International Journal of Engineering &Technology, 7 (4) (2018) 6473-6480

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet.v7i4.24178
Research paper



Robust skin diseases detection and classification using deep neural networks

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Abstract

Since from last decade, there is significant growth in the design of Computer-Aided Diagnosis (CAD) Systems using image processing. There are different images processing steps on which the efficiency of such CAD systems relies such as image pre-processing, image segmentation, feature extraction, and classification. There are recent attempts by proposing novel algorithms in either of CAD model steps, however designing robust, useful and accurate CAD system for skin diseases' detection is still challenging research problem. In this paper, unique skin disease identification was proposed for three types of skin diseases such as Melanoma, Nevus, and Atypical. For pre-processing, an adaptive filtering method was designed to remove unwanted noisy areas from the input skin image. For segmentation, adaptive region growing technique was developed for efficient localization and region of interest (ROI) extraction of disease area. This segmentation adaptively selects the next region to grow for accurate lesion segmentation. For feature extraction, we exploited a hybrid feature extraction method composed of 2dimensions discrete wavelet transform (2D-DWT), geometric and texture features. The deep learning algorithm performs the classification. Convolutional neural networks (CNN) is used for the efficient prediction of skin disease. The experimental analysis is performed usingInternational Skin Imaging Collaboration (ISIC) dataset. The proposed method can classification the skin diseases with accuracy of 96.768%. The results obtained showing that the proposed method outperformed the state-of-art techniques.

Keywords: *Lesions; Skin Disease; CAD; Segmentation; Deep Learning; Melanoma; Nevus.*

1. Introduction

Nowadays skin cancer is common in human beings because of significant changes in surrounding environments. Skin cancer is a massive disease observed among people. Skin cancer happens because of skin tissues abnormal development. The skin cancers are of various types such as Squamous Cell Carcinoma, Melanoma, and Basal Cell Carcinoma. The Melanoma is most harmful skin disease among other diseases [1]. Melanoma is the disease in which skin structures in the form of melanocytes. The melanocytes are the area consist of skin cells that make color [1]. The appearance of Melanoma skin disease is significantly increasing in Anglo-Americans male and females. The prevention of such skin disease rises if it's early detected. The early recognition of Melanoma skin disease helps to cure its severity or completely cure [2]. The melanoma cured by removing the cancerous tissue entirely at the initial stage only; else it may go into the second stage of cancer.

Therefore, there is the requirement of adequate melanoma detection framework to diagnose the disease at the early stage. The common practice in the medical field uses the biopsy tests and clinical data analysis for the melanoma diagnosis. The study of clinical data is performed by the trained dermatologist using the dermatoscopy device. The dermatoscopic is a medical device utilized by dermatologists to extract the enhanced and magnified perspective of skin structure using the skin surface reflection. The detection of melanoma performed based on visual analysis. The Asymmetry Border Colour Diameter Evolving (ABCDE) rule used by dermatologist for the visual examination [3]. The rules are elaborated as (1) Asymmetry: the two halves will be different, if the line is drawn through this mole, (2) Border: The borders viewed as irregular with notched or scalloped edges for the early melanoma, (3) Colour: presence of various colors is another symptom for the early stage malignant melanoma. Various shades of tan, brown or black could visualize, (4) Diameter: Another property to detect the malignant melanomas. The diameter of Malignant Melanomas appears to be more copious in diameter (1/4 inch or 6 mm), however, at early stage detection, it is viewed as smaller, (5) Evolving: Variation in shape, size, color, elevation, or another trait.

In the early stage clinical screening, if any tissue of melanoma disease found, the patient further recommended for the biopsy tests. In the biopsy test, the trained pathologist conducts the patient analysis in the outpatient section by extracting the complete or part of the skin for the full review [4]. However, such tests are time-consuming and costly. Also, the biopsy tests analysis mainly depends on the expertise level of the pathologist for correct diagnosis which increases the chances of false negative and false positive outcomes [5,6]. Such results from the biopsy tests may lead to the second stage and further investigations. Additionally, biopsy tests having the number of side effects such as health problems and scarring, etc. Therefore, the automated system needed for the accurate early detection to eliminate the biopsy tests and other clinical trials. The automated system based on the computerized technology called Computer Aided Diagnosis (CAD) systems. Without the need for time-consuming and costly dermatological screening and biopsy tests, the accurate initial phase diagnosis results obtained using automated systems. Based on the outcome of early detection, immediate treatments started in case of disease detected and hence reducing the probability of death. The automated screening method needs to

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recognize the patient's risk of skin diseases such as Melanoma, Nevus, Atypical, etc. by capturing the images of the skin lesion. The skin lesion images further processed using the various image processing steps such as pre-processing, segmentation, feature extraction, and classification [3], [5].

Figure 1, showing the essential steps of skin disease detection and classification. The number of many image processing based methods presented in the literature recently [9-23]. The accuracy of skin disease detection mainly depends on image segmentation and feature extraction techniques. Various segmentation techniques used for ROI extraction such as statistical region merging [4], iterative region merging [5], adaptive threshold [6], iterative segmentation [7], multi-level threshold [8], etc. The standard feature extraction methods are color, shape, and texture [20-23]. For classifications, most of the methods based on either state of art classifiers such as SVM, KNN, ANN, naïve Bayes, etc.

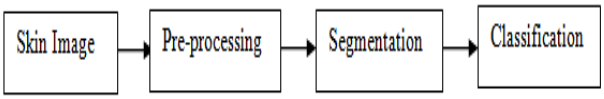


Fig. 1: Steps of Skin Disease Detection.

Most of the existing solutions focused on satisfying the ABCDE rule in feature extraction steps without actually bothering about the correctness of disease identification. The accurate and efficient classification of skin diseases under various illumination conditions and the environment is a challenging task by using the state of art methods. The generalized framework is proposed for efficient and robust skin disease diagnosis by considering the three different skin diseases under investigation such as Melanoma, Atypical, and Nevus. The key contributions are:

- Image denoising based on combining the filtering technique to suppress the impact of various illumination conditions.
- Introduced new region growing technique for the efficient ROI extraction and early detection of skin disease. This region growing method based on the constraint of intensity values and orientation values.
- Various feature extraction techniques such as color, texture (GLCM), DWT features used.
- Deep learning (CNN) based classification on improving the robustness and accuracy.
- Performance evaluation of various classifiers such as SVM (Support Vector Machine), FFNN (Feed Forward Neural Network), KNN (k-nearest neighbor), and CNN.

In section II, a brief review of previous methods for skin disease detection is present. In section III, the methods and materials discussed. Section IV shows the simulation results and comparative analysis. Results and discussion in section VI. Finally, section V, conclusion and future work.

2. Related works

Recently The methods based on ABCDE visual run is proposed by H. S. Ganzeli et al. [9], which was regularly utilized by dermatologists for recognizable melanoma proof, to characterize which qualities are broke down by the product. That applies different calculations and methods, including an oval fitting calculation, to concentrate and measure these attributes and choose whether the spot is a melanoma or not. The achieved results presented with particular focus on the adaptive decision making and its effect on the diagnosis. Finally, other applications of the software and its algorithms filed.

M. Shamsul Arifini et al.[10], the authors presented an automated dermatological analytic framework. Etymologically, dermatology is the medicinal teach of examination and treatment of skin abnormalities. That framework exhibited is a machine intercession rather than the human intervention into the general medicinal workforce based belief system of dermatological conclusion. That framework chips away at two ward steps - the primary recognizes skin peculiarities, and the last distinguishes the sicknesses. The framework works on visual info, i.e., high determination shading images and patient history.

The goal of Catarina Barata et al. [11] was to decide the best framework for skin lesion grouping. The other target was to look at the part of shading and surface highlights in lesion order and figure out which set of highlights is more discriminative. It presumed that shading highlights beat surface highlights when utilized alone and that the two strategies accomplish great outcomes, i.e., Sensitivity = 96% and Specificity = 80% for common techniques against Sensitivity = 100% and Specificity = 75%, for nearby strategies. The characterization comes about that was getting on an informational index of 176 dermoscopy images from Hospital Pedro Hispano, Matosinhos.

Rahat Yasir et al. [12], the introduced a method that utilizations PC vision based strategies to distinguish different sorts of dermatological skin illnesses. They have utilized distinctive kinds of image handling calculations for highlight extraction and nourish forward manufactured neural system for preparing and testing reason. That framework chips away at two stages first pre-process the shading skin images to remove critical highlights and later distinguishes the infections. That framework efficiently recognizes nine different sorts of dermatological skin sicknesses with an exactness rate of 90%.

Naser Alfred et al. [13], proposed a productive framework for skin malignancy identification on dermoscopic images. That demonstrates the factual attributes of the shade arrange, disengaged from the dermoscopic picture, and utilized as productive segregating highlights for growth location. The approach evaluated on a dataset of 200 dermoscopic images of the 'Healing center Pedro Hispano' and the consequences of cross-approval has demonstrated high recognition exactness.

Adheena Santy et al. [14] presented the study on various segmentation techniques that applied for melanoma detection using image processing. Statistical region merging, iterative stochastic region merging, adaptive thresholding, color enhancement, and iterative segmentation, multilevel thresholding are discussed. A comparative study of these segmentation methods is also performed based on the parameters accuracy, sensitivity, and specificity. Multilevel thresholding has the highest efficiency and specificity, and maximum sensitivity obtained for iterative stochastic region merging.

The new technique for the image segmentation proposed by Sumithra Ra et al.[15]. The input skin image pre-processed to remove the noise and hairs in the first step. Then segmentation applied to the pre-processed skin image to extract the lesion areas. Here, the modified region growing technique designed based on the automatic seed points initialization. There are various well know measured author used to evaluate the effectiveness of the segmentation method. From the segmented regions, two common features extracted texture and color. Finally, they used state-of-art classifiers for the detection.

Shivangi Jain et al. [16] proposed machine helped strategy for the acknowledgment of Melanoma Skin Cancer used to the Image Processing tools. The method reported is similar to [15]. The input to the system was the skin disease image on which the first preprocessing method applied for the noise and hair removal. The segmentation of lesion regions from the filtered image performed by region growing method. The feature extraction from the segmented image performed using color and texture features. The SVM and k-NN classifiers used to measure skin disease detection accuracy. Our method is different from the method of [15]&[16], we focused on designing the skin lesion extract and feature extraction to improve the detection performance.

Recently Palak Mehta et al. [17] proposed more proficient methods to diminish the rate of errors in skin disease detection. Authors designed the automatic skin disease diagnosis method in two phases such as detecting the skin anomalies and detection of malignant or benign melanoma.

Supriya Joseph et al. [18], applied another non-intrusive computerized skin disease analysis framework for the early determination of melanoma based on the image processing techniques introduced by Supriya Joseph et.al. Hair identification and removal from the input image performed for improving accuracy. The method proposed

mainly for hair detection and removal. The hair removal performed according to the algorithm of fast marching in painting.

Another recent method to detect different kinds of skin diseases proposed by Vinayshekhar Bannihatti Kumar et al. [19]. They used dual stage approach which effectively combines Computer Vision and Machine Learning with clinically evaluated histopathological attributes to accurately identify the disease. In that first stage, consist of pre-processing and feature extraction methods on input skin disease image. In the second phase, the machine learning technique used for the detection of skin disease using histopathological attributes. The experimental results of this method suggest accuracy improvement.

The method for skin disease detection and classification reported based on k-means clustering for image segmentation Suganya R et al. [20]. After segmentation the features like shape, text and color features extracted. For the classification, they used SVM classifier to perform detection of lesions like Seborrhoeic keratosis (SK), Basal Cell Carcinoma and Nevus.

Teck Yan Tan et al. [21], they proposed an approach to recognizing kind difficult and threatening skin lesions utilizing various advances proposed, including pre-handling, for example, clamor evacuation, segmentation, and highlight extraction from injury districts, highlight choice, and characterization. In the wake of extricating a great many crude shapes, shading and surface highlights from the injury zones, a Genetic Algorithm (GA) is utilized to recognize the most separating substantial element subsets for solid and carcinogenic cases.

The essential objective was to group the skin sicknesses utilizing image arrangement techniques proposed by Pradeep Mullangi et al. [22]. For inspecting the surface of the image, a measurable technique deep level co-event grid (GLCM) employed. GLCM considers the spatial relationship of pixels and describes the surface of an image by figuring how regularly matches of the pixel with particular esteem and determined spatial relationship happen in the image.

Nishtha Garg et al. [23], the authors presented intended to take a digital image, followed by pre-processing of the image to filter the extra noise present in the image. After this, skin lesion subjected to segmentation and feature extraction with the implementation ABCD rule which will test the skin lesion on various parameters like asymmetry, border irregularity, color, and diameter of the wound.

From the study of above all modern skin disease methods, it is clear that effectiveness and robustness of skin disease methods based on crucial steps such as pre-processing algorithms, skin ROI segmentation, feature extraction, and classifier. The present work is different than state-of-art techniques discussed above in which we designed the pre-processing method, effective segmentation, feature extraction, and deep learning based classification. The reason for using the CNN classifier is to exploit spatial or temporal invariance in the skin disease detection process. The next section presents the architecture and working of CNN.

3. methodology

The methodology for proposed skin cancer detection is depicted in figure 2, with actual outcomes.

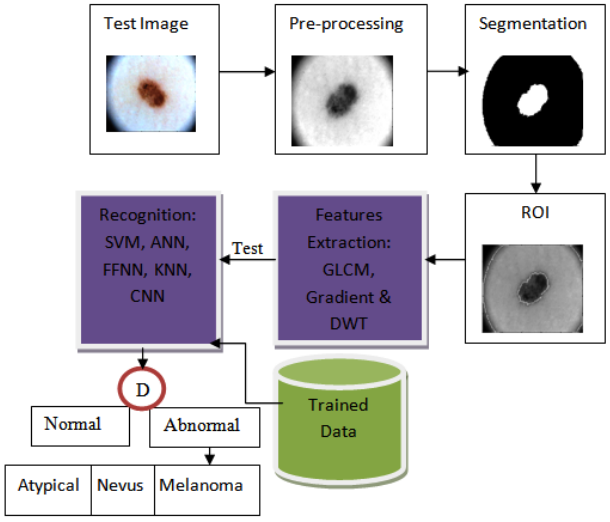


Fig. 2: Proposed System Architecture.

As observed in figure 2, the input skin image first processed through noise suppression and smoothing task to address the different illumination and uncontrolled environmental conditions. The proposed segmentation method applied to pre-processed skin image to get an accurate ROI estimation. From the segmented skin lesions, the various set of features extracted such as GLCM, gradient, and wavelet. The fusion of feature vector performed to prepare a test feature vector. Different classifiers are used to classification task as shown in figure 2. From the classification step, two levels of diagnosis results are received using either of classifiers such as disease identification and type of disease if disease detected in the first step. Each step of the proposed framework elaborated in below sub-sections:

3.1. Pre-processing

In image processing, pre-processing used for image enhancement, illumination correction, artifacts removing and smoothing. For skin image, it is just to work on noisy factors such as small particles on the skin area, hairs in disease area for the accurate prediction of skin disease. In this paper, we used the adaptive noise cancellation method to suppress the noisy parts and enhance the disease regions. The process designed by using filters like Gaussian and average filters together. The algorithm 1 for pre-processing is below. As observed in algorithm 1, the outcomes of both filtering methods utilized to get the pre-processed image in which the difference of both filters estimated.

3.2. Segmentation

After image pre-processing step, we next novel efficient image segmentation algorithm designed based on region growing segmentation method. In skin disease detection, accuracy based on accurate localization of lesion and its extraction from the input skin image. Before performing the steps like feature extraction as well as classification, it is must extract the ROI to improve the accuracy of detection. In this paper, we designed the adaptive region growing method to enhance segmentation efficiency. The algorithm 2 for this method explained below:

Algorithm 1: Image Pre-Processing
Input: Image RGB I; Output: Pre_processed gray scale image G;
1) Browse digital skin image I 2) I^1= resize (I); 3) if (dim (I^1) != 2) 4) I^2= gray (I^1); 5) else 6) I^2= I^1;

7) end if
8) I^3= filter (Gaussian, I^2);
9) I^4= filter (Average, I^2);
10) G = subtract (I^3, I^4);
11) Return (G)

The conventional region growing based image segmentation is a pixel-based segmentation technique as it based on initial seed point selection. The neighboring pixels corresponding to initial seed points examined by this approach to deciding whether to add into segmentation result or not. The decision based on the constraint of intensity only. The threshold value set for the intensity constraint. The neighbor pixels selected for the region growing if they satisfied the constraint of the intensity threshold. However, the conventional region growing suffered from the limitations such as variation of intensity values may lead to over-segmentation, the method failed to distinguish the shading of the real images. The problems of region growing method of skin disease identification lead to incorrect disease identification. To mitigate the issues of existing region growing, we used additional orientation constraint for the region growing along with the intensity. The consideration of additional constraints provided better outcomes than conventional region growing method. The proposed algorithm for image segmentation described in algorithm 2. The values for the intensity and orientation from the current seed point computed using:

$$(I^{nt}, O^r) = value(SP) \quad \text{.....} \quad (1)$$

Where SP is the current seed point. The values for intensity and orientation based on the current seed point are computed by Eq. (2) and (3).

$$I^{nt} = \|I^c - I^n\| \quad \text{.....} \quad (2)$$

$$O^r = \|O^c - O^n\| \quad \text{.....} \quad (3)$$

Where, I^candO^c are the current pixel (SP) intensity and orientation values respectively. And $I^nO^n$are the neighbor pixel intensity and orientation values respectively. The orientation values are computed using the gradient function. Finally, all regions those satisfied both constraints classified as the segmented region in the input image.

3.3. Feature extraction

Feature extraction is nothing but to process of collecting the unique representation of segmentation areas from the image in digits' form. There is a wide range of feature extraction methods, however, selection of appropriate feature extraction is a challenging task in recognition domains like skin disease detection. We used the three well-known feature extraction methods together to improve the efficiency of detection. Here comes the algorithm 3 for the proposed framework:

Algorithm 2: Image Segmentation

Input:
Pre-processed image G
Intensity threshold I^{thr}
Orientation threshold O^{thr}
Output:
Segmented image S

1) Gradient extraction:
2) [G_x, G_y] = gradient (G)
3) Combining the gradient values:
4) $G^1 = \frac{1}{1+(G_x + G_y)}$
5) Convert G^1 from radians to degrees:
6) G^2 = rand2degree (G^1)
7) G_R = grid (G)
8) N = size (G_R)
9) FOR i = 1: N
10) H[i] = histogram (G_R[i])
11) CH[i] = find (H[i]) // find most frequent histogram of current grid
12) Select pixel value related of CH[i]
13) SP= CH[i] // seed point
14) [I^{nt}, O^r] = value (SP)
15) IF ($I^{nt} \leq I^{thr}$) && ($O^r \leq O^{thr}$)
16) S[i] = G_R[i]; Segmentation
17) ELSE
18) i++; take next grid for region growing
19) END IF
20) END FOR
21) Return S

Algorithm 3: Feature extraction

Input:
Segmented image S
Segment RGB ROI R
Output:
Feature Vector V

1. G^{obi} = glcm (S)
2. F^1 = G^{obj}.Constrast
3. F^2 = G^{obj}.Correlation
4. F^3 = G^{obj}.Energy
5. F^4 = G^{obj}.Homogeneity
6. F^5 = gradient (S)
7. F^6 = 2D-DWT (S)
8. F^7 = color (R)
9. Fusion of features
10. V = { F^1, F^2, F^3, F^4, F^5, F^6, F^7}
11. Return (V)

3.4. Clacification

After the feature extraction, it is essential to classify the input lesion in either of three diseases considered in this paper such as atypical, nevus and melanoma. There are different classifiers we used for the classification purpose; however, the main contribution is using deep learning with CNN classifier method. A convolutional neural network (CNN) system is used for deep learning [24]. In signal processing and image processing domain, such methods are commonly used to classify the scenes and objects as well as to perform the ROI detection and segmentation process. In this work, we are using CNN for disease classification from the input digital skin image features. There are three vital factors due to which CNN is frequently used for deep learning nowadays such as:

- It gets rid of the process of the manual feature extraction as the learning of features is directly performed by CNN.
- CNN delivers modern recognition results
- It can be utilized for the new recognition functions as it allows network building on top of preexisting networks.

There are the numbers of layers in CNN to detect various features of the input image through each layer learning. At different resolutions, filters applied to every trained image, and the outcome of every convolved image utilized in next layer as input. Figure 3, showing the functional working of CNN with many convolutional layers. The CNN algorithm used for disease detection based on extracted features from the input disease. Our aim behind using CNN for skin disease detection is to improve the recognition results as compared to existing classifiers such as SVM, ANN, etc.
We believe that CNN can improve recognition performance as compared to other state-of-art classifiers [23]. The classifiers used are multi-label SVM (Support Vector Machine), ANN (Artificial Neural Network), FFNN (Feed Forward Neural Network), KNN (k-Nearest Neighbour's) and proposed CNN. By considering the proposed methods, the simulation studies are conducted using skin cancer

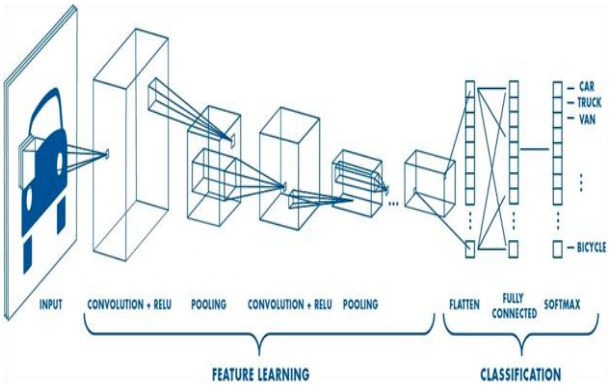


Fig. 3: Working of CNN with Many Convolutional Layers [25].

Dataset concerning different performance metrics such as accuracy, specificity, and sensitivity. Next section is presenting the complete practical work results.

4. performance evaluation

The practical evaluation of the proposed method is performed using MATLAB simulation tool by using the well-known image processing toolbox.

4.1. Dataset

For the simulation and evaluation of the proposed method, we used well know ISIC[1] skin disease dataset [26]. ISIC stands for the International Skin Imaging Collaboration. It contains a large number of lesion diagnosed images through their ISCI project. The lesions like:

- Actinic keratosis
- Fibrous papule
- Angioma
- Atypical melanocytic proliferation
- Basal cell carcinoma
- Dermatofibroma
- Lentigo NOS
- Lentigo simplex
- Lichenoid keratosis
- Melanoma
- Nevus
- Scar
- Seborrheic keratosis
- Solar lentigo
- Squamous cell carcinoma

In this paper, three widely diagnosed skin diseases such as melanoma, nevus and atypical are included in this work. The total abnormal images collected is 811 (11-atypical, 400-melanoma, and 400-nevus) and 100 normal skin images. The training and test samples are divided according to 80-20% criteria respectively.

4.2. Performance metrics

The evaluation of proposed work measured by three performance metrics such as accuracy, sensitivity, and specificity which computed by Eq (4), Eq (5), and Eq. (6). This performance metrics are computed using equations.

$$Auc = \frac{tp+tn}{tp+tn+fp+fn} \quad \text{.....} \quad (4)$$

$$Sen = \frac{tp}{tp+fn} \quad \text{.....} \quad (5)$$

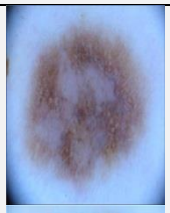
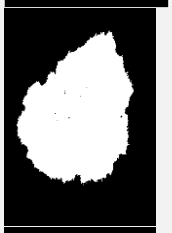
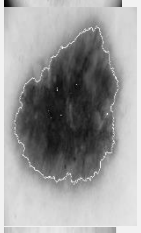
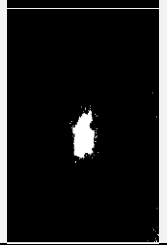
$$Spe = \frac{tn}{tn+fp} \quad \text{.....} \quad (6)$$

Where tp is truly positive, tn is a true negative, fp is false positive and fn is a false negative.

4.3. Segmentation results

The efficiency of ROI extraction using the proposed adaptive region growing method explain in table 1. The proposed segmentation method extracts the lesion area appropriately regardless of different diseases images as input. This is because of the dynamic nature of the segmentation algorithm in which region growing start by changing threshold values.
The effectiveness of segmentation leads to efficiency is disease detection. The comparative study is presenting below.

Table 1: Is Showing Three Diseases Images Segmentation and ROI Extraction Results

Skin Disease	Input Image	Segmentation Result	ROI Extraction
Melanoma			
Nevus			
Atypical			

[1] https://isic-archive.com/#images.

4.4. Disease classification evaluation

This section presents the outcomes of disease classification using different classifiers. Five proposed method for different classifiers SVM, KNN, ANN, FFNN, and CNN is simulated and evaluated. Figure 4, 5 and 6, are showing the comparative results for accuracy, sensitivity, and specificity for five classifiers respectively.
In figure 4, the CNN classifier shows the highest accuracy for disease classification as compared to other classifiers this because of state-of-art recognition results of CNN classifier. The KNN classifier is showing the worst performance for efficiency as compared to different classifiers.

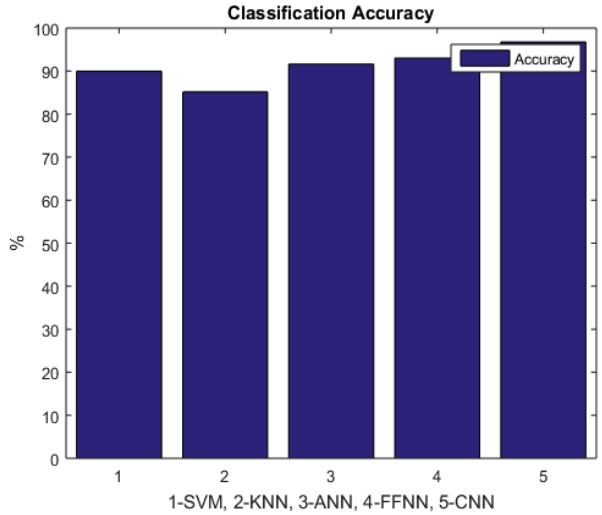


Fig. 4: Performance of Classification Accuracy.

In figure 5, the CNN classifier shows the highest specificity for disease classification as compared to other classifiers. This performance also called a true negative rate. The KNN classifier is showing the worst performance for the true negative rate as compared to other classifiers.

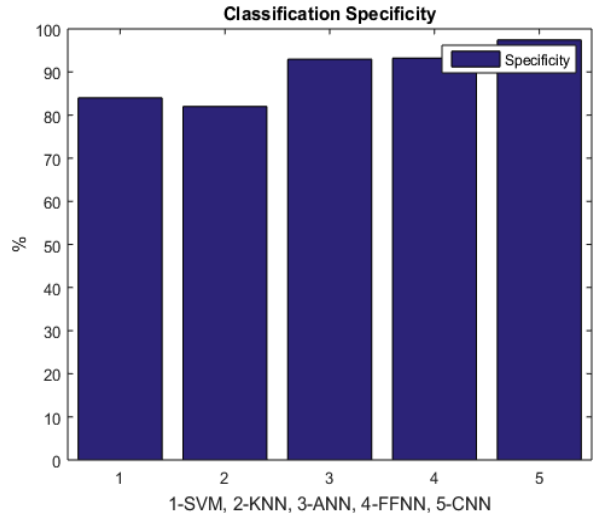


Fig. 5: Performance Analysis of Specificity.

In figure 6, the CNN classifier shows the highest sensitivity for disease classification as compared to other classifiers. This performance called for the true positive rate. The SVM classifier is showing the worst performance for sensitivity as compared to other classifiers due to the limitations of multi-class SVM.

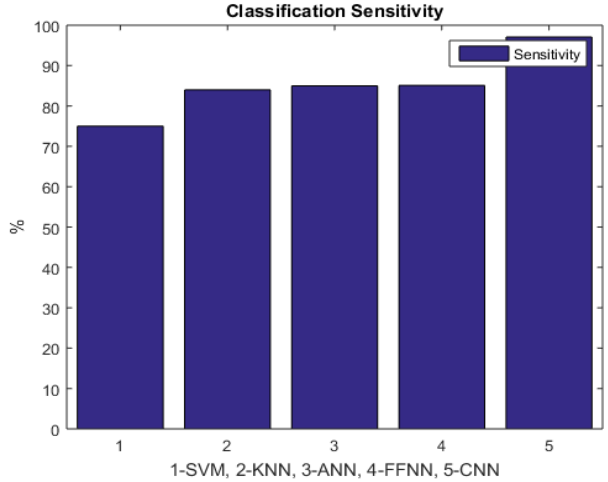


Fig. 6: Performance Analysis of Sensitivity.

Finally, figure 7, shows the average classification performance for all classifiers with the proposed method. This performance computed by considering all three parameters. Overall, the CNN with proposed skin disease detection method is showing efficiency performance. The approximate classification is for CNN based method is 97 % which is significant as compared to state-of-art methods. Table 2 is indicating accuracy, specificity and sensitivity result in digits format based on graphs results.

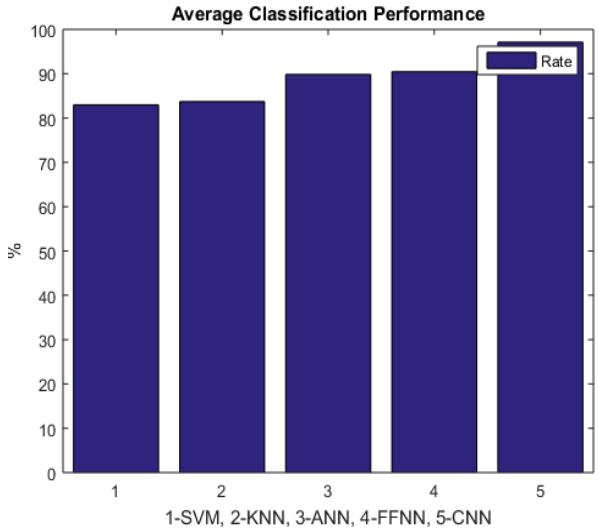


Fig. 7: Average Recognition Rate Performances.

The ARGS adaptive region growing segmentation proposed in this paper. The proposed method with CNN classifier is showing the improved recognition performance concerning accuracy, specificity and sensitivity performances. These results claim the overall efficiency of all three skin diseases considered in this paper. At the second level, FFNN classifier outperformed to all other classifiers excluding the deep learning with CNN method.

Table 2: Disease Classification Analysis

Classifier	Accuracy	Specificity	Sensitivity
ARGS + SVM	89.97	84	75
ARGS + KNN	85.17	82	84
ARGS + ANN	91.61	92.96	84.96
ARGS + FFNN	93.0118	93.0118	85.0923
ARGS + CNN	96.768	97.449	97.09

4.5. Disease detection evaluation

In this section, we present the disease detection evaluation in which the test skin image checked for having skin disease (either of three) or not. The proposed method using the CNN classifier is showing the improved results regarding accuracy, specificity, and sensitivity shown in table 3. The results of disease classification and detection are separately evaluated in this paper to claim the overall recognition rate analysis against the state-of-art methods.

Table 3: Disease Detection Analysis

Classifier	Accuracy	Specificity	Sensitivity
ARGS + SVM	91.13	85.3	78.4
ARGS + KNN	87.46	85.58	85.9
ARGS + ANN	90.78	93.87	87.45
ARGS + FFNN	94.11	94.11	94.11
ARGS + CNN	96.89	98.11	97.5

4.6. Comparison with previous works

The overall accuracy evaluation with previous methods is showing in table 4. The proposed method ARGS+CNN compared with recent methods for different skin lesions detection and classification. The state-of-art methods are discussed with diseases and overall accuracy in table 4.
As observed in table 4, the proposed method has

Table 4: Comparative Study for Recognition Rate

Ref.	Techniques	Diseases	Accuracy (%)
[23]	Thresholding Method	Melanoma	91.6 %
[22]	Fuzzy C-means Clustering and GLCM	Angioedema, Actinic Keratosis, Eczema	84 %
[21]	Adaptive Snake segmentation, shape, color, texture features, and SVM classifier	Melanoma	88 %
[20]	K-means clustering, color, sub-region, text features, and SVM classifier	Melanoma, Nevus.	95.4 %
[19]	YCbCr, Sobel operator, ANN	Psoriasis, Seborrheic Dermatitis, Lichen Planus, Pityriasis Rosea, Chronic Dermatitis, Pityriasis Rubra Pilaris.	95 %
Our Proposed algorithm	Adaptive noise cancellation, adaptive region growing segmentation, GLCM, gradient and DWT features. CNN Classifier.	Melanoma, Nevus and Atypical	97.05 %

Shown maximum accuracy which is approximately 97 % with the limited set of images. However, if the training size is increased, it can be further improved the accuracy rate. The methods in [19-23] are proposed very recently from 2014-2016. The proposed method is as efficient as the other techniques for computational analysis. There is no extra burden imposed by the proposed algorithms designed in this paper.

5. Conclusion and future work

Nowadays it is must have more attention towards the early detection of different types of skin diseases before they spread to the other parts of the human body. The infected areas or spots on the skin called skin lesions. Due to the emergence and growth of computer technologies, nowadays dermatologist is mainly depended on the computer-aided diagnosis (CAD) systems for early and accurate detection of skin disease. This paper presented the novel image processing based method for early prediction of skin disease using efficient techniques such as pre-processing, region growing based segmentation and deep learning based classification. The detailed design of proposed algorithms along with their system architecture for the three well know skin diseases such as melanoma, nevus and atypical is presented in this work. The experimental results claim the effectiveness and efficiency of the proposed approach against state-of-art methods using ISIC research dataset. For the future work, other types of diseases can be presented using proposed designed as well.

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