisonous mushrooms. Our model uses a neural network with one input layer, two hidden layers and one output layer. As input data for predicting the Validity of Mushrooms we used attribute as shown in Figure 2.

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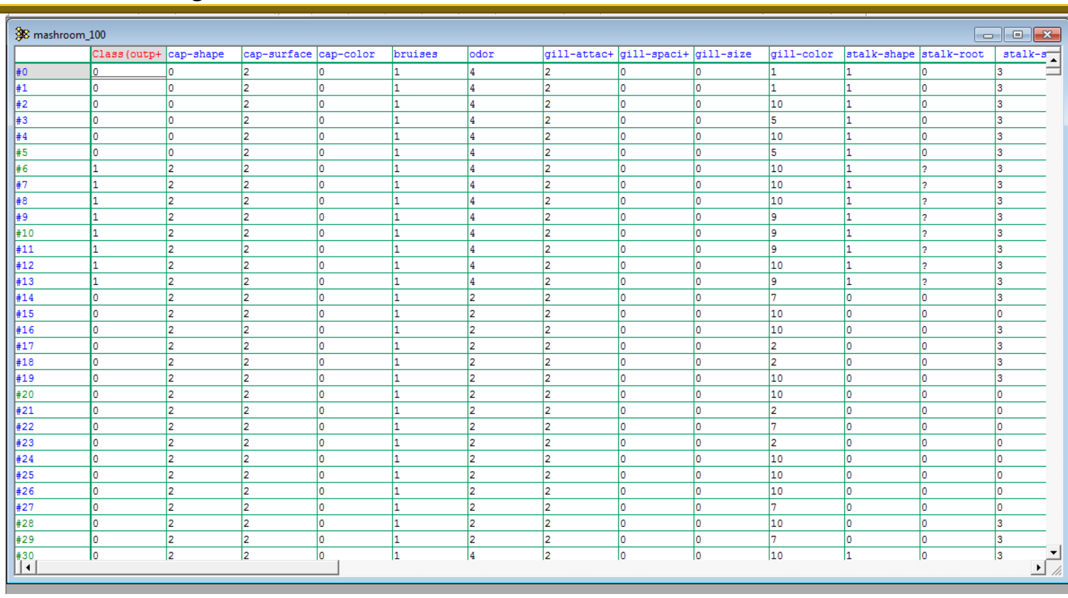

	Class (outp+	cap-shape	cap-surface	cap-color	bruises	odor	gill-attac+	gill-spaci+	gill-size	gill-color	stalk-shape	stalk-root	stalk-s
#0	0	0	2	0	1	4	2	0	0	1	1	0	3
#1	0	0	2	0	1	4	2	0	0	1	1	0	3
#2	0	0	2	0	1	4	2	0	0	10	1	0	3
#3	0	0	2	0	1	4	2	0	0	5	1	0	3
#4	0	0	2	0	1	4	2	0	0	10	1	0	3
#5	0	0	2	0	1	4	2	0	0	5	1	0	3
#6	1	2	2	0	1	4	2	0	0	10	1	?	3
#7	1	2	2	0	1	4	2	0	0	10	1	?	3
#8	1	2	2	0	1	4	2	0	0	10	1	?	3
#9	1	2	2	0	1	4	2	0	0	9	1	?	3
#10	1	2	2	0	1	4	2	0	0	9	1	?	3
#11	1	2	2	0	1	4	2	0	0	9	1	?	3
#12	1	2	2	0	1	4	2	0	0	10	1	?	3
#13	1	2	2	0	1	4	2	0	0	9	1	?	3
#14	0	2	2	0	1	2	2	0	0	7	0	0	3
#15	0	2	2	0	1	2	2	0	0	10	0	0	0
#16	0	2	2	0	1	2	2	0	0	10	0	0	3
#17	0	2	2	0	1	2	2	0	0	2	0	0	3
#18	0	2	2	0	1	2	2	0	0	2	0	0	3
#19	0	2	2	0	1	2	2	0	0	10	0	0	3
#20	0	2	2	0	1	2	2	0	0	10	0	0	0
#21	0	2	2	0	1	2	2	0	0	2	0	0	0
#22	0	2	2	0	1	2	2	0	0	7	0	0	0
#23	0	2	2	0	1	2	2	0	0	2	0	0	0
#24	0	2	2	0	1	2	2	0	0	10	0	0	0
#25	0	2	2	0	1	2	2	0	0	10	0	0	0
#26	0	2	2	0	1	2	2	0	0	10	0	0	0
#27	0	2	2	0	1	2	2	0	0	7	0	0	0
#28	0	2	2	0	1	2	2	0	0	10	0	0	3
#29	0	2	2	0	1	2	2	0	0	7	0	0	3
#30	0	2	2	0	1	4	2	0	0	10	1	0	3

Figure 2: Imported dataset in JNN environment

Our task was to predict the result belongs based on the 22 input variables. We conducted a series of tests in order to establish the number of hidden layers and the number of neurons in each hidden layer. Our tests give us that the best results are obtained with two hidden layers. We used a sample of (8,421 records): 5624 training samples and 2500 validating samples. The network structure was found on a trial and error basis(as seen in Figure 3). We started with a small network and gradually increased its size. Finally, we found that the best results are obtained for a network with the following structure: 22I-2H-1O, i.e. 22 input neurons, 2 hidden layers with (3x1) neurons, and an output layer with 1 neuron. For this study we used Just Neural Network (JNN)[58]. We trained the network for 101 epochs (as shown in Figure 4) on a regular computer with 4 GB of RAM memory under the Windows 10 operating system. We get accuracy of 100%. Figure 5 shows Parameters of the proposed ANN model. Figure 6 shows the factors, their importance and relative importance that affect the mushroom artificial Neural Model using Just NN environment. Figure 7 outlines the detail of the proposed ANN model.

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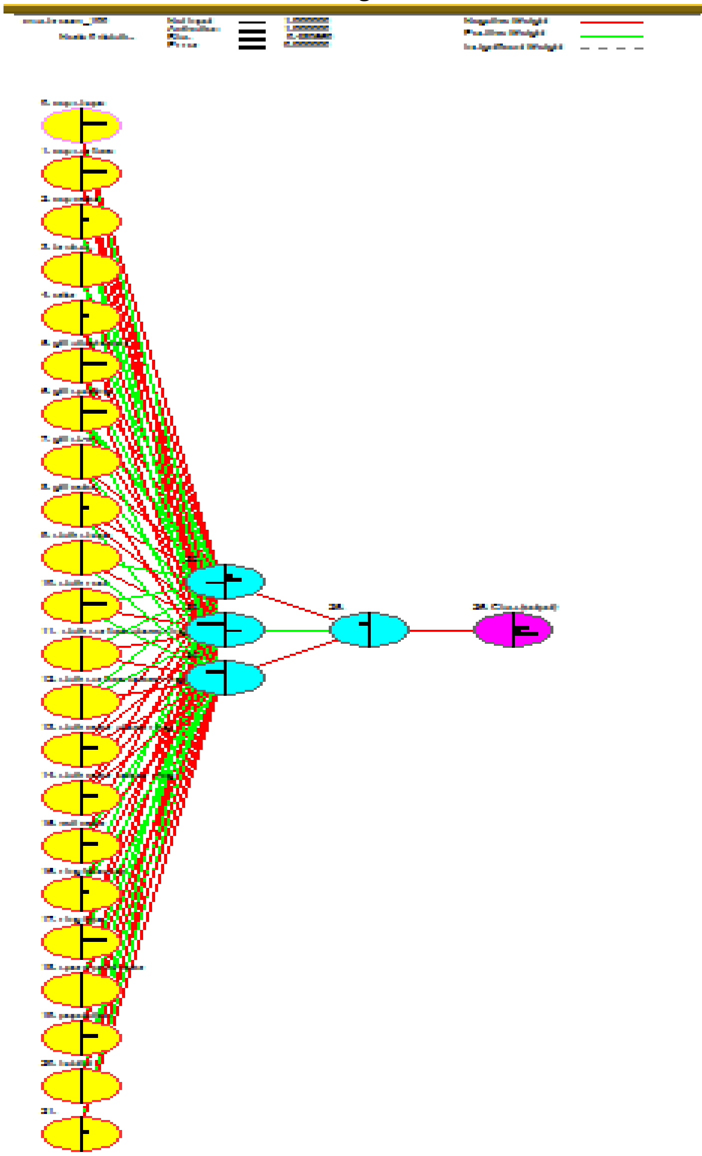

Figure 3: Structure of the proposed ANN model

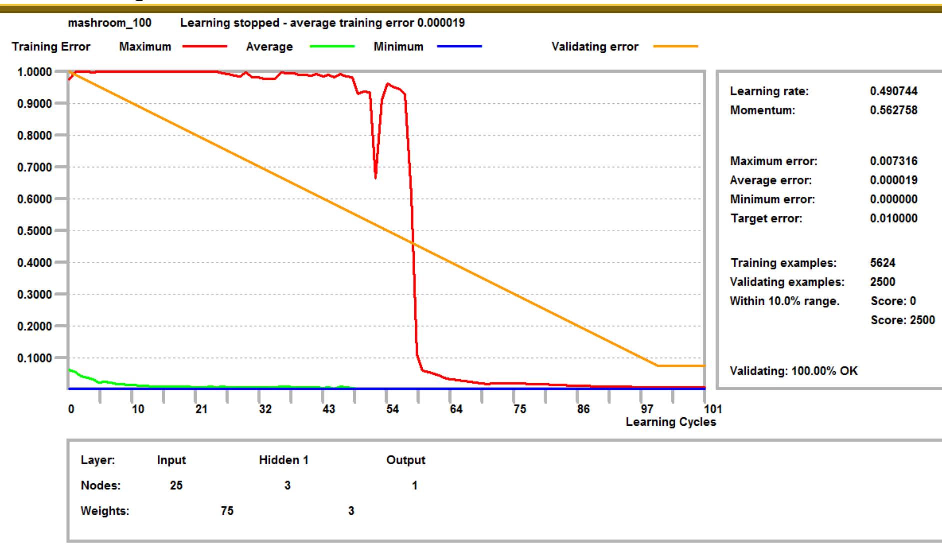

Figure 4: Training and validating the ANN model

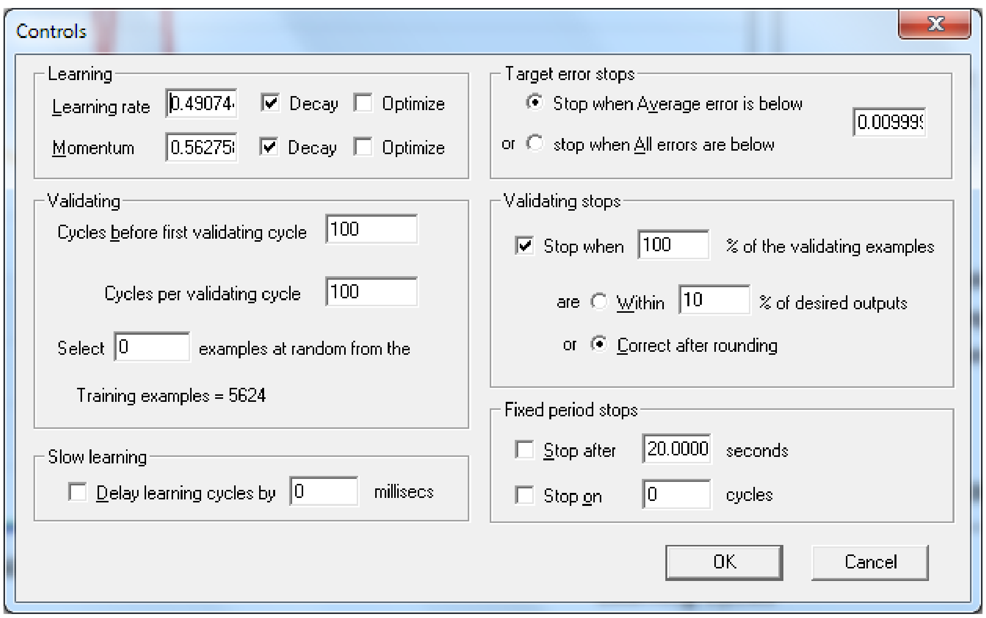

Figure 5: Parameters of the proposed ANN model

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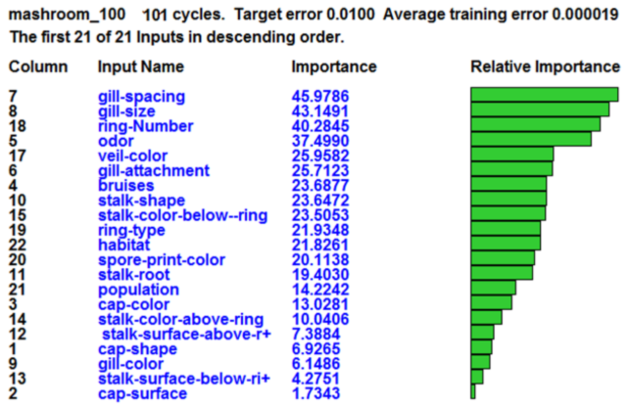

Figure 6: Most influential features in the dataset

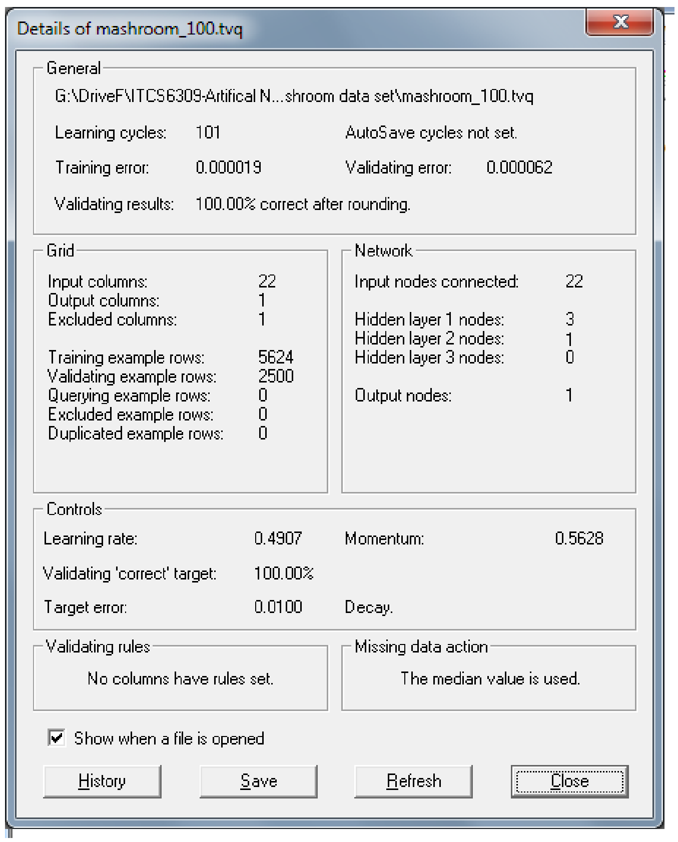

Figure 7: Details of the proposed ANN model

5. CONCLUSION

In This paper, we used the prediction power of a neural network to classify whether a mushroom is edible or poisonous. Our network achieved an accuracy of 100%. We used the JustNN environment for building the network that was a feed forward Multi-Layer Perceptron with one input layer, two hidden layers and one output layer. The average predictability rate was 100% for Prediction of Whether the Mushroom is Edible or Poisonous.

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