Recognition of Skin Diseases using Deep Neural Network Optimized by Group Teaching Algorithm

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Abstract

The most commonly occurring diseases among all ages of people are the skin diseases. Every people have different skin conditions and these diseases create dangerous effects on the skin. It is essential to recognize the difference between the skin conditions to identify the diseases at its initial stage and to control them from spreading. This work aims to improve the accuracy of diagnostic systems using Image Processing and classification techniques. Basically, the classification of skin diseases undergoes five phase's namely pre-processing, image segmentation, feature extraction, feature selection and classification. During pre-processing, the quality of original image gets enhanced and noise is removed. Image segmentation is done using FCM (Fuzzy C Means) combined with morphological operators. Then, the features from the segmented image are extracted using LBP (Local Binary Pattern)-GLCM (Gray Level Co-occurrence Matrix) extraction techniques. Sometimes the extracted features may found in large dimension with relevant and irrelevant features. In order to reduce this, an optimization based feature selection process named BGOA (Binary Grasshopper Optimization Algorithm) is involved before the classification phase. Finally, a deep learning based approach named DNN (Deep Neural Network) is used for classification which is optimized using GTO (Group Teaching Optimization) algorithm. The simulation analysis is carried out with PH2 dataset. The performance metrics like accuracy, specificity, and sensitivity are determined.

Keywords: *Skin Disease, Deep Learning, Image Processing, GLCM, Group Teaching Optimization.*

I. Introduction

The most sensitive and most significant organ in human body is termed as Skin. It helps to protect the interior organs and avoids the contact with viruses and bacteria. Skin offers three key functions namely protection, regulation as well as sensation. The three layers of the skin are epidermis, dermis and hypodermis (deeper subcutaneous tissue). Skin is one of the major organs which cover the bones, muscles and all other body parts. Skin permits the sensations of touch and regulates the body temperature. Melanocytes are the superior cells present in skin; capable of producing a pigment named melanin also gives colour to the skin. The entire functions of the skin are affected by means of wounds [1-5].

The most common diseases among humans are the skin diseases. Usually, these are caused due to the following factors, such as a different diet, internal and external factors and different organism's cells. There are also chronic as well as incurable diseases, namelyBasal cell carcinoma, psoriasis, Squamous cell carcinoma, eczema(Atopic dermatitis) and malignant melanoma. The severe and life-threatening type of skin cancer is melanoma.Skin illnesses significantly vary in symptoms and severity. They can be temporary or else permanent, and sometimes painful or else painless. Some skin conditions are minor, and others can be life-threatening [6-10]. Researchers recently found the availability of cures for these diseases if they are detected in the early stages.

The structure of this article is systematized as follows. Section 2 analyses some research works interrelated to this work. Section 3 explains the proposed scheme clearly. The simulation outcomes obtained from MATLAB is presented in Section 4 with a related explanation. Finally, the overall work is concluded in the last section with future suggestions.

Motivation

More importance is given to the skin structure because even a minor change in its functioning might influence other body parts. Skin surface gets affected easily by infection and also disease occurs more on skin as it is exposed to external environment. So, a greater attention is needed to identify the skin disease. Normally, various skin diseases are very common and of non-cancerous type. Some of the common types of skin diseases are freckles, moles, benign lenities, skin tags and seborrheic keratosis but, the fear about the injury or disease has initiated the patient to make an inquiry also accurate diagnosis is very important. Hence, DNN is optimized by Group teaching algorithm for the effective classification of skin diseases.

Objectives

The overall key objectives of skin disease detection are stated as follows:

- To find skin disease at an early stage in order to provide more accurate result using various image processing techniques.
- To provide better differentiation among various types of diseases based on their appearance and morphological features.
- To present CAD system based hybrid DNN with Group Teaching optimization algorithm.
- To minimize the error during the classification process and to minimize the system errorrate.
- To minimize the execution time and to achieve maximum detection and classification accuracy.

II. Related Work

Anurag et al.[11] introduced various data mining approaches for the prediction of skin disease. Six classification techniques, namely LDA (LinearDiscriminant Analysis), PAC(Passive Aggressive Classifier), RNC (Radius NeighboursClassifier), NB (Naïve Bayes), BNB (Bernoulli Naïve Bayesian) and ETC (Extra Tree Classifier) were used. In order to enhance the accuracy of three classifiers such as AdaBoost, Bagging and Gradient Boosting were also used. The feature selection model used in this work obtained 99.68% accuracy.

Belal *et al.*[12] improved the classification performance of skin disease using deep CNN model combined with triplet loss function. The problems of facial skin disease images were stated using ResNet152 and InceptioResNet-V2. By considering the L2 distance among images the classification task was performed. The dataset used was named as Dermnet, which includes 4 types of skin diseases such as dark circles, acne, spots and blackheads.

SavyGulati and Rosepreet [13] introduced the detection of skin disease based on EP (Electrical Properties) and IPTs (Image Processing Techniques). A comprehensive review was also performed for easier identification of detection performance. Several diseases included were skin cancers, psoriasis, acne, vitiligo, erythematous-squamous, or facial diseases, legs, warts, eczema, tineacorporis and feet ulcers. From the review, it was denoted that finest results were attained when VGGnet CNN was exploited by transfer learning (TL).

Jufeng *et al.*[14] presented an algorithm named Self-Paced Balance Learning (SPBL)for recognition of clinical skin disease (CSD). Also, the issue of class imbalance was addressed. This problem was not caused due to imbalanced class sizes distribution but mainly due to difficulty of imbalanced recognition. Penalty weight updating and curriculum reconstruction strategies were also introduced. Experiments were conducted on dual imbalanced datasets for CSD recognition tasks together with several other imbalanced problems.

Faouzi *et al.* [15] explored the fusion of textural in addition to structural features for the recognition of melanoma. At first the textural features were obtained from the different variants of LBP operator. Also, the structural features were obtained from the first as well as second levels of wavelet and curvelet coefficients. The classifier used was SVM combined with linear kernel. The performance metrics were illustrated in terms of sensitivity, accuracy, and specificity in the PH2 database.

Adegun *et al.*[16] presented a deep learning (DL) model for melanoma detection and segmentation. The identification of melanoma disease was done by performing pixel-wise classification. The classifier used was named as Deep Convolutional Networks linked with softmax. The dataset used for the evaluation of the presented approach was PH2 and ISBI 2018.

Problem Statement

The sign of melanoma disease starts as the change of the colour in the skin. Usually, they are mixed colours (pink, red and brown). The recognition of skin disease is quite difficult because of the following factors: melanoma and non-melanoma type diseases show visual similarity and low-contrast among skin and injury. The image processing is one of the most common methods used to detect and classify this disease. Accurate diagnosis is challenging among physicians due to the excessive dermatologic conditions. To overcome this issue, a systematic approach is needed by the clinician for the evaluation of diseases on the skin. Along with the physical characteristics of the injury, presence of associated symptoms, related systemic disorders, the patient's demographics and location and growth patterns of the injury gives clues to effectively diagnose and treat the skin disease at the early stage.

III. Proposed Methodology

This work aims to detect the different types of skin diseases like Melanoma, Seborrheic Keratosis, Nevus, Basal cell carcinoma, Psoriasis, Squamous cell carcinoma, and Vitiligo etc. It also targets at evolving a system to offer easy and early detection of skin diseases by means of image processing and classification methods. Initially, dermoscopic skin images are given as inputwhich is taken from the publically available data set named Pedro Hispano Hospital (PH2). Pre-processing is the first step in the analysis of skin images. It is essential to performpre-processing, as it enhances the quality of the original image and remove noises. The objectiveis to enhance the image quality by eliminating the unrelated and additional parts inthe background of image. The pre-processed image and given to the segmentation algorithm.The main goal of segmentation is to improve the image quality which is performed using FCM combined with morphological operators. Next, the texture features are extracted using Local Binary Pattern and Gray Level Co-occurrence Matrix (LBP-GLCM). Then the features are selected using Binary Grasshopper Optimization Algorithm (BGOA). Finally, the skin diseases are classified using Deep Neural Network (DNN) optimized by Group Teaching algorithm.

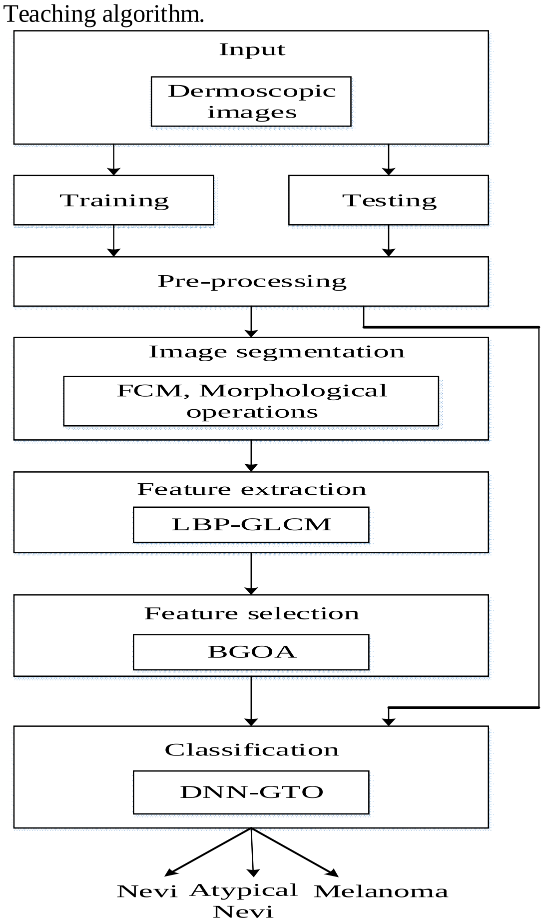

Figure 1. Proposed Work Flow Model

The work flow model of the proposed method is shown in Fig 1. The four steps in CAD systems for identifying the skin diseases: Image Construction and Pre-processing, Image Segmentation, Feature extraction, Feature selection and Classification.

A. Image Constructionand Pre-processing

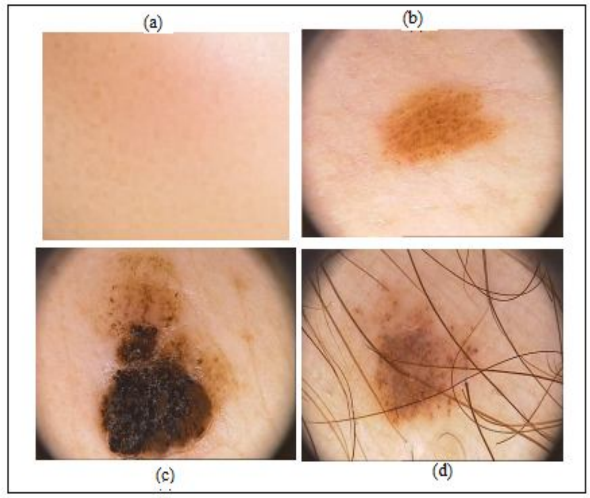

Figure 2. Image Construction (a) Healthy skin (b) Nevi (c) Atypical Nevi (d) Melanoma

In this work the dataset used for the skin disease detection is PH2 data repository. Fig signifies the representation of dermoscopic images. Fig 2 signifies the type of skin disease images. This dataset includes total 200 skin disease images representing the highest resolution of 765×574 pixels. The entire PH2 dataset is divided into training and testing sets which consists of ground truth labels and images respectively. Here, the ground truth is mask image in PNG format and the skin disease images will be in JPEG format. The dataset description is mentioned in Table 1.

Table 1: Dataset Description

No.	Name of image	Total images
1.	Nevi	80
2.	Atypical nevi	80
3.	Melanoma	40

In thePre-processing stage, differentprocesses are applied in order to remove the artifacts. At first, the dermoscopic RGB image is transformed into a grayscale image as it provides the best discrimination between the wound and the skin. The dermoscopic images include the following artifacts such as uneven distribution, hairs, noise shapes, air bubbles, reflection artifacts and ink markings. This stage makes the image to be prepared for further processing and eliminate all the potential noisy factors. The pre-processed output is given as input to perform segmentation process.

B. Image Segmentation

The most important task in image processing is segmentation. It is used to extract the pigments present in the dermoscopy images automatically from the surrounding skin. Image segmentation is a process which distinguishes the image into its constituent or homogeneous areas. The image is segmented on the basis of regularity, which normally relies on its unique situation and specific assignment. The main goal of segmentation is to alter or improve the image quality which helps the extraction process.

a) FCM with Morphological operation: In this method, an adaptive morphological thresholding is applied. Initially, the pre-processed image is clustered using FCM (Fuzzy C-Means) and then the morphological operations are applied for segmentation process. The diseased and non-diseased areas are clustered using FCM and then morphological operations are applied to remove the non-diseased regions from the diseased regions.

Fuzzy C Means clustering: The entire dataset $\{k_m\}_{l=1}^{N}$ is clustered into c clusters using FCM algorithm [17]. This clustering process is accomplished on the basis of objective function which is expressed in eqn (1),

$$F_n = \sum_{m=1}^{c}\sum_{l=1}^{N} s_{ml}^{x}\left\|k_m - r_l\right\|^2 \tag{1}$$

Where, x represents the real number (must be greater than 1), and the membership of k_m data point that belongs to the m^{th} cluster is represented as s_{ml}^{x}. k_m represents the m^{th} data in d-dimensional space and the cluster centroid is represented as r_l. The notation c in equation (1) represents the number of cluster and the total number of data points are represented as N. The cluster centroids and membership values are update by FCM during partitioning. While updating the centroids, the membership value of several data points with respect to each centroid is also attained using eqn (2),

$$s_{ml} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\left\|k_m - r_l\right\|^2}{\left\|k_m - r_k\right\|^2}\right) \times \frac{1}{x-1}} \tag{2}$$

The distance between the cluster centroid and the data point are evaluated to update the cluster centroid which is performed using the eqn (3),

$$v_m = \frac{\sum_{l=1}^{N} k_m s_{ml}^{x}}{\sum_{l=1}^{N} s_{ml}^{x}} \tag{3}$$

The sum of resultant weight between the data and cluster center within the fuzzy cluster is evaluated by the objective function. Better segmentation result is achieved by FCM, but sometimes it may assign incorrect membership value due to the presence of noise. Due to this negative impact, an improper segmentation is achieved by FCM. Therefore, morphological operations are hybridized along with this FCM to improve the segmentation result. Dilation and erosion are the dual morphological operators used along with FCM to enhance the segmentation output. Dilation refers to an expansion process since it includes some additional pixels at the object boundaries in an image. It is applied to fill gaps in pixels of dermoscopic images. Erosion is used to eliminate the non-diseases pixels. Morphological operation includes the following processes like identification of connected components, evaluating the area of each element and removing the non-diseased regions.

C. Feature Extraction

The process of extracting the image information is termed as Feature Extraction (FE). Diseasedimage'sinformationisreduceddue tothecomponents arrangement that is robust towards the lightning, lack of clarity, and camera positioning. In this work, LBP-GLCM techniques are used to extract the texture features. Texture means visual patterns which have homogeneity property. Texture represents the information related to structural arrangement of surfaces and its relationship to surrounding environment.

a) Local Binary Pattern (LBP): LBP is termed as an image operator which is mainly used to compute a local representation of texture. The texture analysis is done based on the differences among central and neighbour pixel. The construction of local representation is accomplished by comparing each pixel with its neighbouring pixels. The image is transformed into array or else integer labels using the image operator that represents the textures of image.

Image is divided into cells using LBP [18]. For each cell, the centre pixel intensity value is compared with the neighbouring pixels intensity values. If the value of centre pixel is greater than the value of neighbourhood pixel, note the value as 1 or else 0. Then, compute histogram and normalize it. After that, merge and collect the histogram of all cells. The expression for LBP feature vector is mentioned as follows:

$$LBP_{p,r} = \sum_{np=0}^{p-1} s\left(g_{np} - g_{cp}\right)2^{np}, \quad s(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{4}$$

Where, r indicates the radius of local neighbourhood, neighbour pixels number is signified as p. Centre pixel grayscale value is denoted as g_{cp} and g_{np} represents neighbour pixel gray scale value.

b) Gray Level Co-occurrence Matrix (GLCM): The 2nd order statistical approach that is applied to analyze the texture (object) in an image is GLCM [19].The texture part in image is modelled as 2D gray level variation to identify the specific texture. This 2D array is referred as GLCM. It is a type of statistical analysis which determines the image properties by considering the spatial relationship among each pixels. The gray scale in-between each spatial positions are altered for developing texture, therefore a particular spatial relationship that exist among the two pixels are separated for a certain distance. In this five different GLCM features are extracted they are correlation, ASM (Angular second moment), energy, homogeneity, entropy, and contrast. A square matrix is defined by GLCM whereas the size of this square matrix represents the probability of the gray value. The expressions for the following features are represented as follows:

$$Contrast = \sum_{a=1}^{N}\sum_{b=1}^{N}|a-b|^2 \times GLCM(a,b) \tag{5}$$

$$Correlation = \sum_{a=1}^{N}\sum_{b=1}^{N}\frac{(a-\delta a)(b-\delta b)(GLCM(a,b))}{\sigma a \sigma b} \tag{6}$$

where, mean is represented as δ and σ is the standard deviation

$$\delta a = \sum_{a}^{N}\sum_{b}^{N} a * GLCM(a,b); \delta b = \sum_{a}^{N}\sum_{b}^{N} b * GLCM(a,b) \tag{7}$$

$$\sigma a = \sqrt{\sum_{a}^{N}\sum_{b}^{N}(a-\delta a)^2 GLCM_{a,b}}; \sigma b = \sqrt{\sum_{a}^{N}\sum_{b}^{N}(b-\delta b)^2 GLCM_{a,b}} \tag{8}$$

$$Energy = \sum_{a=1}^{N}\sum_{b=1}^{N} GLCM(a,b)^2 \tag{9}$$

$$ASM = \sum_{a=1}^{N-1}\sum_{b=1}^{N-1}(GLCM(a,b))^2 \tag{10}$$

$$Entropy = -\sum_{a=1}^{N}\sum_{b=1}^{N} GLCM(a,b)\log GLCM(a,b) \tag{11}$$

$$Homogenity = \sum_{a=1}^{L}\sum_{b=1}^{L}\frac{GLCM(a,b)}{1+|a-b|} \tag{12}$$

Since an image database contains dataset of different images which have different texture features and these features are extracted using the LBP-GLCM techniques and stored in the feature extraction matrix.

D. Feature Selection

The process of choosing the features manually is termed as Feature Selection (FS). It helps to reduce the amount of data particularly in case of high dimensional datasets. The inapt features present in the dataset resultsin worst accuracy and increases the computational time.FS is considered as an optimisation issue and solved using Swarm Intelligence based techniques. It helps to reduce the amount of data particularly in case of high dimensional datasets. In addition, not all features are utilized as classifier inputs.

a) Binary Grasshopper Optimization Algorithm (BGOA):BGOA is the SI technique utilized to choose appropriate features which enhances classification accuracy. In this work, for classification purpose BGOA [20] is employed that selects optimal feature subset and reduces the redundancy, thus making the classification process more robust and less time-consuming.

The objective function used for this optimization is given as,

$$f(x^{(i)}) = \max\left(\frac{f_S}{f_T}\right) \quad (13)$$

where,

f_S = selected features

f_T = total features

Binary values [0, 1] signify the search space. Based on its current position, each solution is updated also best grasshopper position is named as target. In this work, sigmoid function is utilized as transfer function to perform the squash of continuous solutions in each dimension. So that the grasshoppers are forced to move in the binary search space.

Transfer function is given as,

$$T(x^{(i)}) = \frac{1}{1+e^{-x}} \quad (14)$$

The outputs are to be limited by using the threshold to get the binary value as output. The stochastic threshold is applied as,

$$\tau = \begin{cases} 0, & if\ r < T(x^{(i)}) \\ 1, & if\ r \geq T(x^{(i)}) \end{cases} \quad (15)$$

where,

τ=represents the threshold condition and

r = random value.

Based on the outcome of the threshold condition, the decision is taken whether the feature is selected or not. If the output is one means the feature gets selected. Also, feature is not selected when the outcomeis zero. For optimized feature selection the fitness function utilized is given as,

$$F = \psi f(x) \quad (16)$$

where, ψ is the constant and $f(x)$ represents the objective function.

E. Data Classification

The data classification section makes use of deep learning based approach. The group teaching optimization (GTO) algorithm with Deep Neural Network (DNN) is employed for classification of various skin diseases. The detection of skin diseases can be deliberated as a multiple classification task where each image in the dataset is further classified as Melanoma, Nevi and Atypical Nevi.

a) DNN architecture**:** The classification task is performed by DNN model in the proposed method. The architecture of DNN is illustrated in Fig 3, which consists of input layer, output layer with multiple hidden layers in between. The word 'Deep' denotes the multiple hidden layers through which the data is transformed. DNN model differs from Artificial Neural Network, where the number of hidden layers is more. The flow of data in DNN move from input to output layer without twisting back and so it is termed as feedforward network. Initially, a map of virtual neurons is created by DNN model then assigns weights to connect the layers. Thus the inputs and weights are multiplied and yield an output value that ranges between 0 and 1. An optimization algorithm is used to optimize the weights even if the network did not recognize a particular pattern accurately,

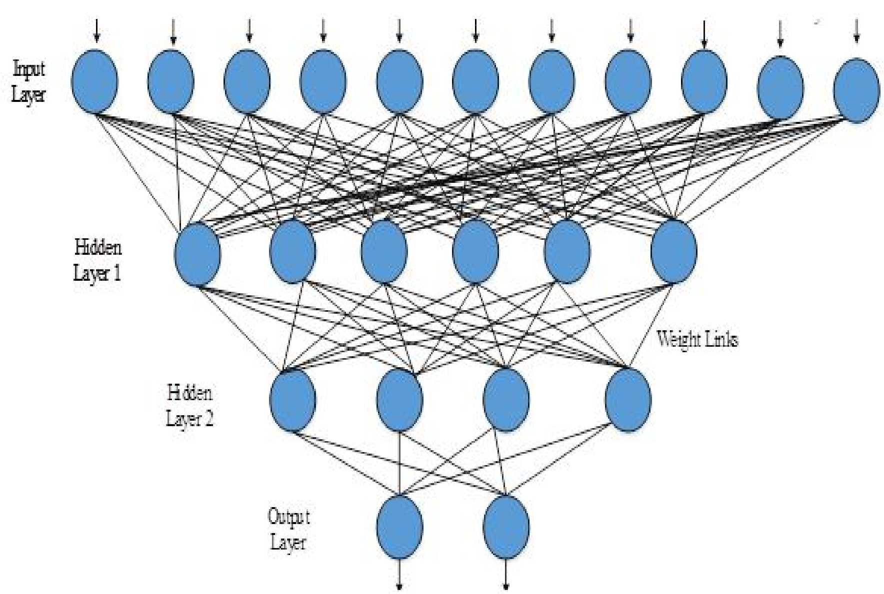

Figure 3. DNN Model

The network model includes the following layers namely input, output and dual hidden layers. The input layer comprises the attributes of skin disease dataset. All these nodes are connected to the hidden layer nodes. The inputs to the network is fed via the input layer then passed unto the hidden layer by multiplying the weight value with each attribute. The hidden layer nodes were configured to compute the weighted sum as well as add a bias value represented as:

$$X_j = \sum_i^m x_i * w_{ij} + \theta_j \tag{17}$$

Where, x_i denotes the input data, θindicates the bias and $w_{ij}$is the weighted link between the nodes. Therefore, X_j is transformed using a sigmoid transfer function:

$$F(X_j) = \frac{1}{1 + e^{-X_j}} \tag{18}$$

Finally, the type of skin diseases is predicted in the output layer. Next, training process of the network starts with the initialization of connection weights by choosing a set of random values. During network training, weights are adjusted accordingly:

$$\Delta w_{ij} = -n \frac{\theta E}{\partial w_{ij}} \tag{19}$$

Where, E denotes the errorand n is learning rate. Moreover, weight in DNN is optimized using the optimization algorithm namedGroup Teaching Optimization.

***b) Group Teaching Optimization*:** The GTO algorithm [21] is motivated by the mechanism of group teaching. This idea is formulated by teaching students based on their ability. Different teaching strategies are conveyed to students according to their understanding capacity. It is noted that there may be huge differences among students in terms of learning ability, intelligence, economic conditions and learning attitude. Hence, GTO is then termed as an effective way to enhance the quality of students. The following assumptions are made to adapt the group teaching (GT) framework. Some of them are information initialization which includes initialization of population and parameters, fitness value and decision variables.

At the initialization phase, a random population Z^t is generated which is expressed as,

$$Z^t = [z_1^t, z_2^t, \ldots, z_N^t]^T = \begin{bmatrix} z_{1,1}^t & z_{1,2}^t & \cdots & z_{1,D}^t \\ z_{2,1}^t & z_{2,2}^t & \cdots & z_{2,D}^t \\ \vdots & \vdots & & \vdots \\ z_{N,1}^t & z_{N,2}^t & \cdots & z_{N,D}^t \end{bmatrix} \tag{20}$$

where, N represents the size of population, the problem dimension is indicated as D.

$$z_{i,j}^t = lb_i + (ub_i - lb_i) \times \chi \tag{21}$$

where, χ denotes the random number ranges between [0, 1], lb_i and ub_i are the lower and upper bound of design variables.

Next, the individualfitness is computed and then optimal parameter S^t is chosen. The total number of current (present) evaluation function is rationalized as:

$$T_{present} = T_{present} + N \tag{22}$$

GTO model mainly includes 4 phases namely grouping phase, ability teacher allocation phase, student phase as well as teacher phase.

Initially, the teacher allocation phase is done to improve the student's knowledge. This phase is inspired by the Grey Wolf Optimization (GWO) approach which is represented as

$$TA^t = \begin{cases} z_{first}^t, & f(z_{first}^t) \le f\left(\frac{z_{first}^t + z_{second}^t + z_{third}^t}{3}\right) \\ \frac{z_{first}^t + z_{second}^t + z_{third}^t}{3}, & f(z_{first}^t) > f\left(\frac{z_{first}^t + z_{second}^t + x_{third}^t}{3}\right) \end{cases} \tag{23}$$

where, the first, second and third best students are denoted as z_{first}^t, z_{second}^t and z_{third}^t. Hence, both the average and outstanding group share the same teacher to accelerate the convergence of GTO algorithm.

At the ability grouping phase, the knowledge (skill) of the entire class is supposed to be in the form of normal distribution (ND) which is defined as

$$F(x)=\frac{1}{\sqrt{2\pi}\delta}e^{\frac{-(x-u)^2}{2\delta^2}} \quad (24)$$

where, the mean knowledge of entire class is u, the value of normal distribution function is expressed as x and the standard deviation is δ. As the value of δ is grater, huge differences is noticed among the knowledge of students. A good teacher needs to focus how to minimize the value of δ. In order to attain this objective, the teacher has to make a proper teaching plan for the students.

Next, in teacher phase the students gain knowledge from his/her teacher. The teacher has to make different teaching strategies for the outstanding and average group of students. To improve the knowledge of the outstanding group, the teacher has to give his/her best effort. Therefore, the knowledge gained by the student of the outstanding group is represented as

$$z_{teacher,i}^{t+1}=z_i^t+t\times\left(T_k^t-F_t\times\left(u\times Mn^t+v\times z_i^t\right)\right) \quad (25)$$

$$Mn^t=\frac{1}{N}\sum_{i=1}^{N}z_i^t \quad (26)$$

$$u+v=1 \quad (27)$$

where, the number of students is expressed as N, t denotes the present number of iterations, T_k^t indicate the skill of teacher at time t, Mn^t represents mean knowledge at time t, teaching factor (TF) is represented as F_t and its value is 1 or 2, $z_{teacher,i}^{t+1}$ be the skill of student i at time t, the random numbers are t,u,v in the range [0, 1].

The teacher gives more care to the students of average group than the outstanding students. Therefore, knowledge gained by the average group student is stated as

$$z_{teacher,i}^{t+1}=z_i^t+2\times w\times\left(T_k^t-z_i^t\right) \quad (28)$$

where, w denote the random number (RN) in range [0,1].

From the strategies followed by the teacher for the outstanding and average group, any one student will not gain any information by means of teacher phase is given as

$$z_{teacher,i}^{t+1}=\begin{cases} z_{teacher,i}^{t+1},\ f\left(z_{teacher,i}^{t+1}\right)<f\left(z_i^t\right) \\ z_i^t,\ f\left(z_{teacher,i}^{t+1}\right)\geq f\left(z_i^t\right)\end{cases} \quad (29)$$

In student phase, the student can gain knowledge by utilizing his/her leisure time in dual ways such as self-learning and interacting with other students which is represented as

$$z_{student,i}^{t+1}=\begin{cases} z_{teacher,i}^{t+1}+l\times\left(z_{teacher,i}^{t+1}-z_{teacher,j}^{t+1}\right)+m\times\left(z_{teacher,i}^{t+1}-z_i^t\right), f\left(z_{teacher,i}^{t+1}\right)<f\left(z_{teacher,j}^{t+1}\right) \\ z_{teacher,i}^{t+1}-l\times\left(z_{teacher,i}^{t+1}-z_{teacher,j}^{t+1}\right)+m\times\left(z_{teacher,i}^{t+1}-z_i^t\right), f\left(z_{teacher,i}^{t+1}\right)\geq f\left(z_{teacher,j}^{t+1}\right)\end{cases} \quad (30)$$

where l,m represents the random number [0, 1] range, the knowledge of *i* student at time *t* is denoted as $z_{student,i}^{t+1}$, at time *t* the skill of *j* student is denoted as $z_{teacher,j}^{t+1}$, since the student *j* is selected randomly as $j\left(j\in\{1,2,...,i-1,i+1,...,N\}\right)$.

However, the second as well as third term on the right of eqn (30) indicate self-learning as well as learning from the other student. If anyone student may not gain any knowledge then by student phase is given as

$$z_i^{t+1}=\begin{cases} z_{teacher,i}^{t+1},\ f\left(z_{teacher,i}^{t+1}\right)<f\left(z_{student,i}^{t+1}\right) \\ z_{student,i}^{t+1},\ f\left(z_{teacher,i}^{t+1}\right)\geq f\left(z_{student,i}^{t+1}\right)\end{cases} \quad (31)$$

Where, at time *t+1*the skill of student *i* at next cycle of learning is represented as z_i^{t+1}.

Finally, a new population is constructed and the optimum solution is selected and updates the present number of evaluations function by eqn (32)

$$T_{present}=T_{present}+2N+1 \quad (32)$$

Sincethe GT is a complex process. GTOA model illustrates the simple GT (Group Teaching) which includes the mechanism of teacher allocation, the teaching methods for various groups and ability grouping criteria. Thus, theoptimized DNN is then used for the classification of skin diseases.

IV. Results and Discussion

The simulation is carried out in MATLAB environment. The proposed skin disease classification with efficient segmentation approach classifies the type of diseases from the dermoscopy images. Skin disease can be predicted using pre-processing, image segmentation, feature extraction, feature selection and then classification. The database utilized for the experimentation is PH2 database.The performance of the proposed approach in terms of statistical measures such as sensitivity, specificity, and classification accuracy is analyzed.

A. Performance Metrices

To evaluate the performance of classifier sensitivity (recall), specificity (precision) and accuracy of data is calculated to represent the effectiveness of the classifier.

- **Precision:** This metric assess the classifier exactness. Precision is a metric that tells us the proportion of positive predicted values that are accurately positive. The Numerator part is the correct positive predictions (True positives) and denominator is the sum of true positive and false positive.

$$\Pr ecision = \frac{(tp)}{(tp + fp)} \times 100\% \qquad (33)$$

- **Recall:** This metric evaluates sensitivity of classifier.Recall is otherwise known as sensitivity.The Numerator part is the correct positive predictions (True positives) and denominator is the sum of true positive and false negative.

$$\text{Re}call = \frac{(tp)}{(tp + fn)} \times 100\% \qquad (34)$$

- **Accuracy:** This metric measures the effectiveness of classifier. Accuracy defines the number of correct predictions in classification problems. The Numerator part is the sum of correct predictions (True positives and True Negatives) and in the denominator, is the sum of all predictions made by the algorithm.

$$Accuracy = \frac{(tp + tn)}{(tp + fp + fn + tn)} \times 100\% \qquad (35)$$

Based on the above formulas, the classifier decides the tweets with dominant sentiment such as Sarcastic and Non- Sarcastic.

B. Performance Analysis

The performance characteristics ofskin disease detectionusing optimized DNN is shown below. The performance of the DNN-GTO classifier is analyzed based on the following measures namely precision, recall, and accuracy.

Table 2: Results of proposed classification algorithm

Classification algorithm	Precision	Recall	Accuracy
DNN-GTO classifier	97.10	98.12	98.75

Table 2 displays the outcomes of DNN-GTO classification algorithm. The outcome of accuracy in terms of percentage is that shows effective nature of the classifier. The proposed classifier exceeds the other classification algorithm performances also increases the robustness of extreme learning machine. The result of precision is which indicate the correctness of the suggested algorithm. The value of recall is that indicates sensitivity of the classifier.

Table 3: Comparison of various classification algorithms

Database	Name of classifier	Accuracy (%)	Precision (%)	Recall (%)
PH2	**DNN-GTO (Proposed)**	**98.75**	**97.10**	**98.12**
	SVM+ χ^2 kernel [15]	84.3	76.3	92.5
	SVM+ Linear kernel [15]	86.07	93.25	78.93
	Deep Convolution Network [16]	95	95	93
	Fully-convolution Network [16]	94	94	95

The table 3 shows the outcomes of classification procedures in terms of precision, recall and accuracy. The effectiveness of the proposed method in skin disease detection is verified by comparing with various algorithms. The existing algorithms used for comparison are SVM+ χ^2 kernel, SVM+ Linear kernel [15], Deep Convolution Network and Fully-convolution Network [16].

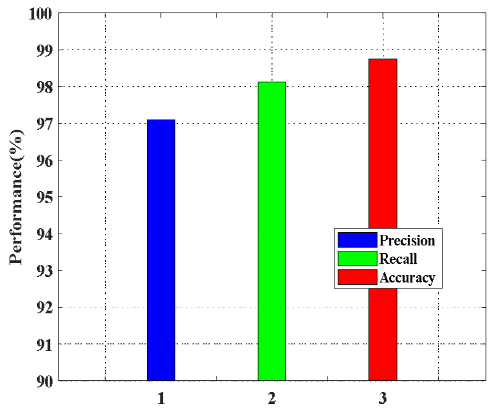

Figure 4. Performance analysis of proposed method

Fig 4 displays the proposed scheme performance analysis. From the plot, accuracy, precision and recall were defined. The outcome of the proposed classifier with highest accuracy defines the effectiveness of the proposed algorithm. Hence, the proposed system makes sure that skin disease detection based on DNN-GTO classifier outperforms other classification algorithms. Comparing with other approaches, the proposed one achieved the highest performance measures. This indicates the better performance of suggested technique.

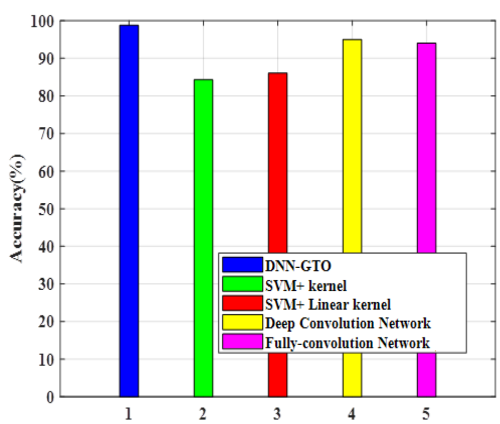

Figure 5. Accuracy Comparison

Figure 5 defines comparison metric accuracy by means of various classification algorithms with proposed technique. Accuracy measures the effectiveness of classifier. Accuracy defines the number of correct predictions in classification problems. As the outcomes of the proposed classifier with highest accuracy defines the effectiveness of the proposed algorithm. From the plot, the accuracy of the proposed DNN-GTO classifier is high (98.75%) whereas the baseline classifiers SVM+ χ^2 kernel, SVM+ Linear kernel, Deep Convolution Network and Fully-convolution Network acquired accuracy of (84.3%), (86.07%), (95%) and (94%). Hence, the proposed system makes sure that skin disease classification based on DNN-GTO classifier outperforms other classification algorithms. Comparing with other approaches, the proposed one achieved the highest performance measures. This indicates the better performance of suggested technique.

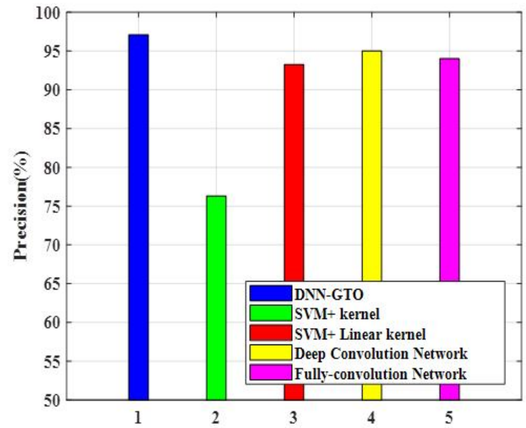

Figure 6: Precision Comparison

Fig 6 displays the proposed precision performance with that of the previous values. Precision defines the exactness of the classifier. As the outcomes of the proposed classifier with highestprecision defines the exactness of the proposed algorithm. From the plot, the precision of the proposed DNN-GTO classifier is high (97.10%) whereas the baseline classifiers SVM+ χ^2 kernel, SVM+ Linear kernel, Deep Convolution Network and Fully-convolution Network acquired precision of (76.3%), (93.25%), (95%) and (94%). Hence, the proposed system makes sure that skin disease classification based on DNN-GTO classifier out performs other classification algorithms. Comparing with other approaches, the proposed one achieved the highest performance measures. This indicates the better performance of suggested technique.

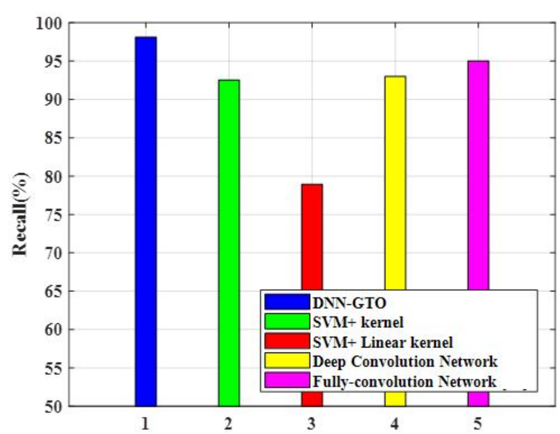

Figure 7. Recall Comparison

Fig 7 indicates the performance comparison of recall with the existing algorithms. From the plot, the recall of the proposed DNN-GTO classifier is high (98.12%) where as the baseline classifiers SVM+ χ^2 kernel, SVM+ Linear kernel, Deep Convolution Network and Fully-convolution Network acquired recall of (92.5%), (78.93%), (93%) and (95%). Hence, the proposed system makes sure that skin disease classification based on DNN-GTO classifier outperforms other classification algorithms. Comparing with other approaches, the proposed one achieved the highest performance measures. This indicates the better performance of suggested technique.

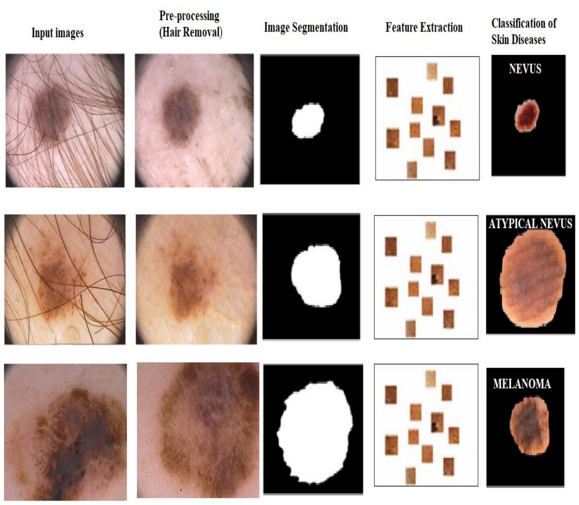

Figure 8: Results of skin disease classification

The performance analysis of proposed method is discussed along with results. Fig 8 shows the type of skin disease classification. The comparison result illustrates that the skin disease classification achieved by proposed DNN-GTO is found better than the other existing techniques. Furthermore, the feature based analysis is also performed in this method which depicts that the combination of these two feature extraction techniques furthermore improves the performance of whole classification process. However, the computation time of proposed DNN-GTO is (0.94sec) and found lower than baseline methods such as SVM+ χ^2 kernel (5.04sec) approach, as the processing time of SVM+ Linear kernel (6.73sec), and Deep Convolution Network (1.77sec) is found higher than proposed technique. This indicates the better performance of suggested technique.

V. Conclusion

In this work, the classification of skin diseases using DNN-GTO is analysed. Normally, the manual detection of skin diseases and its classes seem inaccurate, difficult and a time consuming task. Due to this, segmentation techniques are applied for effective classification of skin diseases. The analysis of skin disease detection includes various approaches like Pre-processing, FCM- morphological operation based image segmentation, LBP-GLCM based Feature extraction, and BGOA based feature selection followed by DNN-GTO classification.Experimental outcomes showed that, DNN-GTO achieved better performance and is less time-consuming comparing with baseline approaches SVM+ χ^2 kernel, SVM+ Linear kernel, Deep Convolution Network and Fully-convolution Network classification algorithms. As a result, a perfect classification with high accuracy is achieved by the proposed DNN-GTO process. The performance metrics of the proposed method is high in terms of accuracy (98.75%), precision (97.10%), and recall (98.12%)when compared with baseline techniques. In future, this system can be improved to detect and classify more diseases as well as their severity. Also, the system can be evaluated and tested on other publicly available database.

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