**International Journal of Academic and Applied Research (IJAAR)**
**ISSN: 2643-9603**
**Vol. 5 Issue 4, April - 2021, Pages: 47-55**

# ANN for the Classification of Eryhemato-Squamous Disease

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***Abstract****: Classification of Erythmato-Squamous Diseases (ESD) is a major challenge in the field of dermatology. The ESD diseases are classified into six categories. The aim of this paper is to use the Artificial Neural Network to classify the six classes of ESD with high accuracy. We used the JustNN tool which a backpropagation feed forward methodology for the classification of ESD for modeling. For this purpose, the dermatology dataset was collected from UCI machine learning repository. In order to evaluate the proposed model we trained and validated it using the pre-process dataset. The proposed model achieved an accuracy of 98.36%. Results indicated that the proposed classifier is useful.*

**Keywords:** classification, ANN, JNN, dermatology, Erythmato-Squamous Diseases

## Introduction

Erythema (from the Greek *erythros*, meaning red) is redness of the skin or mucous membranes, caused by hyperemia (increased blood flow) in superficial capillaries. It occurs with any skin injury, infection, or inflammation. Examples of erythema not associated with pathology include nervous blushes [1].

It can be caused by infection, massage, electrical treatment, acne medication, allergies, exercise, solar radiation (sunburn), photosensitization, acute radiation syndrome, mercury toxicity, blister agents, niacin administration, or waxing and tweezing of the hairs—any of which can cause the capillaries to dilate, resulting in redness. Erythema is a common side effect of radiotherapy treatment due to patient exposure to ionizing radiation [2].

Erythema disappears on finger pressure (blanching), while purpura or bleeding in the skin and pigmentation do not. There is no temperature elevation, unless it is associated with the dilation of arteries in the deeper layer of the skin [2].

In the field of dermatology, differential diagnosis of Erythmato-Squamous Diseases (ESD) is difficult. The six important types of ESD are: psoriasis, seborrheic dermatitis, lichen planus, pityriasis rosea, chronic dermatitis and pityriasis rubra pilaris. All of them have similar clinical and histopathology features such as erythema and scaling which makes it difficult to detect them even with biopsy [3]. However, biopsy is necessary to achieve a correct diagnosis [4]. Usually, clinicians detects these diseases using some clinical features, such as the degree of erythema and scaling, border of lesion, the presence of itching, koebner phenomenon, the formation of papule, involvement of oral mucosa, elbows, knees and the scalp and family history [5].

## Artificial Neural Network

An Artificial Neural Network (ANN) is a mathematical model that is driven by the functional feature of biological neural networks[6-16]. A neural network contains an interconnected set of artificial neurons, and it processes information using a connectionist form to computation. As a rule, an ANN is an adaptive system that adjusts its structure based on external or internal data that runs over the network during the learning process. Current neural networks are non-linear numerical data modeling tools[17-27]. They are usually used to model tricky relationships among inputs and outputs or to uncover patterns in data. ANN has been applied in several applications with significant accomplishment. For example, ANN has been effectively applied in the area of prediction, and handwritten character recognition [28-32].

Neurons are often come together into layers. Layers are groups of neurons that perform similar functions. There are three kinds of layers. The input layer is the layer of neurons that take input from the user program. The layer of neurons that send data to the user program is the output layer. Between the input layer and output layer there are hidden layers. Hidden layer neurons are connected only to other neurons and never directly interact with the user program. The input and output layers are not just there as interface points. Every neuron in a neural network has the opportunity to affect processing. Processing can occur at any layer in the neural network. Not every neural network has this many layers. The hidden layer is optional. The input and output layers are required, but it is possible to have a layer that act as both an input and output layer [33-40].

ANN learning can be either supervised or unsupervised. Supervised training is accomplished by giving the neural network a set of sample data along with the expected outputs from each of these samples. Supervised training is the most common form of neural

network training. As supervised training proceeds, the neural network is taken through several iterations, or epochs, until the actual output of the neural network matches the expected output, with a reasonably small error. Each epoch is one pass through the training samples. Unsupervised training is similar to supervised training except that no expected outputs are provided. Unsupervised training usually occurs when the neural network is to classify the inputs into several groups[41-46].

The training progresses through many epochs, just as in supervised training. As training progresses, the classification groups are "discovered" by the neural network [47-50]. Training is the process by which these connection weights are assigned. Most training algorithms begin by assigning random numbers to the weight matrix. Then the validity of the neural network is tested. Next, the weights are adjusted based on validation results. This process is repeated until the validation error is within an acceptable limit [51-53]. Validation of the system is done once a neural network has been trained and it must be evaluated to see if it is ready for actual use. This final step is important so that it can be determined if additional training is required. To properly validate a neural network validation data must be set aside that is completely separate from the training data [54-55].

**Literature Review**

In the following previous studies the dermatology dataset was used.

The study in [56] presented a classifier algorithm, the voting feature intervals-5. The accuracy of the classifier was 96.2%. In [57] an ensemble of SVM based on random subspace (RS) and feature selection were employed for diagnosis of ESD. It is stated that classifiers using different features offers complementary information about the classifiable patterns. In [58], they investigated the performance of boosting decision tree as an ensemble strategy for the diagnosis of ESD. The result illustrated that the ensemble of un-pruned decision tree had a better accuracy 96.72% than other methods such as genetic algorithm (GA) and k-means clustering in other studies.

In [59] they developed a Support Vector Machine (SVM) model with a novel hybrid feature selection method, called Improved F-score and Sequential Forward Floating Search (IFSFFS) which was a combination of Sequential Forward Floating Search (SFFS) and Improved F-score (IF) to carry out the optimal feature subset selection. The IF and SFFS based on SVM are evaluation criteria for filters and wrappers, respectively. They calculated the accuracy of training and testing data set for different splits. The average testing accuracy was 97.58%.

In [60] they proposed and implemented a novel identification model for diagnosis of ESD based on Extreme Learning Machine (ELM). The new model compared with classic Artificial Neural Networks (ANN). ELM had some advantages, such as higher learning speed, the best performance and ease of implementation. Results showed that the ELM had greater degree of performance than classic ANN in both training and testing data set.

In [61] they used a Fuzzy Extreme Learning Machine (FELM) method to purpose ESD classification. FELM consists of two methods: Fuzzy Logic and ELM. The achieved accuracy of the FELM was 92.84%, which was better than other methods in terms of accuracy. In [62] they combined C4.5 method with one-against-all method and the accuracy was 96.71% was. In [63] an expert system based on three classifier method including decision tree, fuzzy weighted pre-processing and k-NN based weighted pre-processing has been designed in order to help physicians for diagnosis of ESD. In [64] the Adaptive neuro-fuzzy inference system (ANFIS) was used as a classifier and the achieved accuracy reported as 85.5%.

**Methodology**

We have collected the dataset from UCI Machine Learning repository that was developed by University of California, School of Information and Computer Science [65]. This dataset was prepared by N. Ilter from Gazi University and H.A. Guvenir from Bilkent University [65].

**Input and output Features**

The dermatology dataset consists of 366 samples and 34 features. Twelve features are clinical and 22 are histopathological features. The features, age and family history are continuous and ranged between zero - one, respectively. All other features (clinical and histopathological) were given a degree ranged from zero to three in which, zero indicates the absence of the feature, three indicates the maximum degree possible, and one, two indicate intermediate degree values (as shown in Table 1). Table 2 outlines the possible values for the output attribute and its distributions.

Table1: Input Attribute Information

| S.N. | Attribute | Possible Values | Type of Attribute |
|---|---|---|---|
| 1 | erythema | 0, 1, 2, 3 | Clinical |

| | | | |
|---|---|---|---|
| 2 | scaling | 0, 1, 2, 3 | Clinical |
| 3 | definite borders | 0, 1, 2, 3 | Clinical |
| 4 | itching | 0, 1, 2, 3 | Clinical |
| 5 | koebner phenomenon | 0, 1, 2, 3 | Clinical |
| 6 | polygonal papules | 0, 1, 2, 3 | Clinical |
| 7 | follicular papules | 0, 1, 2, 3 | Clinical |
| 8 | oral mucosal involvement | 0, 1, 2, 3 | Clinical |
| 9 | knee and elbow involvement | 0, 1, 2, 3 | Clinical |
| 10 | scalp involvement | 0, 1, 2, 3 | Clinical |
| 11 | family history | 0 or 1 | Clinical |
| 12 | melanin incontinence | 0, 1, 2, 3 | Histopathological |
| 13 | eosinophils in the infiltrate | 0, 1, 2, 3 | Histopathological |
| 14 | PNL infiltrate | 0, 1, 2, 3 | Histopathological |
| 15 | fibrosis of the papillary dermis | 0, 1, 2, 3 | Histopathological |
| 16 | exocytosis | 0, 1, 2, 3 | Histopathological |
| 17 | acanthosis | 0, 1, 2, 3 | Histopathological |
| 18 | hyperkeratosis | 0, 1, 2, 3 | Histopathological |
| 19 | parakeratosis | 0, 1, 2, 3 | Histopathological |
| 20 | clubbing of the rete ridges | 0, 1, 2, 3 | Histopathological |
| 21 | elongation of the rete ridges | 0, 1, 2, 3 | Histopathological |
| 22 | thinning of the suprapapillary epidermis | 0, 1, 2, 3 | Histopathological |
| 23 | spongiform pustule | 0, 1, 2, 3 | Histopathological |
| 24 | munro microabcess | 0, 1, 2, 3 | Histopathological |
| 25 | focal hypergranulosis | 0, 1, 2, 3 | Histopathological |
| 26 | disappearance of the granular layer | 0, 1, 2, 3 | Histopathological |
| 27 | vacuolisation and damage of basal layer | 0, 1, 2, 3 | Histopathological |
| 28 | spongiosis | 0, 1, 2, 3 | Histopathological |
| 29 | saw-tooth appearance of retes | 0, 1, 2, 3 | Histopathological |
| 30 | follicular horn plug | 0, 1, 2, 3 | Histopathological |
| 31 | perifollicular parakeratosis | 0, 1, 2, 3 | Histopathological |
| 32 | inflammatory monoluclear inflitrate | 0, 1, 2, 3 | Histopathological |
| 33 | band-like infiltrate | 0, 1, 2, 3 | Histopathological |
| 34 | Age | linear | Clinical |

**Table 2**: Class feature distribution

| Class code | Class | Number of instances |
|---|---|---|
| 1 | psoriasis | 112 |
| 2 | seboreic dermatitis | 61 |
| 3 | lichen planus | 72 |
| 4 | pityriasis rosea | 49 |
| 5 | cronic dermatitis | 52 |
| 6 | pityriasis rubra pilaris | 20 |

**Dataset preprocessing**

There is a 2.2% of missing in the age feature in the dermatology dataset. The missing data was replaced with average of the age feature. We used the following equation to normalize the features in the dermatology dataset:

$$X_i = (X_i - X_{min}) / (X_{man} - X_{min}) \qquad \text{eq.(1)}$$

For the age feature we have done two things:

- We grouped the age to 4 sets: 0-25, 26-35, 36-45, 46-75
- We normalized the age groups to: 0, 0.33,0.67, 1.0 using the above equation.

For all other features we normalized their values to be in range of 0 to 1 using the normalized equation stated above.

### 3.3 Building the ANN Model

We used Just Neural Network (JNN) tool [66] to build a multilayer ANN model. The proposed model consists of five Layers: Input Layer with 33 nodes, First Hidden Layer with 18 nodes, Second Layer with 10 nodes, Third Layer with 6 nodes, and Output Layer with one node as can be seen in Figure 3.

We have sat the parameters of the proposed model as follows: Learning Rate 0.6 and the Momentum to be 0.8, and Average Error rate to be 0.01 (as shown in Figure 2).

### 3.4 Evaluating the ANN model

The dermatology dataset consists of 366 samples with 35 attributes as in Table 1 and Table 2. We imported the preprocessed CSV file of the dermatology dataset into the JNN environment (as seen in Figure 1). We divided the imported dataset into two sets (Training and Validation) randomly using the JNN tool. The Training consists of approximately 67% (244 samples) and the validation set consists of 33% of the dataset (122 samples). After making sure that the parameter control was sat properly, we started training the ANN model and kept eye on the learning curve, error loss and validation accuracy. We trained the ANN model for 497 cycles. The best accuracy we got was 98.36% (as seen in Figure 4). We determined the most influential factors in the dermatology dataset as in Figure 5. Figure 6 shows the summary of the proposed model.

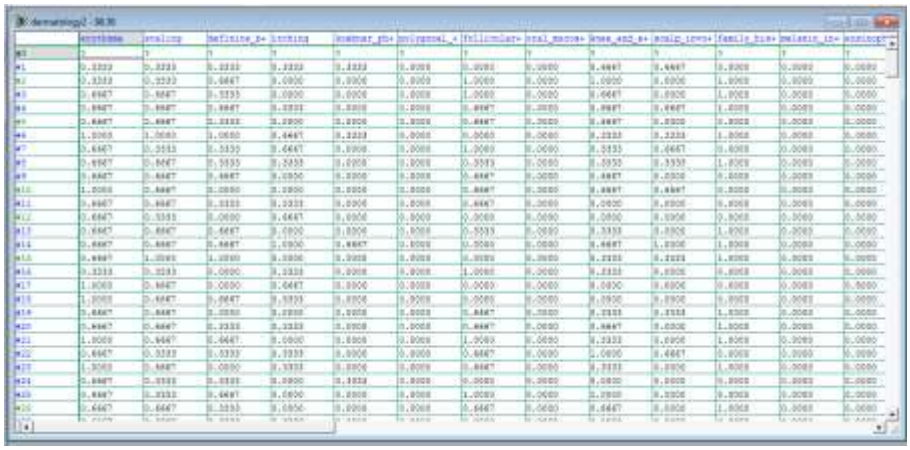

**Figure 1**: Imported dataset into JNN environment

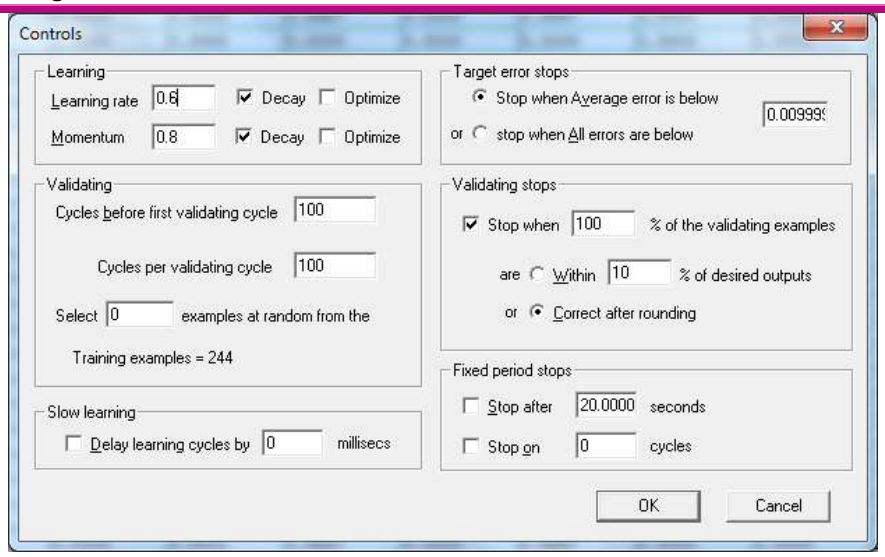


**Figure 2**: Control of the parameters of the proposed ANN model

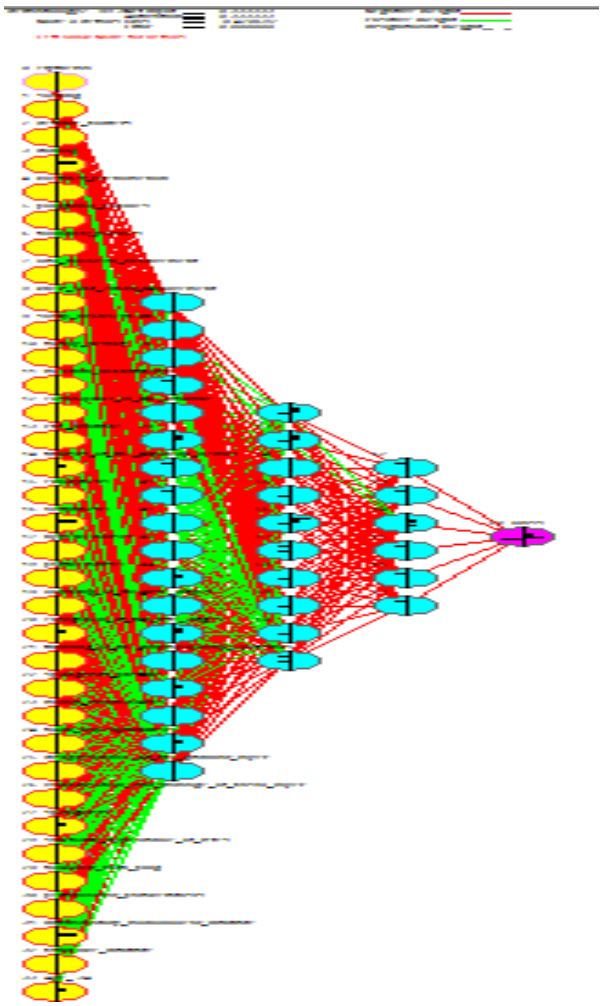

**Figure 3**: architecture of the final ANN model

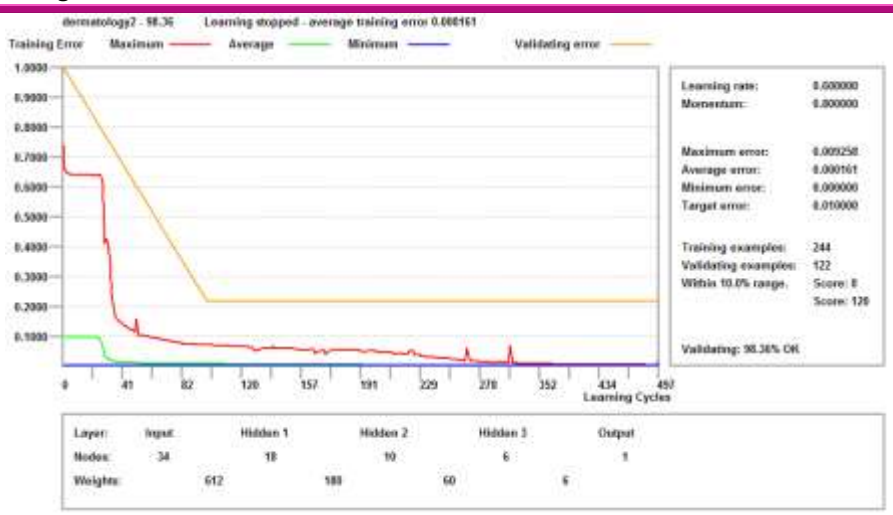


**Figure 4**: Training and validation curves of the proposed ANN model

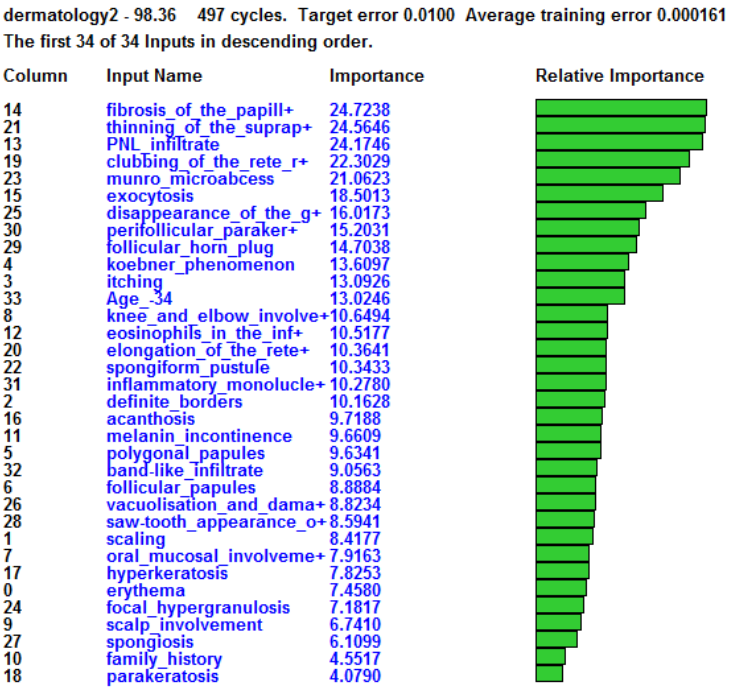


**Figure 5**: The most influential Feature in the proposed ANN model

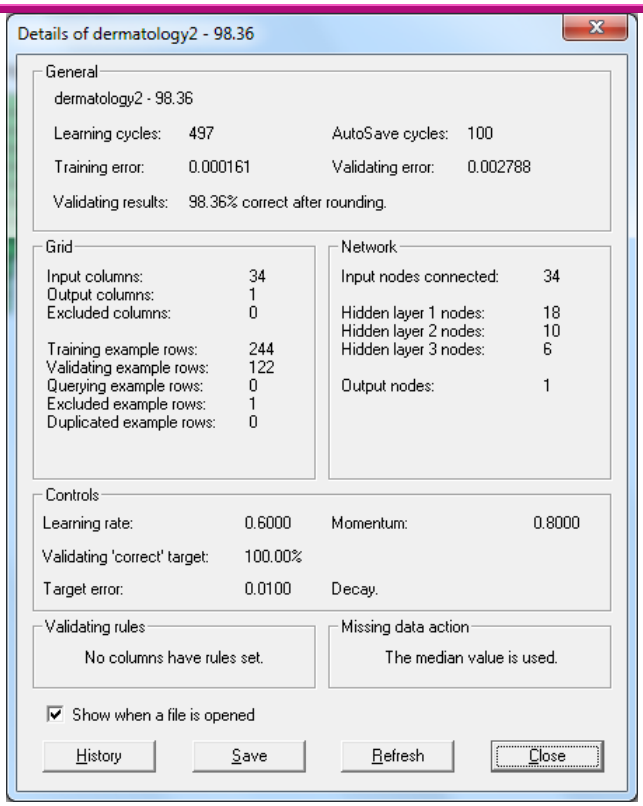


**Figure 6**: Details of the proposed ANN model

## 1. Conclusion

An Artificial Neural Network model for classifying the six categories of dermatology: Psoriasis, seboreic dermatitis, lichen planus, pityriasis rosea, cronic dermatitis, and pityriasis rubra pilaris, using features obtained from UCI Machine Learning Repository was presented. The model used feed forward backpropagation algorithm for training the proposed ANN model using JNN tool. The factors for the model were obtained from dataset which represents dermatology features. The model was tested and the accuracy rate was 98.36%. This study showed that artificial neural network is capable of classifying dermatology accurately.

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