Artificial Neural Network for the Prediction of Dermatology

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Abstract : Skin disease is a major problem among people worldwide. Different machine learning techniques can be applied to identify classes of skin disease. Herein, we have applied machine learning algorithms to categorize classes of skin disease using ensemble techniques, and then a feature selection method is utilized to compare the results obtained. Machine learning algorithms are widely used in medicine. Various disease diagnosis classification algorithms have been developed to provide high accuracy for predicting disease. Many machine learning algorithms are developed for predicting various types of disease at early stages after examining the various attributes of the disease. Feature selection (FS) techniques are necessary for dealing with several dimensional datasets that may incorporate features in the high, little and, medium dimensions. In this research work, a comparative study of several filter feature selection techniques is utilized to diminish the size of the dermatology dataset. Feature Selection methods like SU, IG, CS and optimization techniques like PSO, GA and ACO have utilized and proposed a swarm based Symmetrical Uncertainty feature selection (SSU-FS) method based on SU and PSO. For evaluating the Swarm based Symmetrical Uncertainty feature selection method (SSU-FS), classification techniques like Naïve Bayes and ANN have used**.**

IndexTerms **- Dermatology, Data Mining, Skin, Symmetrical Uncertainty, Feature Selection, Particle Swarm Optimization, Genetic Algorithm, Ant Colony Optimization, Artificial Neural Network, Naïve Bayes, Classification.**

I. INTRODUCTION

In dermatology, the past year and a half have been marked by breakthroughs in machine learning. The advent of deep learning—machine learning algorithms composed of several layers of simple models that sequentially build abstract representations from raw data has made automated diagnosis of some cutaneous lesions achievable [1]. Recent publications by Esteva describe algorithms that approach dermatologist-level classification of cutaneous tumors. These technologies show tremendous promise to improve skin cancer screening and may extend screening far beyond the clinical setting [2]. Despite the potential benefits of these technologies, many aspects of their use have yet to be elucidated. In particular, questions about target end users, delivery of predictions, and their role in guiding diagnosis and management remain. As the adoption of smartphones increases worldwide, mobile apps are a natural way to deliver these deep learning algorithms. In fact, the model developed by Han et al3has already been optimized for mobile use and can be accessed without a subscription or login (http: //modelderm.com/). It is unclear, however, whether the site is designed for patients, no specialist clinicians, or dermatologists [3]. Decisions about the target end user should heavily influence user interface. Apps designed for patients should offer resources and information for patients to obtain a definitive clinical diagnosis and offer educational materials on screening and diagnoses. Moreover, most patients require more thorough explanations of a model's predictions [4]. These convolutional neural network models are made up of layers of simple algorithms, called neurons, that work together to extract various features from an image and then use these features to classify the subject of the image. The first group of layers performs convolution, a process of building meaningful representations of objects in the image from pixel data. After the first layer processes the raw pixels, each subsequent layer uses data produced in the preceding layer to build progressively higher-level understanding of the lesion (eg, first, edge detection; then, mapping of lesion border; and finally, lesion irregularity) [5]. After these features of the lesion are extracted, the neural network can classify the lesion based on an algorithm constructed from a data set of training images. The features described in the Figure shown below are familiar to dermatologists; however, real models may compute features with no diagnostic relevance for a clinician [6]. Ultimately, these predictions are generated as a probability distribution of diagnoses, which may include small probabilities of malignancy for clearly benign lesions—it is yet unclear how a nonexpert clinician, let alone a patient, would interpret a 0.02 probability of melanoma. Interpretation is further complicated by differences in the diagnostic efficacy of each distinct algorithm. The efficacy of these neural networks varies based on the set of images with which they are trained. Each model may have different sensitivities and specificities and may be subject to a unique set of biases and shortcomings in prediction introduced by the training set of images [7]. Ultimately, the input of dermatologists will be paramount for effective use of this technology. The dermatology community should actively lead the discussion on where deep learning fits into the skin cancer screening paradigm, perhaps by first defining thresholds for probability of malignancy that should prompt the patient to immediately seea dermatologist [8][9]. Future discussions may also center on the content patients are provided if given a diagnosis, or whether an app should disclose diagnoses to patients at all. Machine learning systems truly have the potential to transform skin cancer screening. They could increase the number of patients who are screened and prioritize limited resources for patients with the highest risk for cancer. Moreover, their use would likely increase the number of dermatology referrals and streamline patient visits. MobilePASS could also be used by dermatologists for clinical decision support at the point of care. With a decision support app, a clinician could draw insight from a model's prediction in addition to its process of classification: visual explanations of the features used by a model in classification could also be valuable in diagnosis. These data could help a dermatologist broaden or narrow a list of differential diagnoses for patients presenting with a particular lesion or could be incorporated into screening as a part of a total body skin examination, among other potential applications. Without the leadership of dermatologists, however, the tremendous potential of deep learning to change the field may never be fully achieved [10] [19][20][21][22][23].

II. RELATED WORKS

Verma, Anurag Kumar, Saurabh Pal, and Surjeet Kumar [11] In the proposed study, we present a new method which applies six different data mining classification techniques, and then develop an ensemble approach using Bagging, AdaBoost and Gradient Boosting classifier techniques to predict classes of skin disease. Furthermore, a feature importance method is utilized to select the most salient 15 features which will play a major role in prediction. A subset of the original dataset is obtained after selecting the 15 features, to compare the results of six machine learning techniques, and an ensemble approach is applied to the entire dataset.

Thenmozhi, K., and M. Rajesh Babu [12] In this paper, the framework is proposed to deal with the detection and classification of various skin diseases. The two techiques commonly used for reduction of dimensionality are feature extraction and feature selection. In feature extraction, features are extracted from original data using principal component analysis and linear discrimant analysis and then extracted feature is reduced by feature selection technique called Fisher ratio method in which the subset of sufficient features is selected for classification. This technique improves the performance and enhances the speed of classifier. The ensemble-based classifier such as Bayesian, self-organised map and support vector machine are used to classify the various skin diseases from the data set. The proposed technique achieves better accuracy and less execution time than existing approach.

Das, Rik, et al [13] The authors have attempted to design an automated melanoma detection system in this work by means of content based image classification. Extraction of content based descriptors can nullify the requirement for manual annotation of the dermoscopic images which consumes considerable time and effort. The work has also undertaken a fusion based approach for feature combination for evaluating classification performances of hybrid architecture. The results have outclassed the state-of-the-art outcomes and have established significant performance improvement.

Abbas, Ayad R., and Ayat O. Farooq [14] This paper proposes Bayesian Rough Decision Tree (BRDT) classifier to improve the accuracy of human skin detection. Three experiments have been conducted using (RGB) dataset collected from University of California, Irvine (UCI) machine learning repository, RGB (Red, Green, Blue), HSV (Hue, Saturation, Value) and YCbCr (Luminance, Chrominance). The experimental result shows that the proposed system can achieve preferable accuracy in skin detection 98%, 97% and 97% using RGB dataset, HSV dataset and YCbCr dataset respectively.

Abdar, Moloud, et al [15] This study proposes a new evolutionary-based computer-aided diagnosis (CAD) system using machine learning to classify theWDtreatment response. The main architecture of our CAD system is based on the combination of improved adaptive particle swarm optimization (IAPSO) algorithm and artificial immune recognition system (AIRS). The cross-validation protocol was applied to test our machine learning-based classification system, including five different partition protocols (K2, K3, K4, K5 and K10). Our database consisted of 180 records taken from immunotherapy and cryotherapy databases. The best results were obtained using the K10 protocol that provided the precision, recall, F-measure and accuracy values of 0.8908, 0.8943, 0.8916 and 90%, respectively. Our IAPSO system showed the reliability of 98.68%. It was implemented in Java, while integrated development environment (IDE) was implemented using NetBeans. Our encouraging results suggest that the proposed IAPSO-AIRS system can be employed for the WD management in clinical environment.

III. PROBLEM STATEMENT

Nowadays, Dermatology has become a common disease to the mankind from young to the old persons. The growth of the diabetic patients is increasing day-by-day due to various causes such as bacterial or viral infection, toxic or chemical contents mix with the food, auto immune reaction, obesity, bad diet, change in lifestyles, eating habit, environment pollution, etc. Hence, diagnosing the skin disease is very essential to save the human life from skin cancer. The data analytics is a process of examining and identifying the hidden patterns from large amount of data to draw conclusions.

IV. PROPOSED METHODOLOGY

In this research work, Machine Learning, a branch of Artificial Intelligence is used to analyze and make the Dermatology prediction model. Various researchers have also been done to predict the dermatology using machine learning algorithm, but this is an additional effort in the research work based on a specific type of patient in a specific community. In this research work, a comparative study of several filter feature selection techniques is utilized to diminish the size of the dermatology dataset. Feature Selection methods like SU, IG, CS and optimization techniques like PSO, GA and ACO have utilized and proposed a swarm based Symmetrical Uncertainty feature selection (SSU-FS) method based on SU and PSO. For evaluating the Swarm based Symmetrical Uncertainty feature selection method (SSU-FS), classification techniques like Naïve Bayes and ANN have used.

4.1 Feature Selection Method

FS methods have listed as filter and wrapper [6]. Upon this essential concept, many FS approaches have incorporated in machine learning (ML) paradigm. Wrapper method is utilized to decide the features detected on the precision evaluation, and filter method is employed to select the features not based on the precision evaluation; instead, it uses the data features with the relevancy or correlation. Filter-based systems are not reliant on classifiers and usually quicker and extra scalable than wrapper-based methods. Moreover, they have weak computational complexity too. Recently, amounts of hybrid methods are also being introduced to achieve appropriate stability in the feature selection standards by combing both filter and wrapper method [7].

4.2 Symmetrical Uncertainty Feature Selection Technique

The symmetrical uncertainty (SU) [8] among the features and target concept are applied to achieve the best features for classification. The features with greater SU values have the more significant weight. SU estimates the association among R, S features based on the information theory [9]. It will calculate as follows

$$SU\ (R,)\ S = 2\ \frac{I\ (R,S)}{H(SR) + H\ (S)}$$

Estimating I(R, S) as the MI [9] among R, S. H(..) as an entropy function for R, S features. The SU means the [0,1] (normalized range value) as the improvement factor value is 2. The value of SU for one feature is 1, and then it is predictable. The value of SU is 0, then R and S features do not have the relationship [16][17][18].

4.3 Information Gain Feature Selection

Entropy has usually applied in the information theory measure, which describes the purity of an arbitrary set of examples [10]. It is from the base of Symmetrical Uncertainty, Information Gain, and Gain Ratio. The entropy measure has estimated as a measure of the system's unpredictability. The entropy of S is

$$H(S) = \sum_{s\in} Sp(s)\log_2(p(s)) \quad (3.1)$$

Where *p(s)* is the marginal probability density function for the random variable S. If the observed values of *B* in the training data set *D* has partitioned according to the values of a second feature A, and the entropy of *B* for the partitions induced by *A* is less than the entropy of *B* before partitioning, then there is a relationship between features B and A. The entropy of *B* after observing *X* is then:

$$H(B|A) = \sum_{x\in} Ap(x)\sum_{b\in} Bp(b|a)\ \log_2\big(p(b|a)\big) \quad (3.2)$$

where *p(b |a)* is the conditional probability of *b* given a.

Given the entropy is a criterion of impurity in a training set *S*, we can define a measure reflecting additional information about *B* provided by *A* that represents the amount by which the entropy of *B* decreases. This measure is known as IG. It is given by

$$IG = H(B) - H(B|A) = H(A) - H(A|B) \quad (3.3)$$

IG [10] is a symmetrical measure, and it has given by equation (3.3). The information gained about *B* after observing *A* is equal to the information gained about *A* after observing *B*. A weakness of the IG criterion is that it is biased in favor of features with more values even when they are not more informative [16][17][18].

4.4 Chi-Square Analysis

Feature Selection via chi-square χ^2test [11] is another, very commonly used method. Chi-squared attribute evaluation evaluates the worth of a feature by computing the value of the chi-squared statistic for the class. The initial hypothesis H_0 is the assumption that the two features are unrelated, and the chi-squared formula tests it:

$$\chi^2 = \sum_{i=1}^{r}\sum_{j=1}^{c}\left(\frac{O_{ij}-E_{ij}}{E_{ij}}\right)^2 \quad (3.4)$$

Where O_{ij} is the observed frequency, and E_{ij} is the expected (theoretical) frequency, asserted by the null hypothesis. The greater the value of χ^2, the greater the evidence against the hypothesis H_0. [16][17][18].

4.5 Evolutionary Algorithm for Feature Selection

Metaheuristic algorithms are algorithms [12] which, in order to leave from local optima, make some fundamental rule: either a useful heuristic beginning from a void solution and joining elements to make a valid complete one, or a local search heuristic beginning from a whole solution and iteratively adjusting any of its elements in order to make a better one. The metaheuristic part allows the low-level heuristic to get solutions better than those it could have accomplished alone, even if emphasized. Normally, the regulating mechanism is performed either by randomizing or by constraining the collection of local neighbor explications to consider in local search [16].

A. Particle Swarm Optimization

Particle Swarm Optimization (PSO) [13] [14] was based on the social behavior correlated with bird's gathering for the optimization issue. A social behavior pattern of organisms that live and interact with big groups is the motivation for PSO [14] [18]. The PSO is more available to put into effect than Genetic Algorithm. It is for the motive that PSO does not have a mutation or crossover operators and movement of particles has effected by utilizing velocity function. In PSO, each particle adjusts its flying memory and its partner's flying inclusion following in mind the top goal of flying in the search space with velocity.

B. Genetic Algorithm

A genetic algorithm (or GA) [15] is an exploration method utilized in computing to determine approximate or true explications to search and optimization problems. GA have characterized as global search heuristics. GA is an appropriate class of evolutionary algorithms that employ methods motivated by evolutionary biologies such as selection, crossover, mutation, and inheritance (also called recombination). The evolution normally begins from a population of randomly created individuals and appears in generations. In each generation, the fitness of each in the population has estimated, multiple individuals are chosen from the current population (upon their fitness), and transformed to create a new population. The new population has employed in the subsequent repetition of the algorithm. The algorithm ends when a maximum number of generations has generated, or a satisfactory fitness level has reached for the population.

4.6 Proposed Swarm based Symmetrical Uncertainty Feature Selection Method

Swarm-based Symmetrical Uncertainty Feature Selection (SSU-FS) method is the combination of Symmetrical Uncertainty and Particle Swarm Optimization. These are two methods are hybridized to get the relevant features and removing the redundant features [16].

Pseudo code: Swarm-based Symmetrical Uncertainty Feature Selection (SSU-FS) method

Input: Dermatology Dataset

Output: Optimal Dataset

Step 1: Initialize the Decision Feature and Conditional feature from Symmetrical Uncertainty calculation.

Step 2: Initialize the swarm size, random variables, social and cognitive components, inertia.

Step 3: Consider each particle in the swarm.

Step 4: Initialize the variable A as a null set. Moreover, that variable has set to another variable B for comparing the particle in the swarm area.

Step 5: Check the conditional feature with the empty set.

Step 6: Evaluate the Data Fitness Value of each particle by using a Griewangk function.

Step 7: Check whether the Data Fitness Value is higher than Particle Best. If so set Data Fitness Value = Particle best.

Step 8: Again check Particle best is higher than Global best. If so set Particle Best = Global Best.

Step 9: Consider the variable in A and Decision feature in B. Check variable in A is higher than the decision feature in B. Then set the variable A in B.

Step 10: Calculate and update the velocity by the following equation:

$$U_{ud} = U_{ud} + C1i1\big(p_{jd} - y_{jd}\big) + C2i2(p_{gd} - y_{jd})$$

$$Y_{jd} = Y_{jd} + U_{ud}$$

Step 11: Repeat the process until the variable in A = decision feature in B is satisfied.

Step 12: If the condition is true, return the variable in A set

V. RESULTS AND DISCUSSION

5.1 Dataset Description

Dermatology Dataset Description

Attribute Information:

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

5.2 Performance Analysis of the Feature Selection Method

FS is a method of making the subset features from the initial feature space. The proposed method has been utilized in all datasets to choose the relevant features by eliminating the irrelevant one. Table 1 depicts the number of features obtained by the Symmetrical Uncertainty, Particle Swarm Optimization and Proposed hybrid feature selection method.

Table 1: Number of Features obtained by the Symmetrical Uncertainty, Particle Swarm Optimization and Proposed Hybrid Feature Selection Method

Feature Selection Methods	All Features
Original Dataset	35
Symmetrical Uncertainty	30
Particle Swarm Optimization	21
Hybrid Feature Selection	11

5.3 Performance Analysis of the Feature Selection Method for Dermatology Classification using Naïve Bayes

To estimate how well original features and each selected feature by various feature selector including SU, PSO, and Hybrid Feature Selector will able to increase the detection performance of Naïve Bayes classifier is empirically estimated. And also, the proposed method is efficient and effective when compared with other possible feature selection methods. Table 2a gives the classification accuracy and error rate analysis of the proposed Hybrid Feature Selector, SU, PSO and original dataset using Naïve Bayes classifier. From table 2a proposed hybrid Feature Selector gives higher classification accuracy, kappa statistic value. Error rates are reduced for proposed method than the existing methods. Table 2b to Table 2e depicts the detailed accuracy of the dermatology dataset using NB classifier.

Table 2a: Classification Accuracy of SU, PSO and Hybrid Feature Selector using Naïve Bayes Classification Method for Dermatology Dataset

Dataset Name	Naïve Bayes Classification Method			
	Original	SU	PSO	Hybrid Feature Selection
Classification Accuracy	60.6557%	76.5027%	75.6831 %	91.5301 %
Kappa Statistics	0.2746	0.5416	0.3923	0.746
Mean absolute error	0.2045	0.1179	0.1219	0.0484
Root mean squared error	0.395	0.311	0.302	0.1717
Relative absolute error	72.1469 %	47.8843%	72.7628 %	28.3996 %
Root relative squared error	105.1173 %	88.9097 %	105.1364 %	59.2331 %

Table 2b: Detailed Naïve Bayes Accuracy by Class for Original Dermatology dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0	0.835	0.437	0.751	0.835	0.791	0.836
1	0.257	0.091	0.4	0.257	0.313	0.732
2	0.167	0.067	0.3	0.167	0.214	0.758
3	0.444	0.098	0.19	0.444	0.267	0.771
Weighted Average	0.607	0.299	0.59	0.607	0.589	0.801

Table 3c: Detailed Naïve Bayes Accuracy by Class for SU Processed Dermatology dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0	0.904	0.061	0.97	0.904	0.936	0.943
1	0.286	0.068	0.258	0.286	0.271	0.743
2	0.609	0.142	0.476	0.609	0.534	0.875
3	0.261	0.038	0.316	0.261	0.286	0.889
Weighted Average	0.765	0.074	0.788	0.765	0.774	0.912

Table 2d: Detailed Naïve Bayes Accuracy by Class for PSO Processed Dermatology dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0	0.834	0.186	0.95	0.834	0.888	0.868
1	0.474	0.107	0.34	0.474	0.396	0.83
2	0.462	0.121	0.226	0.462	0.304	0.86
3	0	0	0	0	0	0.926
Weighted Average	0.757	0.17	0.82	0.757	0.781	0.865

Table 2e: Detailed Naïve Bayes Accuracy by Class for Hybrid Feature selection Processed Dermatology dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0	0.997	0.014	0.997	0.997	0.997	0.986
1	0	0	0	0	0	0.319
2	0.837	0.068	0.621	0.837	0.713	0.954
3	0.231	0.024	0.429	0.231	0.3	0.929
Weighted Average	0.915	0.021	0.904	0.915	0.906	0.973

Table 3a gives the classification accuracy and error rate analysis of the proposed Hybrid Feature Selector, SU, PSO and original dataset using ANN classifier classifier. From table 3a proposed hybrid Feature Selector gives higher classification accuracy, kappa statistic value. Error rates are reduced for proposed method than the existing methods using ANN classifier.

Table 3a: Classification Accuracy of SU, PSO and Hybrid Feature Selector using ANN Classification Method for Dermatology Dataset

Dataset Name	ANN Classification Method			
	Original	SU	PSO	Hybrid Feature Selection
Classification Accuracy	47.8142 %	51.0929 %	61.4754 %	90.9836 %
Kappa Statistics	0.2841	0.3239	0.1324	0.7225
Mean absolute error	0.2898	0.2843	0.2637	0.056
Root mean squared error	0.4402	0.4208	0.3799	0.1872
Relative absolute error	78.362 %	76.8524 %	93.0107 %	32.8346 %
Root relative squared error	102.3606 %	97.8487 %	101.0956 %	64.5845 %

Table 3b: Detailed ANN Classifier Accuracy by Class for Original Dermatology dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0	0.686	0.194	0.628	0.686	0.656	0.767
1	0.222	0.109	0.333	0.222	0.267	0.61
2	0.54	0.308	0.397	0.54	0.458	0.639
3	0.316	0.1	0.453	0.316	0.372	0.748
Weighted Average	0.478	0.189	0.471	0.478	0.466	0.697

Table 3c: Detailed ANN Classifier Accuracy by Class for SU_Processed Dermatology dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0	0.78	0.202	0.648	0.78	0.708	0.794
1	0.194	0.065	0.424	0.194	0.267	0.605
2	0.58	0.316	0.408	0.58	0.479	0.647
3	0.303	0.09	0.469	0.303	0.368	0.764
Weighted Average	0.511	0.183	0.501	0.511	0.488	0.711

Table 3d: Detailed ANN classifier Accuracy by Class for PSO_Processed Dermatology dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0	0.942	0.775	0.657	0.942	0.774	0.577
1	0.086	0.041	0.333	0.086	0.136	0.522
2	0.148	0.048	0.348	0.148	0.208	0.57
3	0	0.011	0	0	0	0.487
Weighted Average	0.615	0.49	0.517	0.615	0.531	0.561

Table 3e: Detailed ANN classifier Accuracy by Class for Hybrid Feature Selection Processed Dermatology dataset

Class	TP Rate	FP Rate	Precision	Recall	F-Measure	ROC Area
0	0.997	0.069	0.983	0.997	0.99	0.979
1	0	0	0	0	0	0.372
2	0.884	0.074	0.613	0.884	0.724	0.914
3	0.077	0.012	0.333	0.077	0.125	0.853
Weighted Average	0.91	0.065	0.885	0.91	0.889	0.958

VI. CONCLUSION

Data mining is an emerging Computer Science field with many applications. Autism is a disorder that has been increasing at an incredible rate. Pre-processing is an early stage of data mining for the prediction of the level of skin disease. In this research work, Swarm based Symmetrical Certainty Feature Selection (SSU-FS) method has proposed to get the most relevant features and to remove the redundant and irrelevant features. This method has evaluated by using NB and ANN classification methods. Among these two methods, the proposed SSU-FS method performs well in Naïve Bayes classification environment for ASD dataset. From the above-obtained results, it has concluded that proposed SSU-FS method gives the better result than the existing methods like Symmetrical Certainty, Information Gain, Chi-Square, Particle Swarm Optimization and Genetic algorithm in the pre-processing stage by utilizing NB and ANN classification methods.

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