Identification of Melanoma from Nevus Images

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Abstract. Melanoma is one of the fatal type skin cancers. The mortality rate is more severe than the present skin related diseases. Humans are prone to various diseases and are easily infected by them due to their adaptive and constrained lifestyle and melanoma is not an exception. Melanoma spreads faster and is less responsive to treatment in its later stages. Thus, harnessing the disease rate becomes more enigmatic and initial diagnosis is the need. Melanoma and nevus are akin and show analogous symptoms and traits. In order to overcome this, we use the technique of image processing to segregate Melanoma and nevus. The input image is processed in such way that the noise in the image (skin lesion) is removed using median filter and is segmented using improved K-means clustering. From the lesion necessary textural and chromatic features are extracted and a unique feature vector is formulated. Melanoma and Nevus are segregated using both Adaptive Neuro-Fuzzy inference System (ANFIS) and Feed-Forward Neural Network (FFNN). The skin images from DERMIS dataset is used in this work and it has 1023 skin images including 104 melanoma and 917 nevus images. Our proposed methodology provides efficient results having 97.3% and 96.8% accuracy for ANFIS and FFNN classifiers.

1. Introduction

Skin cancer is a leading cause of death globally [1]. There are several cancers that have been identified and are being treated. Skin cancer, on the other hand, is now one of the most rapidly spreading cancers. Skin cancer diagnoses are growing at a faster rate than any other cancer type, according to recent studies. The most common form of melanoma is Melanocytes affecting the surface cells in the epidermis of the skin. It is made up of cells that make the skin dark (black) and is also blue, tan, dark brown, light grey, red etc.,[2]. This form of cancer is alarming because of its proclivity for metastasis. Melanoma is most prominently found beside the knee around calf muscles of the legs and can be omnipresent on the human body. Diagnosing this disease at its initial stage significantly reduces the mortality rate and increases the survival rate. According to the findings, the mortality rate may be lowered. If skin cancer is detected at an early stage, it can be cured in up to 90% of cases. Detection and classification of melanoma (Skin cancer) at its initial outset is an uphill task [3]. ABCD rule is one of the traditional methods used by researchers to diagnose melanoma and nevus. Each of the ABCD features [4] receives a total dermoscopic ranking, with ‘A’ representing asymmetry and ‘B’ representing border irregularity. Color variations are represented by ‘C’ and Diameter is represented by ‘D’. Each feature is given a weight, based on its importance in the feature space.
2. Review of related works

In [5], authors have developed an epidermal disease classification system incorporating an advance methodology of image transformation in order to detect skin diseases such as skin cancer, psoriasis and dermatophilosia, the disease diagnosis and classification are built on statistical parameter analysis. Delia-Maria and Adriana [6] attempt to develop a System that put forward a classification erythematous class, the system was embellished and reinforced using MATLAB with 6 neurons in the output layer and 10 neurons in the hidden layer of its neural network. It has been trained using back propagation learning algorithm, the system also has 33 inputs of clinical and histopathological feature of the patients, based on these features and the predicted disease, the system provides suggestions of the medical treatments of the patient.

Sarika Choudhari and Seema Biday [7] have proposed a computer assisted disease recognition system for Skin Cancer, based on images from the skin that were enhanced by applying many preprocessing techniques, Dull Razor technique to remove hair, obtaining the grayscale of the image, contrast enhancement and median filter to remove noise, the infected area was segmented from the rest of the skin according to its binarized grey level by applying Maximum Entropy. Histogram of grey scale values (co-occurrence matrix) was implemented to bring out the features of the enhanced image, multilayers ANN along with back propagation algorithm was implemented as a classifier and they are trained based on the extracted features and their methodology has got 86.66% as accuracy. Rahat Yasir et al., [8] have proposed techniques based on computer vision in order to identify specific dermatosis from colour images and their proposed system effectively detects nine varieties of dermal illness at 90% accuracy. From the ten, seven features were extracted from user’s input and three features were extracted from the image. They have trained these ten features as input using an ANN to find the skin illnesses.

In [9], authors have proposed a system which enables users to recognize only three skin diseases and provides treatments, also many image processing and data mining techniques have been implemented in this system, skin images were enhanced using both median and Gaussian filters, thresholding segmentation was applied, then Morphological operations are used to extract the enhanced image, these features along with external information from the user present the input to many classifiers (Ada Boost, Bayes Net, J48, MLP, Naïve Bayes), both MLP and J84 were better than the rest with accuracy more that 85%, but the system can only recognize 3 diseases (Eczema, Impetigo and Melanoma), also camera lens was placed at a distance of 5cm from the affected skin 5cm in Addition it only developed for window operating system. Computer aided skin disease detection system [10-13] using digital image transformation techniques for segmented classification of diseased skins was developed and unique features of the images were extracted for classification. Total Dermoscopy score (TDS) index is calculated from the extracted features to determine the existence of a cancer disease. The output given by this system will help the dermatologist to detect the lesion and its type, but it can’t be implemented as standalone equipment for the diagnosis process.

Haofu Liao [14] examined deep into a reliable diagnosis system using deep convolutional neural network (CNN), the dataset used in the model is from two main sources, Dermnet dataset and OLE dataset. The resultant accuracy of the test using the Dermnet dataset was 73.1% and the accuracy when testing with OLE dataset was 61.7%. This model can be improved by collecting data from extra resources and in addition to its low accuracy their system is of high computational cost. Since training CNN requires computational resources of high performance and will be very time consuming.

3. Proposed method

The flow of work is described in the block diagram in figure 1. It has various image processing stages like pre-processing, segmentation of image, extraction of feature and classification of images.
3.1. Pre-processing

This technique is applied to modify the image to the required format for further analysis. Here, initially the input image is resized and its contrast is enhanced such that affected portion is distinguished from the normal one. Then it is subjected to filtering process in order to withdraw the unwanted noises in the present image. Here a median filter is employed to do the noise removal process. Median Filtering is a non-linear technique to remove noise from an image. The edges of the image are preserved during the noise removal process proving to be efficient and hence it is broadly used. When the probability density of the noise amplitude has large tails and periodic patterns, median filters are used in reducing random noise. Using this filter, a kernel slides throughout the image, and the output pixel intensity becomes the median value of the intensity of pixels within the kernel. The images at the various stages of pre-processing are shown in figure 2.

3.2. Segmentation

Image segmentation is used to group similar set of pixels in an image for further processing. There are varieties of segmentation techniques available in order to partition the image pixels. Out of them K-mean clustering is most widely used in various applications. K-means is the peculiar technique for k-number of cluster formation from data points and grouping such that based on the intensity of image, it is divided into non-overlapping pixel groups. It involves the criteria of choosing optimum centroids and based on the minimum distance from the centroids they are grouped. Following, successive trails, centroids are identified from the mean values of the obtained clusters for the next iteration. The cycle of iteration continues till no variation is obtained from the centroids. The put forth k-means uses a centroid selection technique to initialize its centroid as depicted in the equation (1).
Where, \( C \) is the total number of clusters, ‘\( p \)’ is the greatest pixel value and ‘\( c \)’ range between 1 to ‘\( C \)’. The method of selection pretends to be more proficient and prolific ensuring substantial difference between the initialized centroids by converging to the last location in few iterations. In our system, the input images are lesions present on the skin such that \( C \) is made as 3, so that from the background, lesion present in the foreground is extracted.

3.3. Feature extraction

The texture of the image varies at different locations based on the intensities of the pixel. This enables us to extract textural features from the given image leading to adopt global feature extraction method. The statistical distribution of the pixel intensities are extracted using Grey level histogram matrices. The varying intensity in the different locations of the image yields the order of statistical distribution. Usually, the color of the object is decided by the color which is reflected from it. The color space of the picture can be found by analyzing the basic primary colors called red, green and blue present in it. Through these color spaces of RGB, many values along with skewness are utilized to extract color feature from the visible color of the segmented lesion.

3.4. Classification

After extraction of the required features from the segmented images, the melanoma and nevus are identified from the classifier. In order to achieve enhanced accuracy, many algorithms with its default parametric conditions are trained and trailed with the segmented images. Here in this proposed work, Adaptive neuro-fuzzy inference along with Feed-Forward neural network are used for classification.

3.4.1 Adaptive Neuro Fuzzy Inference System

Fuzzy system frameworks are determined using a combination of neural network and fuzzy system algorithms. Using neural fuzzy system, incorporating appropriate procedures the unexplored parameters of the system is defined. As an architecture, the ANFIS uses various learning algorithms that are composed of input-output data and if-then-else rules. Moreover, unreliable and noisy images can be handled by ANFIS along with complex mappings to be manipulated. This also involves some of the fuzzy inference techniques. The membership function and the parameters that are associated with the datasets are trained using ANN. In this work, triangular membership function (equation 2) and Mamdani’s model are used for classification. The ANFIS architecture is depicted in figure 3. Figure 4 represents the triangular function and is defined by a lower limit \( a \), an upper limit \( b \), and a value \( m \), where \( a < m < b \)

\[
pq = (1 : C) * \frac{p}{c+1}
\]
3.4.2 IF-THEN Rules:

The Antecedent or precondition belongs to the IF part and consequent belongs to THEN part. In order to implement IF-THEN rules the former precondition along with attributes of the tests are logically ANDed. Appropriate nonlinear learning capabilities are possessed by ANFIS system along with IF-THEN rules. The following if-then rules are implemented in the proposed work.

\[
\mu_A(x) = \begin{cases} 
0, & x \leq a \\
\frac{x-a}{m-a}, & a < x \leq m \\
\frac{b-x}{b-m}, & m < x < b \\
0, & x \geq b 
\end{cases}
\]  

(2)
Rule 1: If (x is A₁) and (y is B₁) then (z₁ = p₁x + q₁y+r₁)

Rule 2: If (x is A₂) and (y is B₂) then (z₂ = p₂x + q₂y+r₂)

where x and y are the inputs, Ai and Bi are the fuzzy sets, zi (i = 1,2) are the outputs within the fuzzy region. fuzzy rules specify the fuzzy region. The parameters such as pi, qi, ri are identified.

3.4.3 Feed-forward neural network (FFNN)

It is an artificial neural network. The nodes present in them do not configure a loop or cycle among them and simple neuron-like processing units are encoded in layers that are biologically inspired. All the units in the layers are connected with every other unit. The connections are unequal and they have varied strengths and weights. The knowledge of the network connection is encoded on the weights. Nodes are the units of neural network. The output is obtained only after layer-by-layer processing of data stating from the input of the network. In the feed-forward neural networks, feedback between layers is nil when it pretends to be a classifier. Input, hidden and output layers are the three major layers present in this architecture. The complexity of the network is governed by the layer formed from nodes. The nodes present in the sequential layers are completely connected. Accordingly, new features can be obtained when there are higher numbers of layers and nodes. The Feed-forward neural network structure is shown in figure 5.

In this proposed work, we have used three hidden layer comprised of 70 features present in our data governs the total number of hidden layers. Based on the modelling type the output data is formulated. In this case, a binary output (Melanoma/Nevus) is to be predicted and the output layer contain only one node in order to predict the probability of success.

![Figure 5. Structure of Feed-forward neural network](image)

3.5. Dataset and Evaluation metrics

Skin images used in this work are obtained from DermIS skin image database [18]. There are totally 1023 skin images in the database, out of which 104 belongs to malignant melanoma and 919 nevus images. Sample images from Dermis dataset are shown in figure 6. The classification performance of the proposed system is deliberated here in terms of the metrics such as true positive, true negative, false positive and false negative. If the system detects the input melanoma image as melanoma then it belongs to a true positive (TP) class and when it detects the output image as nevus when it belongs to melanoma then it falls under the category of True negative. Whereas when the input image categorized as melanoma even when it does not belong to melanoma then it is false positive and a false negative (FN) occurs when the input is melanoma and is categorized as nevus.
Accuracy can be defined as the ratio between the total sum of truly detected cases and the total number of input test images and the formula is depicted in the equation (3).

\[
Accuracy = \frac{TP + TN}{TP + TN + FP + FN}
\]  

(3)

Figure 6. Sample images from Dermis dataset

4. Results and Discussion

The experimental results of the proposed method for identifying melanoma from nevus in the skin images are discussed here. The preprocessed image is subjected to segmentation and from that the required features are extracted and classified using ANFIS and Feed forward neural network. Figure 7 depicts the metrics of the system incorporating the classifiers. From the graph it is observed that using ANFIS the system performance increases with the number of features of the input image and using FFNN the best training performance is 8.0764e-07 and it occurs at 72nd epoch. This shows the improved performance of the system.

The confusion matrices obtained for the system using ANFIS and FFNN are shown in the tables 1 and 2 respectively.
From the above tables, Accuracy value of the system using ANFIS and FFNN are found to be 97.3% and 96.8%. These results are compared with the existing methodologies on the same DermIS data base and its analysis is instantiated in the table 3.

| S. No | Author                  | Number of images | Database | Technique adopted | Features                          | Accuracy |
|-------|-------------------------|------------------|----------|-------------------|-----------------------------------|----------|
| 1     | Proposed method         | 1023             | DermIS   | ANFIS             | GLCM, Statistical features        | 97.3%    |
|       |                         |                  |          | FFNN              | GLCM, Statistical features        | 96.8%    |
| 2     | Robert Amelard [17]     | 206              | DermIS   | SVM               | HLIF                              | 94%      |
| 3     | Ebtihal Almanur [16]    | 227              | DermIS   | SVM               | GLCM+ LBP                         | 90%      |
| 4     | M. Ali [15]             | 112              | DermIS   | SVM               | Color, shape, GLCM                | 80%      |
| 5     | Rebecca [13]            | 89               | DermIS   | KNN               | ABCD                              | 89%      |
5. Conclusion

As mentioned earlier this disease is severe and dermatologists struggle to harness the rate of its spreading. This proposed system is used to identify the melanoma from Nevus in the skin images easily. Computer aided system is proposed here to resolve the difficulties using ANFIS and FFNN as a classifier. The developed system performs the required work with accuracy 97.3% using ANFIS and 96.8% using FFNN classifiers. The proposed system determines the accuracy from the various evaluation parameters. The experimental results proclaim improved performance in regard with the state of art approaches, authenticating the reliability of our work.

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