

# IDENTIFICATION OF ERYTHEMATO-SQUAMOUS SKIN DISEASES USING EXTREME LEARNING MACHINE AND ARTIFICIAL NEURAL NETWORK

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## Abstract

*In this work, a new identification model, based on extreme learning machine (ELM), to better identify Erythemato – Squamous skin diseases have been proposed and implemented and the results compared to that of the classical artificial neural network (ANN). ELMs provide solutions to single- and multi- hidden layer feed-forward neural networks. ELMs can achieve high learning speed, good generalization performance, and ease of implementation. Experimental results indicated that ELM outperformed the classical ANN in all fronts both for the training and testing cases. The effect of varying size of training and testing set on the performance of classifiers were also investigated in this study. The proposed classifier demonstrated to be a viable tool in this germane field of medical diagnosis as indicated by its high accuracy and consistency of result.*

## Keywords:

*Extreme Learning Machine, Artificial Neural Network, Erythemato-Squamous Skin Diseases*

## 1. INTRODUCTION

Diagnosis of Erythemato – Squamous diseases is a difficult problem in dermatology. There are six groups of Erythemato – Squamous diseases: psoriasis, seboric dermatitis, lichen planus, pityriasis rosea, chronic dermatitis and pityriasis rubra pilaris. These are the most commonly seen diseases in outpatient dermatology departments. Due to the fact that Erythemato – Squamous diseases all share the clinical features of erythema and scaling, with very little differences, it made it very challenging to identify which particular variant of the diseases is present in a patient.

With the recent advancement in artificial intelligence based techniques and their successful applications in real life engineering and medical diagnosis, it definitely present an interesting research to look into how these diseases could be identifies easily based on these Artificial Intelligence (AI) techniques. Although Erythemato – Squamous diseases' diagnosis have recently caught the attention of AI researchers leading to the use of some AI techniques [1-4], no one has yet implemented extreme learning machines in the identification of these diseases.

Extreme learning machine (ELM) was introduced not-long-ago as a learning algorithm for single-hidden layer feed-forward neural networks (SLFNs). ELMs randomly choose hidden nodes and determine the output weights of SLFNs [5]. It was introduced to resolve some of the challenges of the classical neural network. Since it was introduced, it has featured in several unique problem solving applications areas, including

biomedical, forensic science, engineering etc, [6-12] often with promising results.

Therefore, this work is set to present ELM based model for the identification of Erythemato – Squamous skin diseases, and then compare its performance to the standard artificial neural network results. The effect of varying size of training and testing set on the performance of classifiers were also investigated in this study. To do this, we partition the available dataset into training and testing set based on four different ratios, which include 80:20, 70:30, 60:40 and 50:50 percentages of training and testing respectively. Each of these ratio partitioning were used to carry out experiments involving training and testing proposed classifier models.

Results from experiments carried out indicated that ELM outperformed ANN in both training and testing results. The testing set is the most crucial, as it is where the ability to identify unseen sample is tested. It must be reiterated that the ELM classifier demonstrated superior performance indicated by its high accuracy and consistency of results even in the face of varying training-testing dataset percentages. The remaining part of this work is organized as follows: section two contains the literature review; section three describes the proposed models, while empirical works and results' discussions are presented in section four. Conclusion and recommendations are presented in section five.

## 2. LITERATURE REVIEW

In [1] Juanying Xie et al. proposed hybrid feature selection algorithms to build efficient diagnostic models based on a new accuracy criterion, generalized F-score (GF), and SVM. The hybrid algorithms adopt Sequential Forward Search (SFS), and Sequential Forward Floating Search (SFFS), and Sequential Backward Floating Search (SBFS), respectively, with SVM to accomplish hybrid feature selection with the new accuracy criterion to guide the procedure. These hybrid methods are called modified GFSFS, GFSFFS and GFSBFS, respectively. These combine the advantages of filters and wrappers to select the optimal feature subset from the original feature set to build efficient classifiers. Xie et al. conducted 10-fold cross validation experiments on training subset as well as on the whole Erythemato – Squamous diseases datasets to obtain the best and statistically meaningful classifiers. Experimental results showed that their proposed hybrid methods construct efficient diagnosis classifiers with high average accuracy when compared with traditional algorithms. The results of 10-fold cross validation experiments on Erythemato – Squamous diseases dataset show that the proposed hybrid feature selection algorithms, modified

GFSFS, GFSFFS and GFSBFS, have obtained the average classification accuracies of 99.17%, 98.33% and 95.28% with the average size of selected feature subsets of 22, 13.2 and 17.1 respectively. While the classification accuracy of GFSFS, GFSFFS, and GFSBFS are 98.89%, 98.06%, and 95.81% and the size of selected feature subset of them are 22.2, 13.3, and 19.3 respectively.

Xie and Wang developed a diagnosis model based on support vector machines (SVM) with a novel hybrid feature selection method to diagnose Erythemato – Squamous diseases [2]. They proposed an improved hybrid feature selection method, named improved F-score and Sequential Forward Search (IFSFS), which is a combination of filter and wrapper methods to select the optimal feature subset from the original feature set. The news IFSFS method improved the original F-score from measuring the discrimination of two sets of real numbers to measuring the discrimination between more than two sets of real numbers. The improved F-score and Sequential Forward Search (SFS) are combined to find the optimal feature subset in the process of feature selection. The best parameters of kernel function of SVM are found out by grid search technique. Xie and Wang then conducted experiments on different training-test partitions of the Erythemato – Squamous diseases dataset taken from UCI (University of California Irvine) machine learning database. Their experimental results show that the proposed SVM-based model with IFSFS achieves 98.61% classification accuracy and contains 21 features. The authors conclude that their method is very promising compared to the previously reported results.

In their research paper Kecman and Kikec [3] present the results of using Support Vector Machines (SVMs) and Radial Basis Function Neural Networks (RBF NNs) for diagnosing Erythemato – Squamous diseases. The paper shows an application of RBF NN and SVM for diagnosing skin diseases by transforming a K-class problem into K two class problems (one-vs.-all approach for multiclass problems). The data set contains 358 data pairs of 34 dimensional input records of patients with six known diagnosis (outputs). Thus, the data set is sparse and fairly unbalanced. The paper also discusses the strategies for training SVMs. Both networks design six different one-against-other classifier models which show extremely good performance on previously unseen test data. The training and the test sets are obtained by randomly splitting the dataset into two groups ensuring that each group contains at least one patient for each disease. 100 random split trials (equivalent to performing 10-fold-crossvalidation 10 times independently) were carried out for estimating the tests error rates. SVM models perform better than RBF NN ones, and the SVM models using both and polynomial kernels can perfectly classify, during the training unseen, test data. For a given data set SVMs using the polynomials of second order were particularly efficient and accurate. They use only between 5% and 10% of training data as the support vectors achieving perfect, error-less, diagnosis. Kecman and Kikec claim that the results shown are the best known to date for diagnosing Erythemato – Squamous diseases which represent difficult dermatological problems.

Ubeyli and Guler [4] presented a new approach for detection of Erythemato – Squamous diseases based on adaptive Neuro-fuzzy inference system (ANFIS). Neuro-fuzzy systems are fuzzy systems which use artificial neural networks (ANNs) theory in

order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of two paradigms: fuzzy logic and ANNs, by utilizing the mathematical properties of ANNs in tuning rule-based fuzzy systems that approximate the way man processes information. The ANFIS learns features in the data set and adjusts the system parameters according to a given error criterion. The six ANFIS classifiers were used to detect the six Erythemato – Squamous diseases when 34 features defining six disease indications were used as inputs. Each of the ANFIS classifiers was trained so that they are likely to be more accurate for one type of Erythemato – Squamous disease than the other diseases. The predictions of the six ANFIS classifiers were combined by the seventh ANFIS classifier. To improve diagnostic accuracy, the seventh ANFIS classifier (combining ANFIS) was trained using the outputs of the six ANFIS classifiers as input data. The performances of the ANFIS model were evaluated in terms of training performances and classification accuracies, and the results confirmed that the proposed ANFIS model has good potential in detecting Erythemato – Squamous diseases. The total classification accuracy of the ANFIS model was 95.5%. The ANFIS model achieved accuracy rates which were higher than that of the stand-alone neural network model.

### 3. PROPOSED MODELING TECHNIQUES

Although ELM is the target of this work, ANN will be briefly considered to facilitate, comparing the results of ELM experiments with those of ANN.

#### 3.1 ARTIFICIAL NEURAL NETWORK

Artificial neural networks are models that were developed from studying how biological systems work, in particular the human brain. ANNs consist of interconnected neurons with adaptive weights that can be used for training and prediction.

A multi-layered neural network consists of several layers of a large number of neurons. Each layer is interconnected with the layer immediately before and after it. The first layer receives external inputs and is therefore named the input layer. The last layer is the output layer which provides the classification solution. In-between the input and output layers are a number of hidden layers. A three-layered network can accurately classify any non-linear function [13].

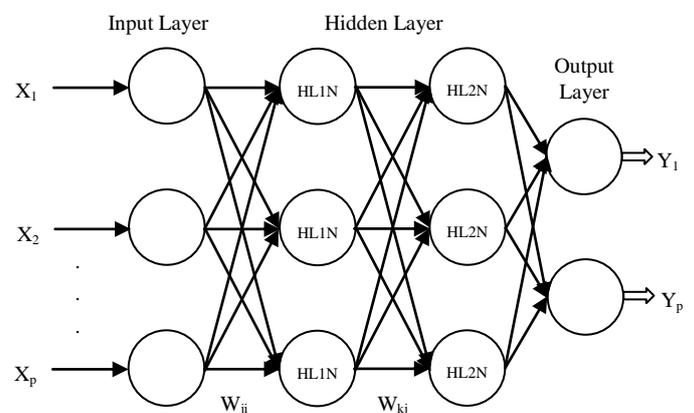


Fig.1. Multilayer Perceptron with two hidden layers

### 3.2 EXTREME LEARNING MACHINES

Extreme learning machine (ELM) was introduced not-long-ago as a learning algorithm for single-hidden layer feed-forward neural networks (SLFNs). ELMs are known to provide high learning speed, good generalization performance, and ease of implementation. In general, the learning rate of feed-forward neural networks (FFNN) is time-consuming than required and this has become bottleneck in their applications. According to [5], there are two main reasons behind this behavior; one is slow gradient based learning algorithms used to train neural network (NN) and the other is the iterative tuning of the parameters of the networks by these learning algorithms. To overcome these problems, [5, 14-15] proposed a learning algorithm called extreme learning machine (ELM) for single hidden layer feed-forward neural networks (SLFNs). It is stated that “In theory, this algorithm tends to provide the best generalization performance at extremely fast learning speed since it is a simple tuning-free algorithm” [15]. Therefore, it is an interesting option to be considered in predictive modeling applications, particularly in reservoir characterization applications, where better generalization ability is often sought for.

The introduction of ELM has been considered as a welcome development because it is much faster than feed-forward networks which take a very long time for training. Also ELM tends to reach the minimum training error while considering magnitude of weights which is different from the classic gradient-based learning algorithms [5]. ELM learning algorithm can be used to train SLFNs with non-differentiable activation functions, unlike the classical gradient-based learning algorithms which only work for differentiable activation functions, [14].

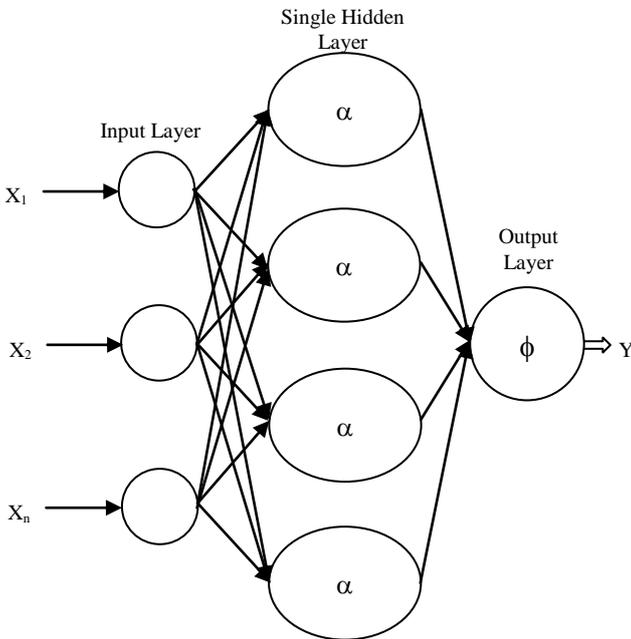


Fig.2. Schematic Representation of ELM ( $x_1 \dots x_n$  are the input values,  $\alpha$  is the activation function, and  $y$  are the output values)

### The Learning Process for the Proposed Erythemato – Squamous Skin Diseases’ model based on ELM Framework:

Before looking at the ELM framework, the standard SLFN (single-hidden layer feed-forward neural networks) needs to be defined first. If there are  $N$  samples  $(x_i, t_i)$ , where  $x_i = [x_{i1}, x_{i2}, \dots, x_{in}]^T \in \mathbf{R}^n$  and  $t_i = [t_{i1}, t_{i2}, \dots, t_{im}]^T \in \mathbf{R}^m$ , then the standard SLFN with  $\tilde{N}$  hidden neurons and activation function  $g(x)$  is defined as,

$$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i \cdot x_j + b_i) = o_j, \quad j = 1, \dots, N \quad (1)$$

where,  $w_i = [w_{i1}, w_{i2}, \dots, w_{im}]^T$  is the weight vector that connects the  $i^{\text{th}}$  hidden neuron and the input neurons,  $\beta_i = [\beta_{i1}, \beta_{i2}, \dots, \beta_{im}]^T$  is the weight vector that connects the  $i^{\text{th}}$  neuron and the output neurons, and  $b_i$  is the threshold of the  $i^{\text{th}}$  hidden neuron. The “ $\cdot$ ” in  $w_i \cdot x_j$  means the inner product of  $w_i$  and  $x_j$ .

The goal of an SLFN is to minimize the difference between  $o_j$  and  $t_j$ . This can be expressed mathematically as,

$$\sum_{i=1}^{\tilde{N}} \beta_i g(w_i \cdot x_j + b_i) = t_j, \quad j = 1, \dots, N \quad (2)$$

Or, more compactly, as

$$\mathbf{H}\beta = \mathbf{T} \quad (3)$$

where,

$$\mathbf{H}(w_1, \dots, w_{\tilde{N}}, b_1, \dots, b_{\tilde{N}}, x_1, \dots, x_N) = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \dots & g(w_{\tilde{N}} \cdot x_N + b_{\tilde{N}}) \\ \vdots & \dots & \vdots \\ g(w_1 \cdot x_N + b_1) & \dots & g(w_{\tilde{N}} \cdot x_N + b_{\tilde{N}}) \end{bmatrix}_{N \times \tilde{N}}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \vdots \\ \beta_{\tilde{N}}^T \end{bmatrix}_{\tilde{N} \times m} \quad \text{and} \quad \mathbf{T} = \begin{bmatrix} \mathbf{T}_1^T \\ \vdots \\ \mathbf{T}_{\tilde{N}}^T \end{bmatrix}_{N \times m}$$

$\mathbf{H}$  is called the neural network output matrix, as proposed by Huang and Babri [16].

With the above SLFN specification background, the training procedures for the proposed ELM based model for Erythemato – Squamous disease identification can be summarized in the following algorithmic steps. Refer [5, 15] for further details on the workings of ELM algorithm.

**Input** – The inputs to the system, include clinical attribute obtained from patients, which represent the inputs parameters (input  $x_i \in \mathbf{R}^n$  and target  $t_i \in \mathbf{R}^m$ ), activation function, and the number of hidden neuron,  $\tilde{N}$ .

**Output** – The outputs of the ELM system is the target classes identified as the skin diseases type presented and then the weights of the layer.

Mathematically, given a training set,

$$N = \{(x_i, t_i) | x_i \in \mathbf{R}^n, t_i \in \mathbf{R}^m, i=1, \dots, N\}$$

activation function  $g(x)$ , and the number of hidden neuron =  $\tilde{N}$  then, perform the following:

**Step 0: Initialization:** Assign random values to the input weight  $w_j$  and the bias  $b_j, j = 1, \dots, \tilde{N}$

**Step 1:** Find the hidden layer output matrix  $\mathbf{H}$ .

**Step 2:** Find the output weight  $\beta$  as follows,

$$\beta = \mathbf{H}^T \mathbf{T}$$

where,  $\beta$ ,  $\mathbf{H}$  and  $\mathbf{T}$  are defined according to the SLFN specification above (Eqs.(1), (2) and (3)).

## 4. EMPIRICAL STUDIES, RESULTS AND DISCUSSIONS

### 4.1 DATASET DESCRIPTION

In this work, the University of California Irvine (UCI) machine learning database containing Erythematous – Squamous diseases dataset was used and analyzed. There are 366 samples in this database and each sample has 34 attributes. Each sample contains 12 clinical features and 22 histopathological features. Patients were first evaluated clinically with 12 features. Afterwards, skin samples were taken for the evaluation of 22 histopathological features. The values of the histopathological features are determined by an analysis of the samples under a microscope. These attributes are listed in Table.1 [17]. The family history feature has the value ‘1’ if any of these diseases has been observed in the family and ‘0’ otherwise. The age feature represents the age of the patient. It has been missed in some samples, so it is removed in the experiments. Every other feature (clinical and histopathological) was given a degree in the range of ‘0’ to ‘3’ so that ‘0’ indicates that the feature was not present, ‘3’ indicates the largest amount possible, and ‘1’, ‘2’ indicate the relative intermediate values.

The dataset contains 34 attributes, 33 of which are linear valued and one of them is nominal. The six diseases in this group are psoriasis, seboric dermatitis, lichen planus, pityriasis rosea, cronic dermatitis, and pityriasis rubra pilaris. The class distribution of the diseases is shown in Table.2.

Table.1. Features in the UCI erythematous-squamous diseases dataset [17]

<b>Clinical Features</b> (take values 0, 1, 2, 3, unless otherwise indicated)	<b>Histopathological Features</b> (take values 0, 1, 2, 3)
Feature 1: Erythema	Feature 12: Melanin incontinence
Feature 2: Scaling	Feature 13: Eosinophils in the infiltrate
Feature 3: Definite orders	Feature 14: PNL infiltrate
Feature 4: Itching	Feature 15: Fibrosis of the papillary dermis
Feature 5: Koebner	Feature 16: Exocytosis

phenomenon	
Feature 6: Polygonal papules	Feature 17: Acanthosis
Feature 7: Follicular papules	Feature 18: Hyperkeratosis
Feature 8: Oral mucosal involvement	Feature 19: Parakeratosis
Feature 9: Knee and elbow involvement	Feature 20: Clubbing of the rete ridges
Feature 10: Scalp involvement	Feature 21: Elongation of the rete ridges
Feature 11: Family history (0 or 1)	Feature 22: Thinning of the suprapapillary epidermis
Feature 34: Age (linear)	Feature 23: Spongiform pustule
	Feature 24: Munro microabcess
	Feature 25: Focal hypergranulosis
	Feature 26: Disappearance of the granular layer
	Feature 27: Vacuolisation and damage of basal layer
	Feature 28: Spongiosis
	Feature 29: Saw-tooth appearance of retes
	Feature 30: Follicular horn plug
	Feature 31: Perifollicular parakeratosis
	Feature 32: Inflammatory mononuclear infiltrate
	Feature 33: Band-like infiltrate

Table.2. Class distribution of Erythematous–Squamous diseases

Class code	Class	Number of instances
1	Psoriasis	112
2	Seboric dermatitis	61
3	Lichen planus	72
4	Pityriasis rosea	49
5	Cronic dermatitis	52
6	Pityriasis rubra pilaris	20

### 4.2 EXPERIMENTAL SETUP AND IMPLEMENTATION PROCESS

As for the implementation of the two methods, we made use of very few ready-made software functions. The entire coding has been largely developed by us using MATLAB, though some built-in MATLAB functions, used especially for ANN, and few others functions made available online, particularly those of ELM, have been called and used in some cases.

To evaluate performance of the proposed ELM modeling scheme, the acquired dataset described earlier is divided, using the stratified sampling approach, into 80% training set and 20%

testing set for estimating how the investigated model performed on new unseen data. For testing and evaluation of the newly developed framework and to carry out effective comparisons, the classification accuracy was calculated using Percent Correct measure, which is a measure of the percentage of correctly classified target classes.

As for the artificial neural network implementation, a single hidden layer feed forward neural network based on back propagation (BP) learning algorithm with both linear and sigmoid activation functions were utilized. These were gotten using the parameters' search to achieve better performance. As usual, the initial weights were produced randomly with the learning epoch set to 1000 or 0.001 goal error and 0.01 learning rate. As for the ELM, hardlim activation function was chosen based on parameter search while the hidden neuron was set to 500.

**4.3 RESULTS AND DISCUSSIONS**

Experimental results are presented in Table.3 to Table.6 representing the performance measure for both ANN and ELM classifier. The results for the four different cases investigated, based on four different percentages of training and testing set choosing, are presented. These include training and testing set respectively in ratios 80:20, 70:30, 60:40 and 50:50 percentages of training and testing respectively.

Table.3. Experimental Results with Training-Testing partition ratio 80:20

	Training results	Testing Results
ANN	86.86	82.74
ELM	100	94.5

Table.4. Experimental Results with Training-Testing partition ratio 70:30

	Training results	Testing Results
ANN	90.08	79.17
ELM	100	98.17

Table.5. Experimental Results with Training-Testing partition ratio 60:40

	Training results	Testing Results
ANN	89.32	77.26
ELM	100	96.58

Table.6. Experimental Results with Training-Testing partition ratio 50:50

	Training results	Testing Results
ANN	89.56	78.09
ELM	100	98.36

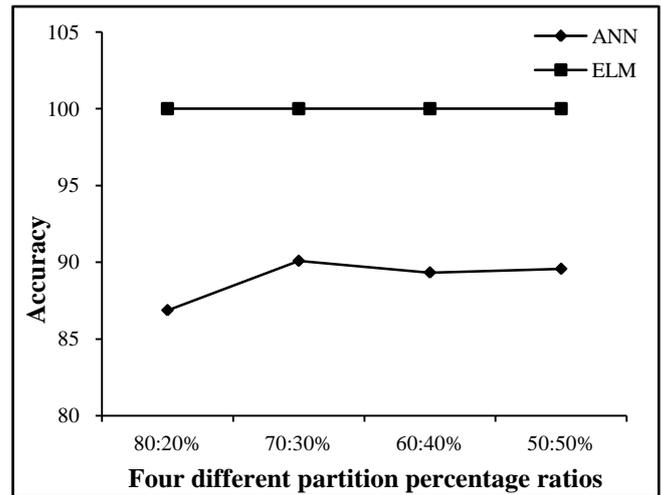


Fig.3. Summary of Training Results for all the Training-Testing partition ratios

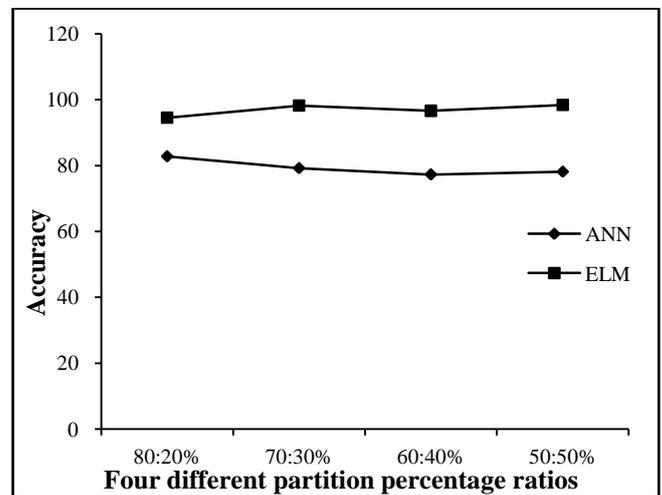


Fig.4. Summary of Testing Results for all the Training-Testing partition ratios

The Fig.3 and Fig.4 summarize the training and testing results, respectively.

It can be easily noticed from the tables and figures that ELM outperformed the classical ANN in all the cases considered. For both training and testing set, ELM performed better than ANN for all the four cases with different training-testing set percentages.

Another important trend that is worth noticing and discussing is the pattern of difference in the performances displayed by each of the two methods for different data partition ratio used. For ELM, it shows consistent high performance for all the cases irrespective of the reduction in training set which portend increase in testing set. In fact, ELM performs slightly better when the percentages of training set decreases with an increase in testing set. Although the training results remain the same for ELM in all cases but the testing results slightly improve with increase in testing set, which is a very rare ability. This interesting discovery is a pointer to investigate ELM further on its ability to perform irrespective of the size of the dataset partition used with respect to training and testing set. On the

other hand, ANN performance slightly decreases as the training size decreases with testing set increasing. This can be particularly noticed for the testing result, which is the actual indicator of any classifier on the unseen dataset.

## 5. CONCLUSION AND RECOMMENDATIONS

A new identification model based on ELM, to better identify Erythematous – Squamous skin diseases have been proposed and implemented and the results compared to that of the classical ANN. Experimental results indicated that ELM outperformed the classical ANN in all fronts both for the training and testing cases. The proposed classifier proved to be a viable tool in this germane field as demonstrated by high accuracy and consistency of result even in the face of varying training-testing dataset percentages. Thus, ELM has been proposed and it has demonstrated its unique ability to achieve excellent results in the field of biomedical diagnosis.

Another unique discovery made in this work is the seeming ability of ELM to maintain consistent results in the face of varying percentages of training and testing set partition ratio. This indeed has opened up potential future research direction to try and investigate deeply the effect of data partition ratio on the performance of classifiers in general and of ELM in particular. In addition, this model could also be applied to other relevant biomedical diagnosis problems.

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