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Fuzzy Neural System Application to Differential Diagnosis of Erythemato-Squamous Diseases

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BACKGROUND/AIMS
In medicine, one of the most important applications of intelligent systems is the fuzzy neural network (FNN) framework, which can be used in the diagnosis and treatment decision-making. We investigated a novel procedure in an integrated fuzzy neural structure (multi-input and -output) based on the Takagi-Sugeno-Kang (TSK)-type rule for the classification of erythemato-squamous diseases.

MATERIAL and METHODS
Designing an FNN system was intelligently aimed at the differential diagnosis of erythemato-squamous disease. Dataset explored for this research included detailed records of diagnosed patients. From the training dataset, our proposed algorithm learns from the domain to differentiate a new case.

RESULTS
Total performance of the inference system was empirically evaluated in terms of classification accuracy, with a total accuracy of 98.37%. Comparison of this result with those of other algorithms by other researchers on the same domain showed that our algorithm was considerably outstanding.

CONCLUSION
The goal of this study is to investigate the capability of the FNN classifier tested on a real-world dataset for the diagnosis of erythemato-squamous diseases. To simplify the uncertainties discovered in the dataset, we integrated the learning capabilities of both the fuzzy logic and neural network. The integrated classifier was used to adequately classify the input space of the domain into the corresponding classes of the erythemato-squamous diseases. The high performance accuracy recorded by our proposed system depicts that the system could be applied to classifying new cases of erythemato-squamous diseases.

Keywords: Dermatology; differential diagnosis; erythemato-squamous; fuzzy logic; fuzzy neural network

INTRODUCTION

Erythemato-squamous diseases are often encountered in the outpatient departments of dermatology. Initially, the disease appears similar to scaling and erythema. After careful analysis, at the predilection sites (localizations of the skin where the disease manifests), some patients show typical clinical features of the disease, whereas others show typical localizations. In dermatology, the differential diagnosis of erythemato-squamous disease is challenging. Different classes of the disease share the clinical features of scaling and erythema, with very few differences. Erythemato-squamous diseases to be classified include pityriasis rubra pilaris, seborrheic dermatitis, psoriasis, lichen planus, chronic dermatitis, and pityriasis rosea. Clinically, patients are first evaluated in terms of 12 features, including degree of scaling and erythema; presence or absence of defined lesion borders; itching and koebner phenomenon; papule formation; family history; and involvement of the oral mucosa, knees, elbows, and scalp, which are important indices in the differential diagnosis of erythemato-squamous diseases. Scaling and erythema in chronic dermatitis are lesser than those in psoriasis, whereas the koebner phenomenon is found only in psoriasis, pityriasis rosea, and lichen planus. Polygonal papules and itching are observed in lichen planus. However, follicular papules are observed in pityriasis rubra pilaris. Lichen is found at oral mucosa (predilection site) while psoriasis is found within the elbow, scalp and knee. Usually, pityriasis rubra pilaris occurs during childhood. Generally, there is a family history for psoriasis.

Only these clinical features are used to diagnose some patients, while a definitive and accurate diagnosis is usually performed using biopsy. Evaluation of 22 histopathological features is performed using skin samples. At the initial stage, a disease may

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show the histopathological features of another disease and may have the characteristic features at the subsequent stages, which is another difficulty faced in the differential diagnosis. Some samples may show the typical histopathological features of the disease, whereas others may not. Papillary dermis fibrosis is observed in chronic dermatitis, and melanin incontinence is a diagnostic feature for lichen planus. Exocytosis could be observed in pityriasis rosea, lichen planus, and seborrheic dermatitis. Different levels of parakeratosis and acanthosis may be seen in all the diseases. Psoriasis is diagnosed using clubbing of rete ridges and thinning of the suprapapillary epidermis. Similarly, lichen planus is diagnosed based on the presence of a band-like infiltrate, disappearance of the granular layer, saw-tooth appearance of rete ridges, and vacuolization and damage of the basal layer. Perifollicular parakeratosis and follicular horn plug are indicative of pityriasis rubra pilaris. The explored dataset consists of a feature of family history with a value of one; if any one of these diseases is observed in the family otherwise, it has a zero value. Another feature identified with the domain is age, i.e., the age of the patient. Other features, including histopathological and clin-ical features, are assigned a value of 0–3, where 0 indicates the absence of the feature, 1 and 2 indicate relative intermediate values, and 3 indicates the highest degree of manifestation.

Among the novel algorithmic approaches since 1965, fuzzy logic designed via fuzzy set theory is the first and was developed by Professor Lotfi Zadeh (1). The term "fuzzy" means vague, unclear, and inaccurate, though. Fuzzy systems define unclear and indefinite phenomena.

An analyzable and acceptable model known as fuzzy was introduced to tackle the complications of uncertainty and imprecise nature of our real world. High importance was given to human knowledge due to the progression to the information era; hence, we needed a hypothesis that could systematically formulate human knowledge and incorporate it into mathematical and other engineering models and systems.

One of the following distinguished forms of knowledge is required as the basic knowledge necessary for many problems under investigation:

- Personal knowledge: This type of knowledge is also known as tacit knowledge. It includes information that could be linguistically expressed and described to some extent but cannot be typically quantified using traditional mathematics.
- Objective knowledge: This includes mathematical equations, models, and formulas that are developed in advance and are employed for solving conventional engineering, chemistry, and physics problems. Practically, both types of knowledge are needed. These two types of knowledge are coordinated in a mathematically, logically, and orderly plausible manner by fuzzy logic.

Humans utilize and perceive many concepts of the real world in a fuzzy manner (vague, unclear, and inaccurate perceptions). For instance, the human mind understands concepts and words such as a cold, warm, long, young, old, and short with astonishing flexibility and very quickly and employs them in its deductions and decision-making even when such concepts do not denote a certain specific number. However, the computer system works precisely and only understands numbers. There are basically two types of variables: nature or calculations. These are qualitative values expressed on the basis of a feature and quantitative values represented by a number. Each trait is described using the membership function, and a value of zero or one is assigned to it, as expressed in a fuzzy set.

Currently, we have been using soft computing in many applications, ranging from the most complex creative processes of humans to normal routine tasks. One of its applications is used in medicine, i.e., the use of a fuzzy expert system with the aid of determining the skin type, and also in diagnosis and treatment decision-making. One of the unique features of humans is the skin. In fields such as identity confirmation, skin detection has applications based on military applications, facial characteristics, video conferences, skin tracking in video, camera remote control, information access, and managing banks' pictorial information.

In medical domains, several machine learning approaches have been applied for rightly predicting outcomes. For example, considering the prognostics of recurrence of breast cancer, localization of a primary tumor, rheumatology, and diagnosis of thyroid diseases, two classification systems were utilized (2). In biomedical domains, the CRLS system is used for learning categorical decision criteria (3). We can observe that by adopting the rule-based system behavior for the most recent information available about a patient, the case-based BOLERO system can learn both the goals and can plan states to improve the performance of a rule-based system (4). To determine the diagnostic value of clinical data, DIAGAID is used as a connectionist method (5). Others include k-NNFP (6) and VFI representation based on Feature Projections (7). Several fuzzy and neural topologies have been explored to solve different classification and feature extraction problems (8-14). Adaptive Neuro-Fuzzy Inference System (ANFIS) was applied for feature extraction (8, 9). Furthermore, Ahmed et al. (10) used the neuro-fuzzy system for Crohn's disease classification, and Samanta et al. (11) used Haralick features and backpropagation neural networks (NNs) for glaucoma classification. We applied NNs to a distinctive medical problem: one-year survival prediction of myocardial infarction (12). A genetic algorithm was applied to design a multi-input and single-output neuro-fuzzy system (13). The renowned ANFIS algorithm was utilized to optimize chiller loading (14).

MATERIAL and METHODS

Dataset Analysis

The database used in this study is owned and maintained by Nilsel Ilter and Altay Guvenir and first explored in one of their researches (15). Briefly, the database was created to determine and differentiate erythemato-squamous disease types. The domain contains 34 attributes, of which 33 are linear-valued and one is noted to be nominal. In dermatology, erythemato-squamous disease identification and diagnosis is a difficult task because all the six classes share the clinical features of scaling and erythema, with slight differences. These six classes of erythemato-squamous diseases include pityriasis rubra pilaris, seborrheic dermatitis, psoriasis, lichen planus, chronic dermatitis, and pityriasis rosea. Biopsy is usually important in diagnosing these diseases. Unfortunately, histopathological features are also shared among the diseases. A disease may have the features of another disease at the initial stage and characteristic features of following stages, which is another difficulty faced by dermatologists when performing the differential diagnosis of these diseases. Clinically, patients were first examined with 12 features, after which the evaluation of 22 histopathological features was performed using skin samples. With the analysis of the samples under a microscope, the histopathological features were determined. The family history feature in the dataset constructed for the domain had the value of 1 if any of these diseases have been observed in the family and the value of 0 if none had been observed. The patient's age was used for denoting the age feature. All other features (histo-pathological and clinical) were assigned a value ranging from 0 to 3 (0 = absence of features; 1 and 2 = relative intermediate values; 3 = highest amount). Recently, the patients' ID numbers and names were removed from the database. There are six classes of erythemato-squamous disease, with 366 instances and 34 attributes in the domain. Table 1 summarizes the contents of the do-main.

Missing Values Imputation Method

The dataset explored in this study is known to encounter the problem of missing data, which arises when values of one or more variables are missing from the recorded observations. Missing data are attributed to various factors such as faulty equipment, incorrect measurements, value forgotten or lost, and human errors. Most researchers handle missing data problem by simply discarding or eliminating the whole record which essentially contains the missing value of an attribute. But this does not solve the problem because there is every chance that this record may be a deciding factor for prediction and classification. The problem of missing data has been widely treated by data mining practitioners and researchers by exploring various approaches to handle missing values (15-18).

In this paper, we used the minimum distance method of generating the missing values. The method includes two stages: determining cluster space according to output signals and finding the minimum value of the sum of distances. In the first stage, the data set was classified according to output signals. The missing values were generated according to the corresponding clustering space. To achieve this, the distance between the input data having a missing value (called missing row) and other input data samples (another row in the clustering space) was determined. In computing the distances, the Hamming distance or Euclidean distance was used. After calculating the distances between the missing row and other rows of the clustering space, the minimum value of the sum of distances from all the cluster spaces was determined.

TABLE 1. Summary of the explored database

	Features	
Classes	**Clinical**	**Histological**
C1: psoriasis	f1: erythema	f12: melanin incontinence
C2: seborrheic dermatitis	f2: scaling	f13: eosinophils in the infiltrate
C3: lichen planus	f3: definite borders	f14: PNL infiltrate
C4: pityriasis rosea	f4: itching	f15: fibrosis of the papillary dermis
C5: chronic dermatitis	f5: koebner phenomenon	f16: exocytosis
C6: pityriasis rubra	f6: polygonal papules	f17: acanthosis
	f7: follicular papules f18: hyperkeratosis	
	f8: oral mucosal	f19: parakeratosis
	f9: knee and elbow	f20: clubbing of the rete ridges
		involvement
	f10: scalp involvement	f21: elongation of the rete ridges
	f11: family history	f22: thinning of the suprapapillary
	f34: age	epidermis
		f23: spongiform pustule
		f24: munro microabscess
		f25: focal hypergranulosis
		f26: disappearance of the granular layer
		f27: vacuolization and damage of basal layer
		f28: spongiosis
		f29: saw-tooth appearance of rete ridges
		f30: follicular horn plug
		f31: perifollicular parakeratosis
		f32: inflammatory mononuclear
		infiltrate
		f33: band-like infiltrate

The missing values were generated according to the values of parameters of the row with a minimum distance. The missing value was replaced with the value of the corresponding input parameter of that row. This process was repeated for other cluster spaces with missing values.

Cross-Validation Method

Mostly, the cross-validation technique is called rotation estimation. It is a technique of model validation for analyzing how a statistical analytical result will generalize to an independent dataset. Generally, cross-validation is utilized in settings where prediction is the objective, i.e., to evaluate how precisely a predictive model will perform. For a given predictive problem, known data (training dataset) is usually fed onto the model for training purposes, and unseen data (testing dataset) is used for model validation. Also, cross-validation averages/combines measures of fit (prediction error) to infer a more precise estimate of model prediction performance. Our goal of using cross-validation technique in this study was to characterize a dataset to test the model in the training phase (validation dataset), with a specific end goal to restrict issues of overfitting and provide knowledge on how the model will generalize to an independent dataset (first seen dataset).

In this study, we implored 10-fold cross-validation where the original sample was randomly segmented into 10 equal subsamples. A single subsample from the 10 subsamples was considered as the validation data to test the model, and the remaining 9 subsamples were utilized as a training dataset. This process was then repeated 10 times, with each of the 10 subsamples utilized precisely once as the validation dataset. These 10 outcomes were then averaged to produce a single prediction. The major advantage of this technique over randomly iterated sub-sampling is that all perceptions are utilized for both training and validation, and every perception is utilized for validation precisely once.

Proposed Algorithm [Fuzzy NN (FNN)]

This research work proposed FNN for erythemato-squamous disease classification using the dataset donated by Nilsel Ilter and H. Altay Guvenir (15). A typical illustration of fuzzy logic is shown in one of Zadeh's researches, where he proposed fuzzy logic mimicking the reasoning processes of the human brain (19). Widely, fuzzy logic architectures are utilized to solve several problems, including classification, control, identification, and prediction. One of the most convenient and easy methods for mapping an input space to the corresponding output space is the fuzzy logic. The mapping is achieved using the if–then rule with both the antecedent and consequent parts. While the antecedent part comprises the input variables, the consequent part comprises the system's output variables. A typical function of a pattern recognition system is mapping input variables to their corresponding output variables, wherein the inputs represent the patterns while outputs are the corresponding classes. Basically, linguistic terms or fuzzy values are used to describe the values of variables in the fuzzy rule base system. Specifically, a membership function characterizes each fuzzy value. Membership functions enable the quantification of linguistic terms. In constructing the fuzzy system part of our algorithm, we precisely designed the rules' antecedent and consequent parts.

Considering the construction of the if–then rule, one of the effective technologies is the use of NNs. They have characteristics such as generalization, self-learning ability, nonlinear mapping, vitality, and computational parallelism. Here, self-learning characteristics led to the improvement of the accuracy of the NN base model. Implementation of fuzzy logic led to the reduction of the complex nature of the data and handling of uncertainty and imprecision. Combination of fuzzy logic and NNs allows us to design nonlinear systems characterized by uncer-tainties described by a fast-learning system. Here, we combined these two techniques to construct FNN for solving pattern classification problems.

The dataset obtained from erythemato-squamous disease diagnosis represents FNN base classifier's input signals. This FNN classifier classifies the input signals of the domain into the six specified classes. Our designed algorithm (FNN) achieved the process of fuzzy reasoning via the NN structure. This FNN was designed using the generation of a proper rule base having the "IF–THEN" structure. It is necessary to determine the accurate description of both the fuzzy IF-THEN rule premise and consequents part for the classification system using learning capability (20, 21). We achieved this through error response evaluation of the constructed framework. Also, Mamdani and Takagi-Sugeno-Kang (TSK)-type fuzzy rules were respectively utilized to design the frameworks (22, 23). The architecture of this paper explores the latter, i.e., the TSK-type fuzzy rule to design the system. The TSK-type fuzzy rule comprises the fuzzy antecedent and crisp consequent parts. The nonlinearity and linearity are approximated via fuzzy systems having the following structure:

If x_1 is A_{1j} and x_2 is A_{2j} and x_m is A_{mj} then $y_j = b_j + \sum_{i=1}^{m} a_{ij} x_i$ (1)

Here, x_i and y_j represent the signals of the system's input and output, respectively. i=1,...,m denotes the number of input signals while j=1,…,r represents the number of rules. We denotes A_{1j} as the fuzzy set input and bj and a_{ij} as coefficients. Our FNN structure was used for differentiating the six classes of the erythemato-squamous disease, as shown in Figure 1.

The proposed FNN consists of six layers. In the first layer, the xi (i=1,…,m) input signals of the system are evenly distributed. There are membership functions in the second layer that describe the linguistic terms. Here, considering each input signal fed into the model, we calculated the degree of membership of a fuzzy set to which an input value belongs. As demonstrated in (24), we used the Gaussian membership function to describe the linguistic terms as shown below:

$$\mu 1_j(x_i) = e^{-\frac{(x_i - c_{ij})^2}{\sigma_{ij}^2}}, \ i=1..m,\ j=1..r \tag{2}$$

Here, the number of input signals is represented as m, hidden neurons in the third layer, also known as the number of fuzzy rules, are denoted as r. We denoted as the center and width of Gaussian membership functions, respectively. $\mu_{1j}(x_i)$ represents the membership function of the ith input variable for the jth term (21,23,25).

In our construction, the rule layer was mounted in the third layer where a number of rules are equal to the number of nodes. The rules are represented as R1, R2,…,Rr. The t-norm min (∏) operation was used to calculate the output signals of this layer.

$$\mu_j(x) = \prod_i \mu 1_j(x_i),\ i=1,..,m,\ j=1,..., \quad (3)$$

Here, min operation is denoted as π.

In the fifth layer, these $\mu_j(x)$ signals denoted the input signals. The consequent layer was mounted at the fourth layer. This layer comprised n linear systems. At this phase, we calculated the rule output values as follows:

$$y1_j = b_j + \sum_{i=1}^{m} a_{ij} x_i \quad (4)$$

The third layer output signals $\mu_j(x)$ were multiplied by the fourth layer output signals, inducing the next fifth layer. The j^{th} node output was then determined.

$$y_j = \mu_j(x) y1_j \quad (5)$$

The FNN output signals were computed in the sixth layer as follows:

$$u_k = \frac{\sum_{j=1}^{r} w_{jk} y_j}{\sum_{j=1}^{r} \mu_j(x)} \quad (6)$$

where u_k denotes the network output signals (k=1,..,n). The training of the network parameters begins immediately the output signal of the fuzzy rule consequent part is calculated.

FNN Parameter Learning

Initially, the FNN parameters are randomly generated. We expressed these membership function parameters in equation (2) of the fuzzy rules demonstrated in equation (1), mounted in the second layer of Figure 1. The linear function parameters are demonstrated in equation (4) mounted on the fourth and fifth layers. In designing the FNN model, learning of the parameters of the membership functions $c_{ij}(t)$ and $\sigma i_j(t)$, where i=1,..,m and j=1,..,r, are mounted on the premise section. Values of parameters $w_{jk}(t)$, $a_{ij}(t)$, $b_j(t)$ where i=1,..,m, j=1,..,r and k=1,..,n are depicted in the consequent section (21, 24). Here, we applied fuzzy clustering and gradient algorithms to update the parameters of FNN (26). Furthermore, we applied fuzzy c-means clustering technique to obtain the parameters of the antecedent section (parameters of membership functions). The training of parameters was performed immediately after clustering using both adaptive learning rate and gradient descent learning algorithm. To guarantee and expedite convergence, we used the adaptive learning rate. In addition, to expedite the learning processes, we implored the momentum.

At the point of learning on the output of the network, the value of error cost function was calculated as follows:

$$E = \frac{1}{2} \sum_{k=1}^{n} (u_k^d - u_k)^2 \quad (7)$$

where n is the number of output signals of the network and u_k^d and u_k are desired and current network output values (k=1,..,n), respectively. Parameters w_{jk}, a_{ij}, b_j, (i=1,..,m, j=1,..,r, k=1,..,n) of network and membership function parameters c_{ij} and σ_{ij} (i=1,..,m, j=1,..,r) of FNN structure were adjusted and updated using the following formula:

$$\frac{\partial \mu_j(x_i)}{\partial \sigma_{ij}} = \mu_j(x_i) \frac{2(x_i - c_{ij})^2}{\sigma_{ij}^3} \quad (8)$$

The derivative of this formula is demonstrated in other research works (21, 25, 26).

RESULTS

The FNN algorithms demonstrated above were applied for the classification of erythemato-squamous diseases. Here, the dataset characterizing these diseases was donated by Nilsel Ilter and H. Altay Guvenir (15). The dataset included a set of values characterizing 33 input parameters. The number of data items was 366. The key problem was the accurate classification of the six disease classes. During simulation, the input data were normalized and scaled in intervals of 0–1 (27-34). The normalization of input data allowed quick training for the input–output data and helped to decrease the training time. After normalization, these data were utilized as FNN classifi-er input signals. As noted, the clustering technique was used for feature extraction. Using these features, the learning of FNN was performed. To implement classification, the input data set was grouped according to the output clusters. According to the clusters, the data subsets were obtained. Then, the clustering of input data sets was separately implemented for each subset.

The dataset used for the designing of the classification system included 33 input and 6 output signals. The input/output data set was utilized to set up training, evaluation, and data set testing. During simulation, a different number of rules was used for testing the classifier. In the beginning, the membership functions of the antecedent part and consequent part parameters were randomly generated. Using input signals and FNN structure, the output signals were determined; then, in the output of FNN, the deviation of current outputs from the target ones was determined. This deviation was utilized for computing the root mean square error (RMSE). RMSE and recognition rate were applied to deduce the FNN system performance. We computed RMSE using the following formula:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i^d - y_i)^2} \quad (9)$$

where y_i^d and y_i are the target and current output signals, respectively, and N is the number of samples. Using RMSE values, the learning of FNN was performed.

We computed the recognition rate using the following formula:

$$Recog\_rate = \frac{Number\ of\ items\ correctly\ classified}{Total\ number\ of\ items} \cdot 100\% \quad (10)$$

Classification and gradient descent algorithms of fuzzy c-means were employed for learning of the FNN's parameters. At first, the input was fed to the fuzzy c-means classifier to select the

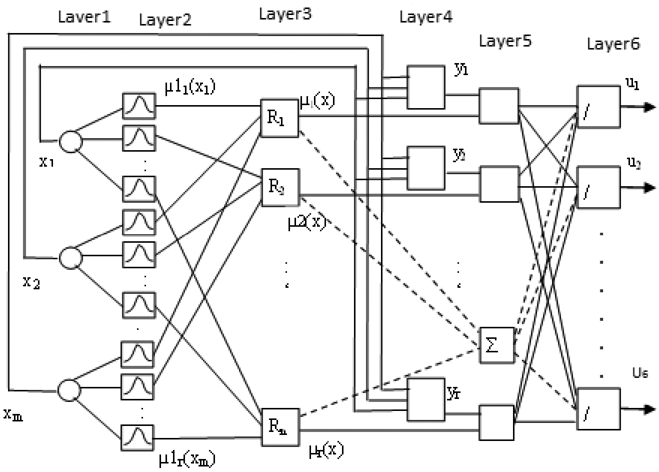

FIGURE 1. Fuzzy neural network (FNN) architecture

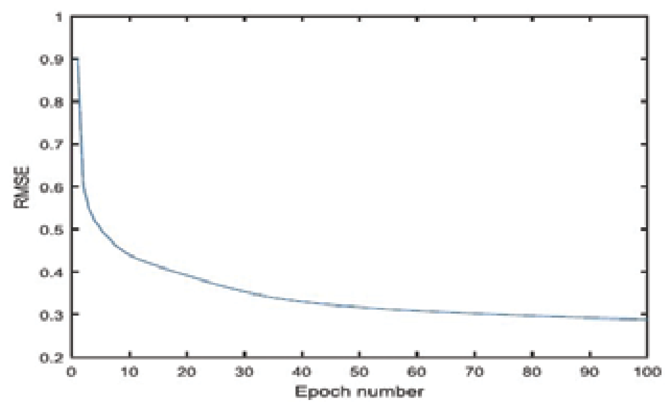

FIGURE 2. The plot of root mean square error (RMSE) obtained from fuzzy neural network (FNN) classifier

TABLE 2. Experimental results of FNN model

		RMSE			Recognition rate
Number of hidden neurons	**Epochs**	**Train (%)**	**Evaluation (%)**	**Test (%)**	**Testing (%)**
16	100	0.434172	0.473242	0.472161	95.733519
24	100	0.371654	0.355761	0.337102	96.722411
32	100	0.293227	0.277821	0.213603	98.373582

RMSE: Root mean square error

TABLE 3. Comparative results of different classifiers

Methods	Recognition rate (%)
CART (35)	94.84
ARFCMC (36)	75.96
ANFIS (37)	95.50
AEC (38)	97.32
Proposed Algorithm (FNN)	98.37

CART: classification and regression tree; ARFCMC: association rules and fuzzy c-means clustering; ANFIS: adaptive neuro-fuzzy inference system; AEC: ensemble of classifiers; FNN: fuzzy neural network

centers of the membership functions of input and hidden layers. We achieved this by referencing formulas given in section 2.4 for classification. The membership function width was computed using the distances between the centers of the membership functions. After clustering, the gradient descent algorithm was applied for learning the parameters of the FNN consequent part. The training was continued for 100 epochs. Learning was performed using 16, 24, and 32 rules. Figure 2 depicts the plot of RMSE of learning with 32 rules. As a result of learning with 32 rules, the value of training error was obtained as 0.298263, and the value of error for evaluation was 0.277821. After training using the original dataset, the testing of the FNN classification system was performed. The input data were fed to the FNN input layer, and at the output layer of the system, RMSE value for testing was obtained as 0.213603. The recognition accuracy of the system was 98.37% for 32 rules. The obtained results satisfied the suitability of using the FNN structure for classifying erythemato-squamous diseases. Table 2 depicts the results of simulation of FNN classification using a different number of rules.

DISCUSSION

As seen in Table 2, the increase in the number of rules led to a decrease in training, evaluation, and testing errors and increase in the recognition rate. The use of clustering techniques in system design allows a decrease in the learning time and an increase in the performance of the identification system.

In the second phase, the performance of the designed FNN identification system was compared with those of some related researches: Classification and Regression Tree (CART) (35), Association Rules and Fuzzy c-Means Clustering (ARFCMC) (36), ANFIS (37), and Ensemble of Classifiers (AEC) (38). Comparison of the recognition rates of these related classifiers, as shown in Table 3, clearly showed the efficiency and dominance of our proposed algorithm over the other few mentioned models.

This study investigated the capability of the FNN classifier tested on a real-world dataset for the diagnosis of erythemato-squamous diseases. We chose to integrate the learning capabilities of both the fuzzy logic and NN in this research because of the uncertain nature of the differential diagnosis of erythemato-squamous diseases. This uncertainty arises due to imprecise boundaries between the six classes of the disease. We implored fuzzy logic to simplify the uncertainty at the construction phase of the classifier, leading to high credibility and performance of the system. The FNN classifier was used to adequately classify the input space of the domain into the corresponding classes of the erythemato-squamous diseases. Based on the analysis of our proposed system (FNN), various deductions about the usefulness of features of the classification of erythemato-squamous diseases were achieved. Total performance accuracy of the FNN classifier was 98.37% for 32 rules. Taken together, we conclude that our proposed classifier could be applied for classifying erythemato-squamous diseases due to its high performance accuracy. Application of other sophisticated fuzzy systems such as type-2 and Z-number would be considered for further research on the same domain.

Ethics Committee Approval: Ethics committee approval was received for this study from the ethics committee of Near East University Applied Artificial Intelligence Research Centre (Approval Date: 31.08.2018; Approval Number: YDÜ/FB/2018/36.)

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