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Deep Learning Framework For Multi Class Categorization Of Skin Disease

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ABSTRACT

Skin disease is caused due to many factors like viral infection, allergies and bacteria. It is one of the most dangerous type of cancers. Early identification and diagnosis of skin diseases may assist the dermatologists to provide effective treatment and to save patient's life. Dermoscopy images are widely used image in the diagnosis of skin diseases. Analysis and diagnosis of skin diseases are usually performed by dermatologists with visual screening of dermoscopy images, which tends to be subjective, tedious, unreliable and prone to errors. Therefore, a fully automated system capable of categorizing several skin diseases is preferred to make accurate diagnosis. Several methods have been developed for skin disease diagnosis using machine learning methods. However, existing approaches have limitation like low accuracy for multi class skin disease classification. To trounce those limitations, this paper intends to design a robust model for multi class skin disease categorization through modified CenterNet. A preprocessing techniques is proposed to remove unwanted data like hair from images and make the images fit for other processes. Modified CenterNet is proposed in which DenseNet-77 is introduced for feature extraction and support vector machine for classification. Effectiveness of the introduced model is investigated by using HAM10000 dataset. Experimental results confirmed that the introduced model is proficient, reliable and robust to detect and diagnose skin problems than other recent methods. Additionally, performance comparison of the presented model with the existing approaches is done for validation.

Index terms: Centernet, deep learning, dermoscopy images, multiclass classification, skin diseases

1. INTRODUCTION

Skin disease is the most common and life threatening disease worldwide. The significant causes behind skin diseases are viral infections, environmental factors, allergies, and bacteria [1]. Skin disease is fifth common causes of all diseases, affecting almost one-third of the people globally. According to a report released by World Health Organization (WHO), around 2 to 3 million people diagnosed by non-melanoma skin cancer and 1,32,000 people affected by melanoma

cancer each year [2]. Melanoma is the harmful form of skin cancer. It can be cured if it is detected at early stage. Else, it could spread to other body organs, causing an irrecoverable effect. Early diagnosis and treatment are the key ways to reduce mortality rate and to increase patient's survivability.

Skin diseases are usually diagnosed by physical test and biopsy. Although biopsy is the standard procedure to diagnose skin diseases, the process is very hard and inaccurate. Recently, two non-invasive techniques namely macroscopic and dermoscopy images have been introduced that can help dermatologists to diagnose skin diseases. Macroscopic images have poor images quality as they are captured using mobile phones whereas dermoscopic images have good image quality and resolution. Hence, dermoscopic images are commonly used to improve the diagnostic accuracy of skin diseases. Accurate diagnosis of skin problem is a very tough task for the dermatologists even with dermoscopic scans due to initial structure of skin lesions, color and texture etc. Further to this, the major drawback of skin cancer diagnosis carried out by the dermatologists is that it relies on subjective analysis and varies among differ dermatologists. Visual scanning of medical images is time consuming, tedious and error prone. To cope with the problems of manual analysis, the researchers have shifted to develop Computer Aided Diagnosis (CAD) system for skin cancer diagnosis. The CAD system is objective and provides more accurate results than manual analysis.

Researchers have developed different CAD systems for skin disease diagnosis using on machine learning (ML) and reported impressive results. Most of the ML based systems suffered from the problem of image quality and isolation. It is crucial to use better algorithm for image enhancement and segmentation. Another problem is feature extraction. Classification accuracy of ML based methods heavily depends on feature and its dimension. It is necessary to utilize sophisticated algorithm to select the most significant features that have high discriminative power. To alleviate the problems of ML based methods, Deep Learning (DL) models have been developed without need of any image preprocessing techniques. These models can identify and learn the salient features that discriminate among types of input images. This fact motivated the authors in considering a modified DL model in categorizing skin diseases. The prime target of this work is to design an efficient and reliable model for multi class skin disease classification. The major contributions of this work are given below: -

- The greatest effort was made on processing dermoscopic images, designing and implementing a suitable method for preprocessing input images.
- A new framework named modified centerNetis developed to enhance classification accuracy while minimizing computational cost.
- Scalability of the introduced framework is validated using HAM10000 dataset [3].
- Extensive investigation has been done in comparison to previous models on aHAM10000 dataset to prove the robustness of the introduced model.

The draft outline of this paper is systemized as follows: Section 2 provides a brief survey of related work. Section 3 presents the detailed description of the developed model. Section 4 proffers the experimental outcomes and comparison. Section 5 infers the paper with future scope.

2. REVIEW OF PREVIOUS APPROACHES

There exist numerous literatures which focus on the classification of skin disease. In this section, this paper focus on the brief review of the former investigations regarding the categorization of skin disease with deep learning models.

Hemsi et al. [1] (2020) presented a framework for skin disease detection which is based on Convolutional Neural Network (CNN). In this approach, transfer learning was applied to five CNNs namely DenseNet 201, GoogleNet, Inception-ResNetv2, Inception V3 and mobile Net V2 to differentiate between seven types skin diseases. Effectiveness of all the five CNNs was validated on HAM10000 dataset.Results showed that the DenseNet 201 provided better results that of other networks by reaching classification accuracy of 87.7%.Chaturvedi et al. [4] suggested deep CNNs to perform multiclass skin disease classification. Five networks were used to develop an ensemble model to perform classification task. Classification accuracy of 92.83% obtained However, this model requires more data for training. Multiclass skin disease categorization using wide- shuffle net was presented by Hoang et al. [5]. Lesion region was isolated from its surrounding tissue employing entropy based weighting and first order cumulative moment. The wide-shufflenet was adopted to categorize the segmented lesion. HAM10000 and ISLC2019 was used to analyze the performance of the model. Results demonstrated that the performance of the model is superior to other DL models in terms of accuracy. However, this model requires more time for segmentation which is considered as major limitation. Adegun and Viriri[6] built an automated system for skin disease diagnosis. The system consists of two phases: (i) segmentation and (ii) classification. Affected region was separated from its background tissue using encoder-decoder Fully Convolutional Network (FCN). FCN-DenseNet was applied to classify the segmented images. The system was tested on HAM10000 database and reported 98% accuracy. However, the drawback of this system is the high computation cost. An integrated method based on MobileNet V2 and Long-Short Term Memory (LSTM) for skin disease classification was propounded by Srinivasu et al. [7]. MobileNet V2 was adopted to perform classification task while LSTM was used to improve the classification performance by keeping the salient features information. However, this method exhibited better accuracy at the expense of economic burden. Huang et [8] proffered Efficient B4 for multi class skin classification. Image preprocessing techniques such as flipping and normalization was used to process input images. Results showed classification accuracy of 85.8% for HAM10000dataset.However, this approach has low classification accuracy. Carcagni et al. [9] recommended a skin cancer diagnosis system grounded on DenseNet. This system works well for skin disease diagnosis. However, exhibits poor results for noisy images. An ensemble framework by combining ResNet-50 and Inception V3 was introduced by Shahin et al. [10]. Ensemble model provided better performance than other DL models by achieving mean accuracy of 89.9%.However, results are reported for data division technique and need to be evaluated for K-fold cross validation.Khan et al. [11] presented a computerized framework for multi class skin cancer classification. Initially, skin lesions were separated using CNN and image fusion method. Subsequently, features were extracted from two pretrained networks and combined. Improved whale optimizer algorithm was employed for selecting optimal features. This framework shows better results. However, inaccurate localization of affected region is the major drawback of this framework.

In the literature, researchers have developed skin disease classification system using different DL models. Most of the developed systems not only lacks in generalization but also failed to attain higher classification rate for multiclass skin disease categorization. Unfortunately, some existing methods does not use large database which is mandatory for the performance of DL methods. Keeping this in context, this paper aimed to develop a robust model for multi class skin cancer classification and achieved high classification rate for HAM10000 data over seven types of skin diseases.

3. MATERAIL AND METHOD

A generalized framework of the introduced multi class skin disease classification model is evinced in Figure.1. Preprocessing is done to discard unwanted data like hair and to improve the quality of the image. The preprocessed images are then input to the proposed DL model for feature extraction and classification.The architecture of the modified CenterNet is depicted in Figure.2.

3.1 Details of dataset

In this work, Dermoscopic image set, HAM10000[3] is utilized for experimentation purpose. The HAM10000 database has 10015 images that are acquired from different people. The HAM10000 database is publicly available benchmark dataset of skin disease diagnosis which widely used by earlier methods for evaluation. This dataset is divided into seven types of skin diseases which are listed in Table.1.As given in Table. 1 it is noted that there is high imbalance in the number of images in the dataset. The database contains 67% C_{nv} images, 3.2% C_{akiec}images, 5.1 % C_{bcc}images, 10.9% C_{bkl} images, 1.1% C_{df}images, 11.1% C_{mel}images and 1.4% C_{vasc} images. This fact severely affects the training performance. Therefore, it is required to use some augmentation techniques to balance the data and make training performance more robust. For augmentation horizontal flipping, vertical flipping, rotation and brightness rangeare used to balance all typed of skin diseases. Distribution of different classes of images is graphically represented in Figure.3. Sample images of skin diseases from HAM10000 dataset is shown in Figure.4.

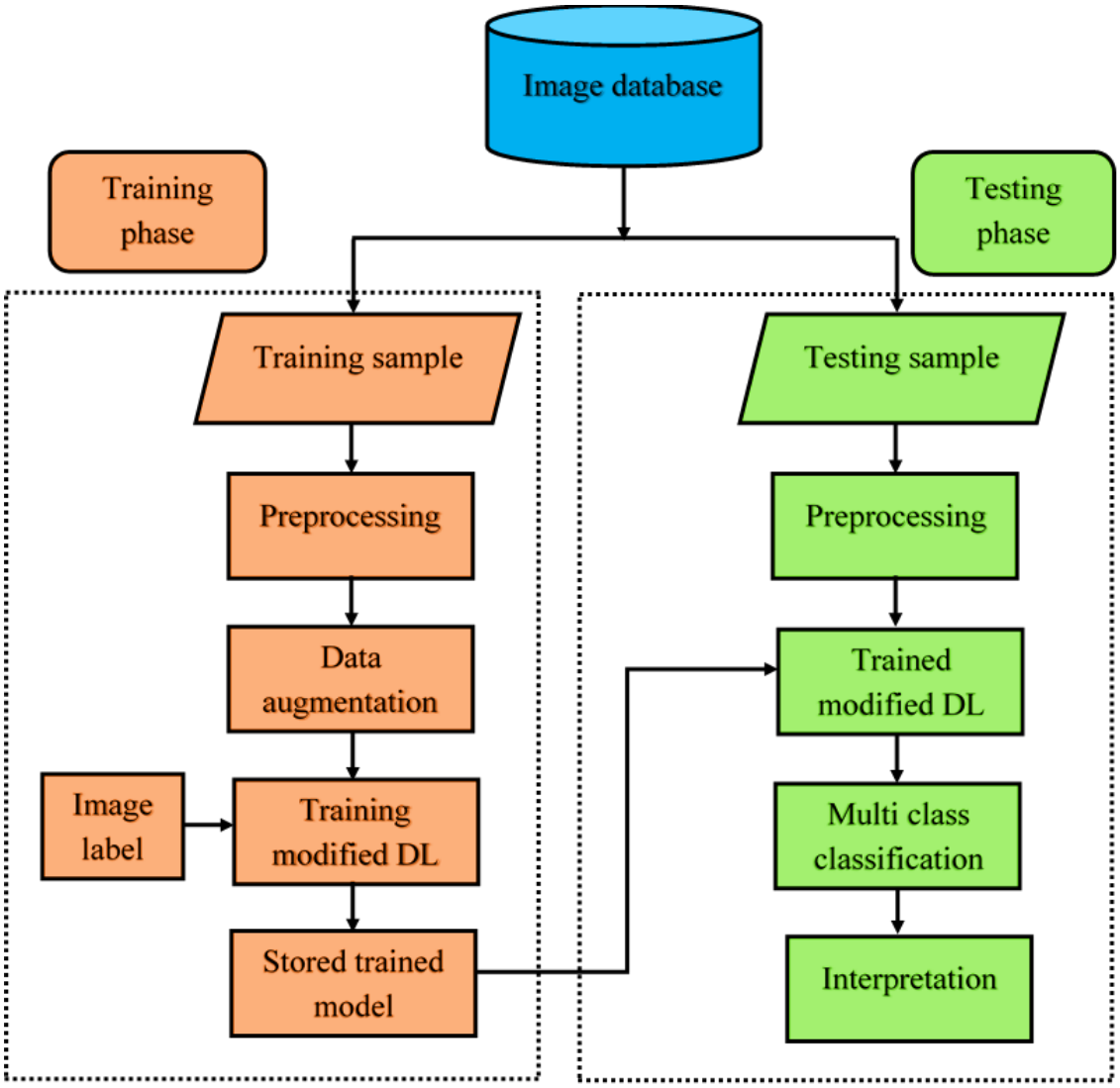


Figure.1 Process of the introduced model for multi class skin disease classification

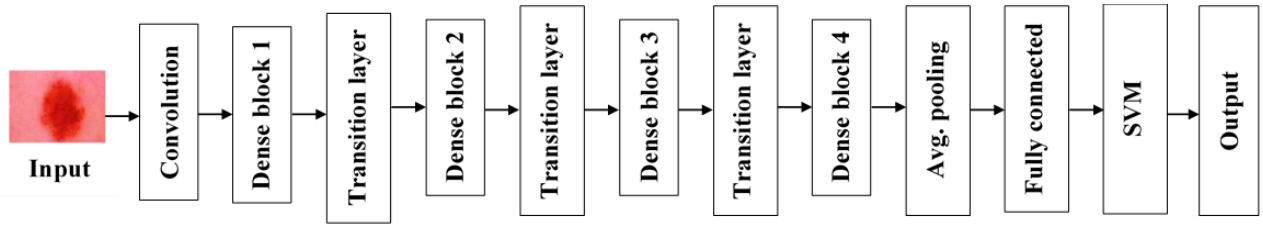


Figure.2 Architecture of the proposed modified Center net

Table.1 Data source information

Name of disease	Diagnostic label	No. of images	Image distribution (%)
Actinic keratosis	C_{akiec}	325	3.27
Basal cell carcinoma	C_{bcc}	514	5.13
Benign keratosis	C_{bkl}	1099	10.97
Melanoma	C_{mel}	115	1.15

Dermatofibroma	C_{df}	1113	11.11
Melanocytic nevus	C_{nv}	6705	66.95
Vascular lesion	C_{vasc}	142	1.42

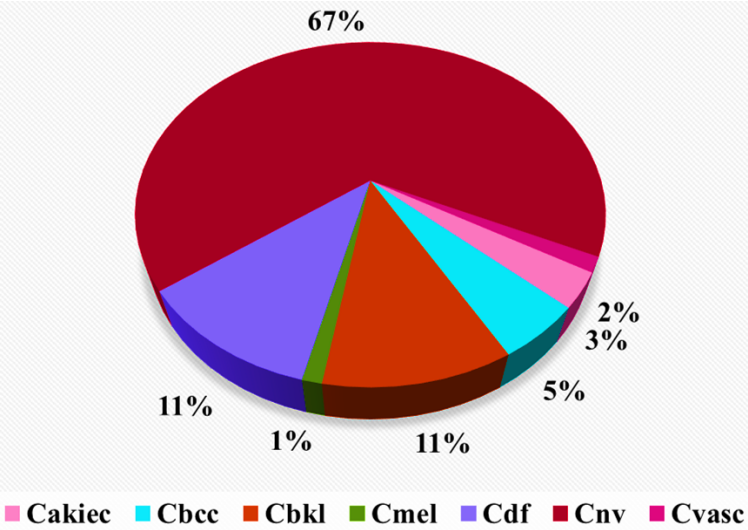
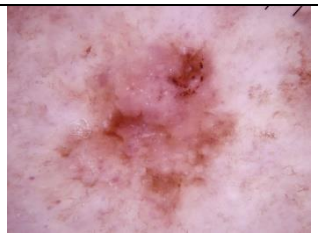
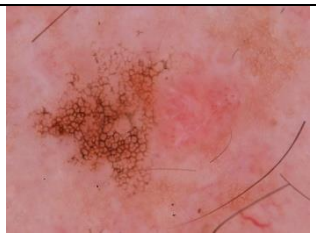
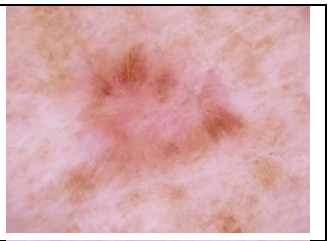
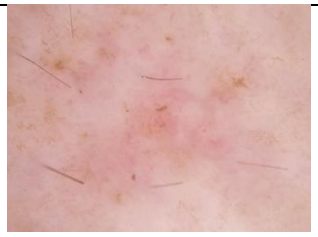
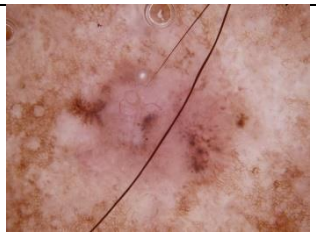
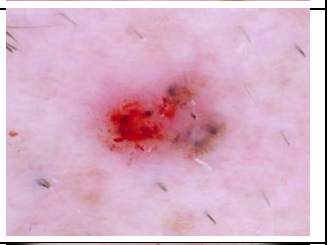
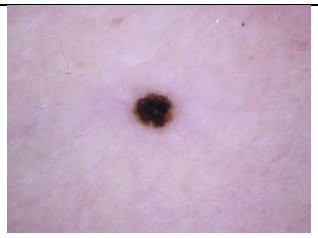
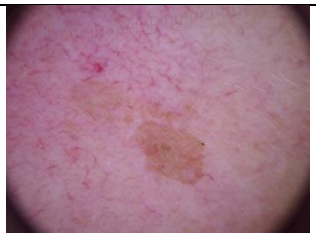
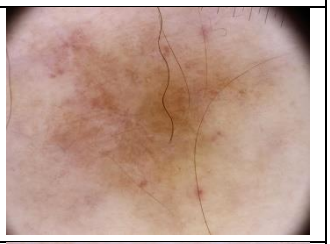
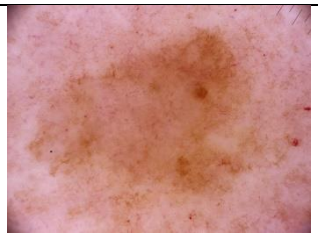
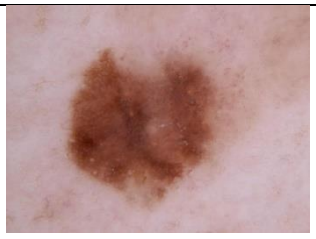
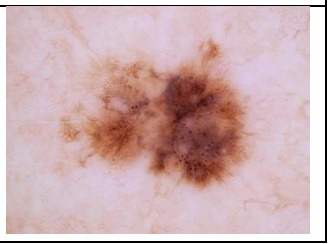


Figure.3 Distribution of images

C_{akiec}			
C_{bcc}			
C_{bkl}			
C_{mel}			

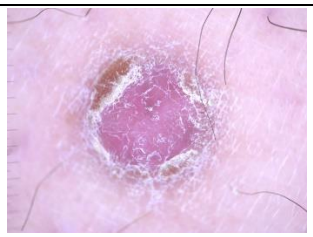
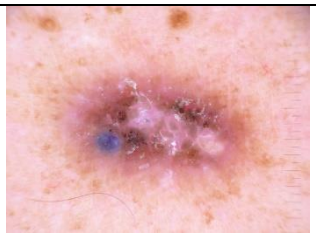
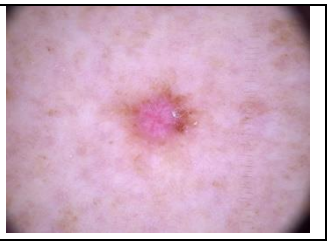
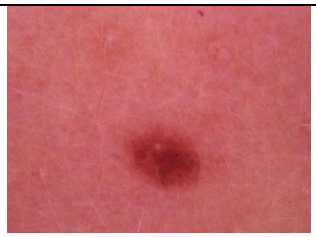
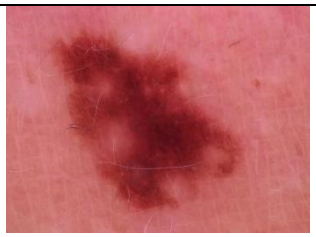
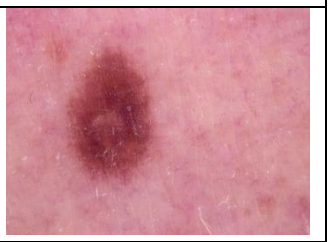
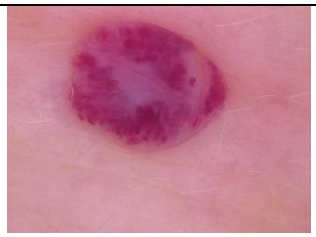
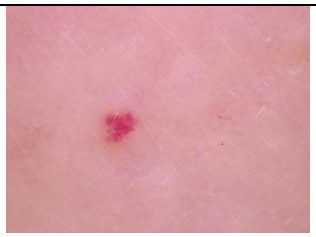
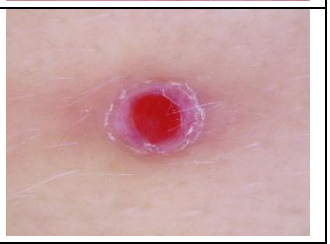
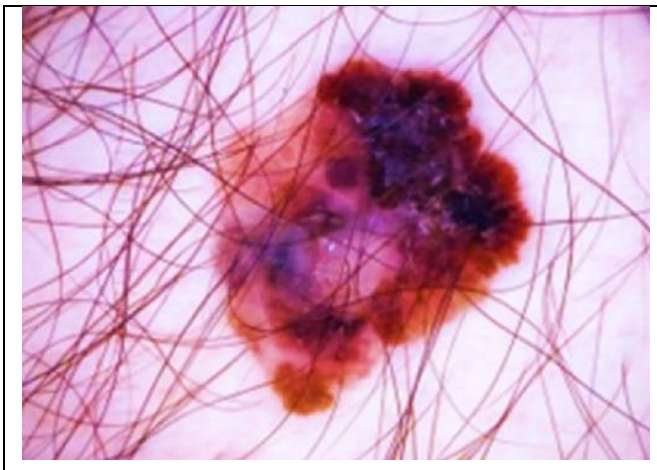
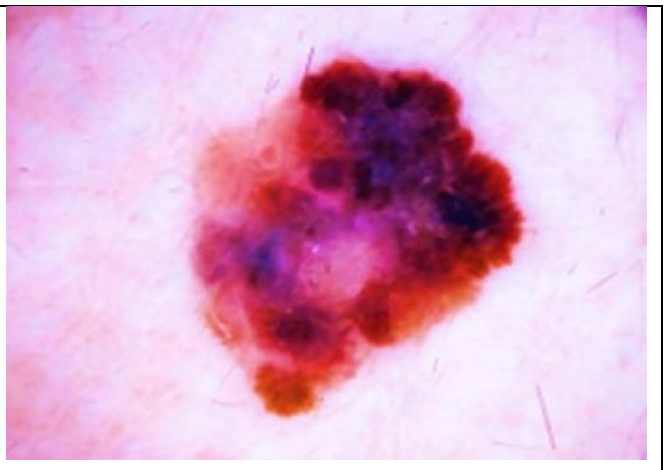
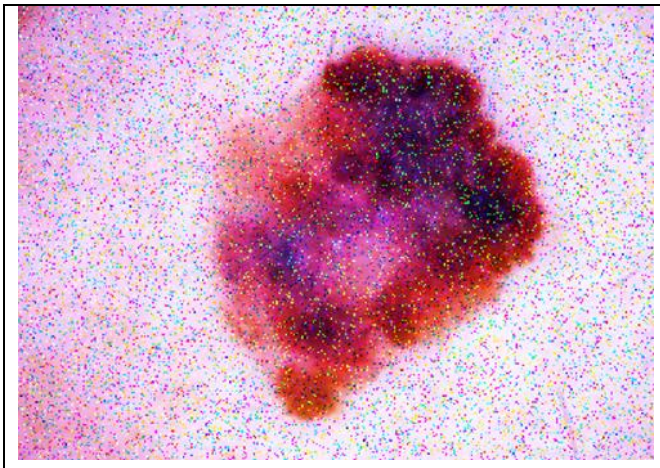
C_{df}			
C_{nv}			
C_{vasc}			

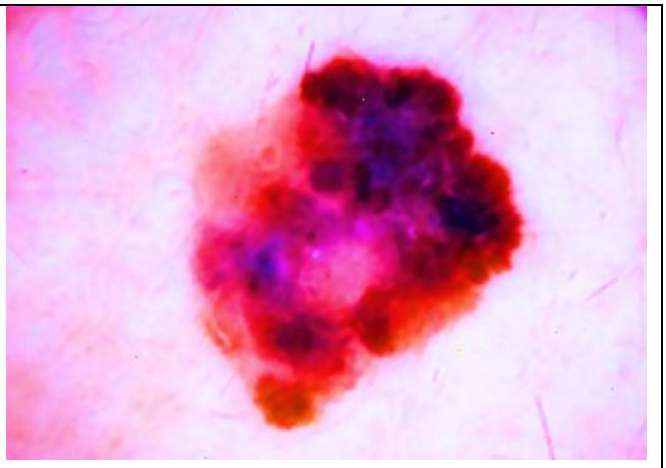
Figure.4 Sample images from HAM10000 database

3.2 Preprocessing

	
(a) Original image	**(b)Fur removed image**



(C)Noisy image



(d)Denoised image

Figure.5 Preprocessed skin image

The goal of this work is the characterization of skin diseases, the existence of hair is irrelevant. The presence of hair in the image contributes to noise. DL will have to learn the features spread across the lesion are not relevant to classification. Additionally, there is a chance for DL to determine correlations between target and noise. Three preprocessing techniques are used to improve quality of the image and to remove hair. Fast matching method and black hat transform [12] are employed for removing unwanted data. Medical images are inherently affected by noise during acquisition. Median filter with kernel size of 3x3 is used for denoising the images. Filtering process can be expressed as,

$$Y_{m,n} = \text{median}(A_{i,j} : (i,j) \in \gamma) \quad (1)$$

Where, A-input image, Y-filtered image and γ-neighborhood of the pixel in position (m, n). Sample of preprocessed image is shown in Figure.5. After preprocessing, adaptive thresholding technique [16] followed by k-means algorithm is used to isolate lesion region from its background tissue.

3.3 Feature extraction and classification

The standard centerNet used ResNet101 as a feature extractor for classification problem. However, the main limitation of ResNet-101 is gradient vanishing problem. To solve this problem, CenterNet is integrated with DenseNet-77 and used for extracting features. The DenseNet-77 architecture has small number of parameters compared to ResNet-100 which helps to reduce computational complexity. DenseNet-77 has many Dense Blocks (DBs) that are connected each other via using added conventional and subsampling or pooling layers in sequential dense blocks. The architecture layer details of the proposed DenseNet-77 are summarized in Table.2.Table .3 lists the trainable parameters of the proposed modified CenterNet.In DenseNet-77, DB is the most important element for calculation feature maps.The output of DB is represented by m x m x p, where m x m signifies the size of feature maps and

p represents the channels. To reduce the channels, non-linear transformation is adopted which consists of batch normalization, Rectified Linear Unit (ReLU), and 1 x 1 Convolution (conv.) layer. 3x3 conv. layer is responsible for key points reorganization. Transition layer is introduced between DBs in order to reduce the size of key points. The obtained features are down sampled and then passed to calculate three different types of heads.

The heatmap head calculates a key point from the DenseNet-77 to locate affected parts with respect to class. Affected region can be calculated as,

$$\hat{x}_{p,q,c} = \exp\left(-\frac{(p-\hat{r}_p)^2+(q-\hat{r}_q)^2}{2\sigma_r^2}\right) \quad (2)$$

Where, p and q-actual key point coordinates,$\hat{r}_p$ and $\hat{r}_q$ -locations of predicted down sampled key points, c-number of classes and $\hat{x}_{p,q,c}$–center for a candidate key points if has a value of 1 else it is marked as background. Dimension head predicts the coordinates of the bbox. The size of bbox for an object N with class C having coordinates (x1, x2,y1,y2) can be computed via L1 norm(x2-x1,y2-y1).Offset head is calculated to reduce the error which occurs due to down sampling process. The proposed modified CenteNet uses multi loss methods to enhance its power and accurately extract features from the affected region.Multi loss function can be represented as,

$$L_{\text{modified centnet}} = L_{\text{heatmap}} + \beta_d L_{\text{dimension}} + \beta_o L_{\text{offset}} \quad (3)$$

Where, $\beta_d$and β_o-constant [0.1 and 1].L_{heatmap} ,$L_{\text{dimension}}$ and L_{offset} can be defined as,

$$L_{\text{heatmap}} = \frac{-1}{m}\sum_{p,q,c}\begin{cases}(1-\hat{x}_{p,q,c})^{\alpha}\log(\hat{x}_{p,q,c}) & \text{if } \hat{x}_{p,q,c}=1\\ (1-\hat{x}_{p,q,c})^{\alpha}\log(\hat{x}_{p,q,c}) & \text{if } \hat{x}_{p,q,c}=1\end{cases} \quad (4)$$

$$L_{\text{dimension}} = \frac{1}{m}\sum_{i=1}^{m}\left|\hat{b}_i - b_i\right| \quad (5)$$

$$L_{\text{offset}} = \frac{1}{m}\sum_{p1}\left|\hat{F}_{\widehat{p1}} - \left(\frac{p1}{r1} - \widehat{p1}\right)\right| \quad (6)$$

Table.2 Structure of the proposed DenseNet-77

Name of Layer		**Size, stride**
Conv.1		7 x 7,2
P1		3 x 3,2
DB1		$\begin{bmatrix}1 \times 1\\3 \times 3\end{bmatrix}$ X 6, 1
Transition layer1	Conv.2	1 x 1,1
	P2	2 x 2, 2
DB2		$\begin{bmatrix}1 \times 1\\3 \times 3\end{bmatrix}$ X 12, 1
Transition layer 2	Conv.3	1 x 1, 1
	P3	2 x 2 ,2
DB3		$\begin{bmatrix}1 \times 1\\3 \times 3\end{bmatrix}$ X 12,1

Transition layer 3	Conv.4	1 x 1, 1
	P4	2 x 2 ,2
DB4		$\begin{bmatrix} 1 \times 1 \\ 3 \times 3 \end{bmatrix}$ X 6,1
Classification layer		Global avg. pool. (7 x 7) FC SVM

Table.3 Simulation parameters

Parameters	**Value**
Epochs	500
Learning rate	0.001
Batch size	32
C	0.001

4. NUMERICAL RESULTS AND DISCUSSION

This section provides detail regarding the performance evaluation indices, experimental setup and the obtained results after conducting set of experiments. It also compares the classification potential of the developed model with the prevailing methods to prove its power more intuitively.The experiments are performed on MATLAB2019a platform and intel core i5 processor @ 2.5 GHZ and 8 GB GPU.

4.1 Performance Evaluation metrics

There is no standard metrics for assessing the efficiency of any image classification system. Several metrics reported on the literature that depend upon the user's requirement. The performance of the introduced model is evaluated by computing several metrics which are tabulated in Table.4.

Table.4 Performance measuring metrics

Metrics	**Formula**
Classification accuracy	$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$
Specificity	$\mathrm{SPE} = \frac{\mathrm{TN}}{\mathrm{TN} + \mathrm{FP}}$
Sensitivity/Recall	$\mathrm{SEN} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$
Precision	$\mathrm{P} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$

F1-score	$\mathrm{F1-score} = 2\,\mathrm{X}\frac{\mathrm{P}\ \times\ \mathrm{SEN}}{\mathrm{P}+\mathrm{SEN}}$
MCC	$\mathrm{MCC} = \frac{\mathrm{TP}.\mathrm{TN}-\mathrm{FP}.\mathrm{FN}}{\sqrt{(\mathrm{TP}+\mathrm{FP})(\mathrm{TP}+\mathrm{FN})(\mathrm{TN}+\mathrm{FP})(\mathrm{TN}+\mathrm{FN})}}$
Balanced Classification Rate (BCR)	$\mathrm{BCR} = \sqrt{\mathrm{SEN}\ \times \mathrm{SPE}}$
Jaccard Similarity Index (JSI)	$\mathrm{JSI} = 2\,\mathrm{X}\frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FN}+\mathrm{TN}}$
TP-True Positive, TN-True Negative, FP-False Positive, FN-False Negative	

4.2 Experimental treatment

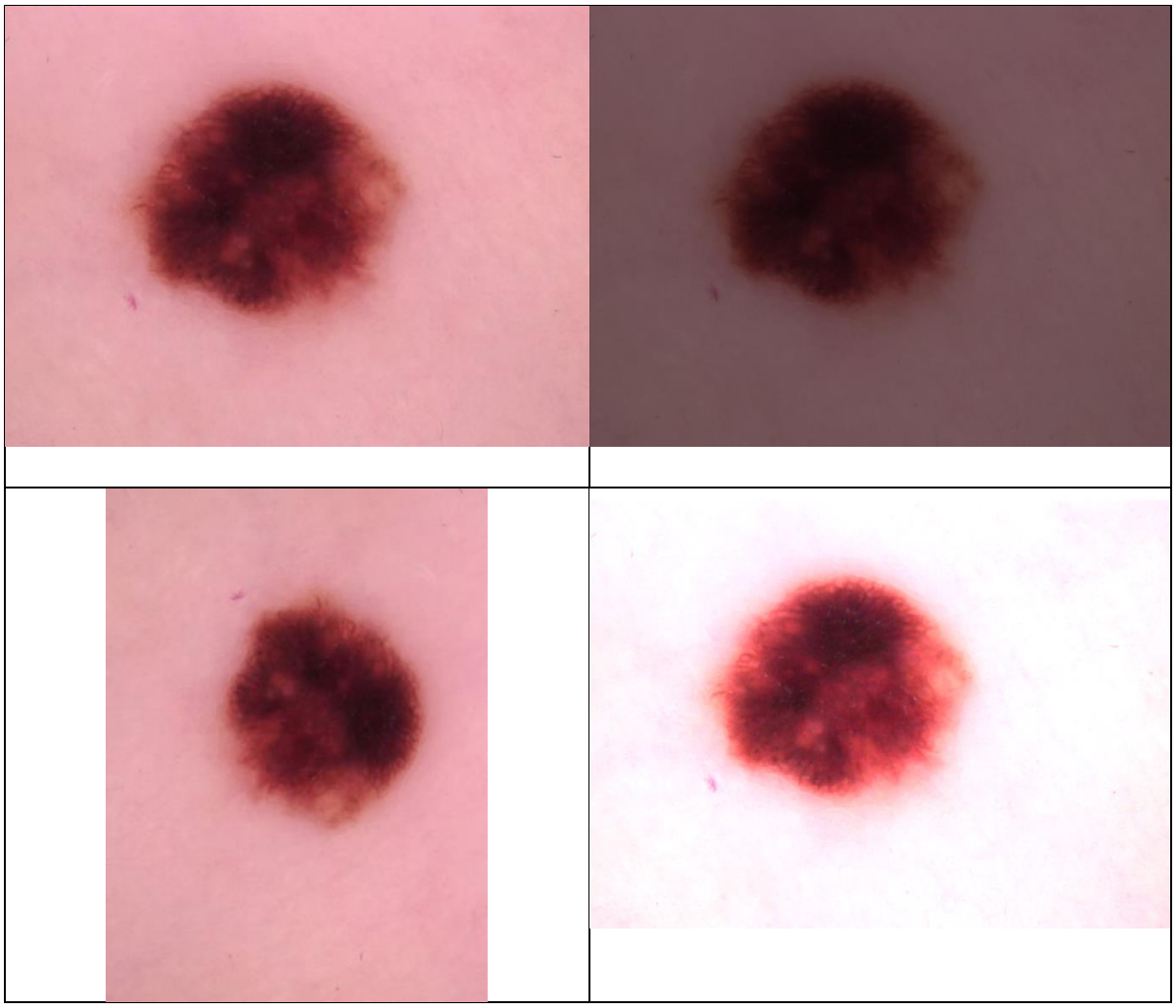


Figure.6 Sample of augmented images

The introduced multi class skin disease classification method outcomes are discussed in this section. The HAM 10000 dataset is used for evaluating the classification power of the introduced model. The major limitation of this database is the uneven distribution of the number of images in each class. Therefore, data augmentation technique is used to tackle the imbalance problem. Sample of augmented images is shown in Figure.6. Table.5 compares the efficacy of the presented method with the earlier models in categorizing the region of interest region more preciously. It is noted from the Table.5 that the proposed model outperforms the other models in terms of all metrics. Graphical representation of Table.5 is presented in Figure.7.

Table.5 Lesion segmentation comparison the proposed method and earlier models

Contributors	Network	ACC (%)	SEN (%)	SPE (%)	JSI (%)	MCC(%)
Srinivasu et al. [7]	MobileNet V2 – LSTM	85.34	88.24	92	91.07	86
Rathod et al.[14]	CNN	80	80.41	85	85.16	80
Haragi [15]	Ensemble	83.44	85.16	89	87.12	83.1
Haratanto [17]	MobileNet V2	84	86.14	90	89.95	84
Proposed		90.1	91.57	93.15	96.59	87.6

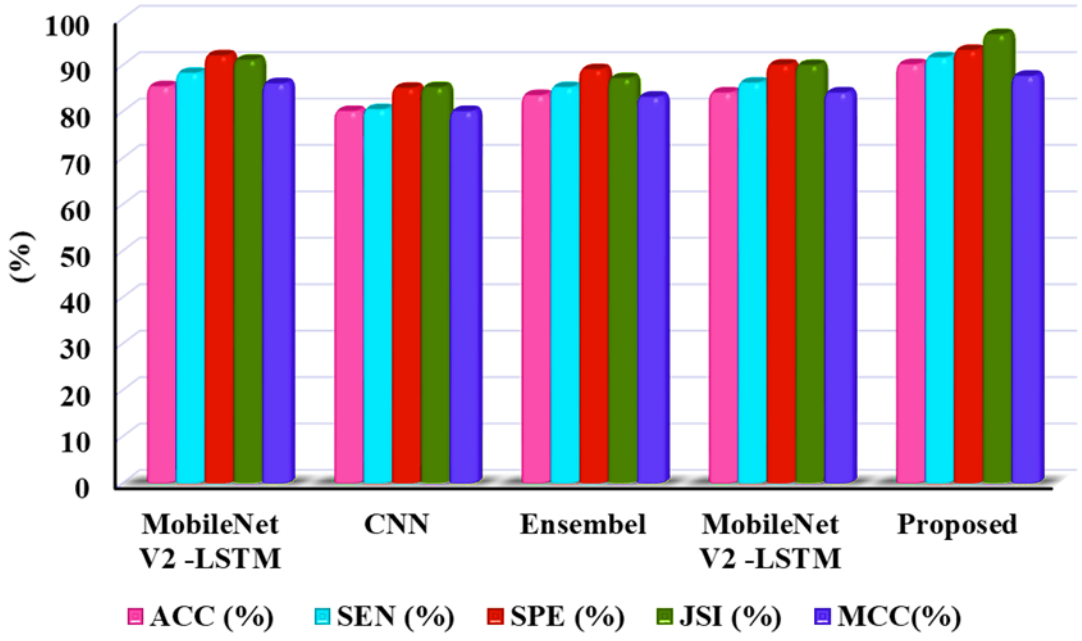


Figure.7 Comparative analysis of the proposed method with the earlier methods

For experimentation, both original and augmented data are considered. The introduced method is separately trained and tested using augmented and non-augmented data. The simulation parameters are used in this investigation are given in Table.2 and these values are fixed by experimentation to ensure the robustness of the proposed method. Additionally, 10-fold cross validation is considered. The classification performance of the developed method is assessed by computing ACC, SEN, SPE, P, F1-score, MCC and BCR.Classification performance of the

proposed method for both original and augmented data in terms of mean classification accuracy is given in the form graph in Figure. 8. It can be seen from the Figure.8 that the developed method has a testing accuracy of 87.41% for original data while the accuracy of augmented data is 97.37% which shows 9.96% performance improvement.

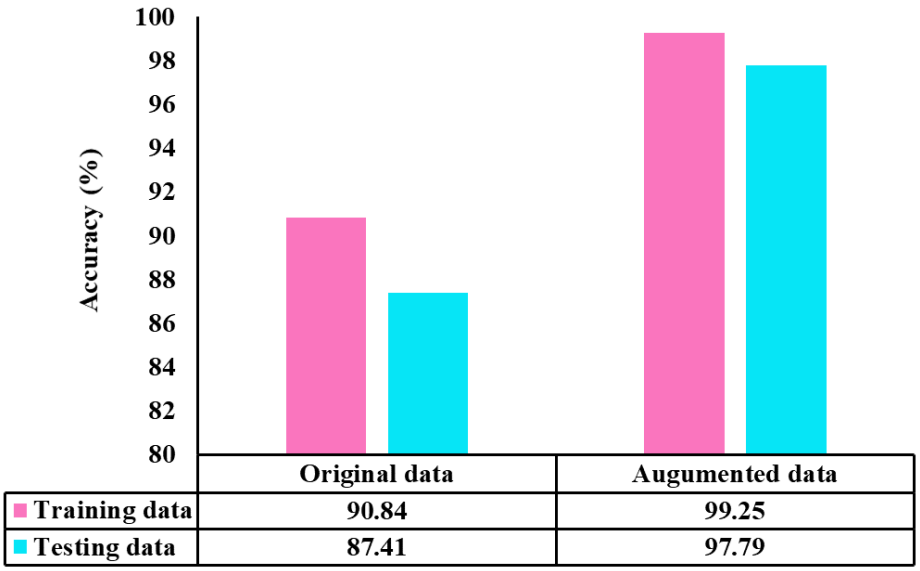


Figure.8 Classification accuracy comparison between non-augmented and augmented data

Class wise performance

An accurate classification of skin diseases is mandatory to gauge the performance of any classification system. Therefore, the efficacy of the designed model in characterizing the class of each skin disease was assessed viz. experimentation.The class-wise skin disease categorization power of the designed framework in terms of metrics precision, recall and F1-score is provided in Table.6. From the Table.6, it can be seen apparently that the suggested framework exhibits excellent performance in light of all metrics for all classes. The main reason for the feature computation method, which support the designed model to preciously classify the images. Figure. 9 evinces the graphical delineation of Table.6.

To further demonstrate the class-wise detection performance, classification accuracies of seven skin problems are shown in the form of graph in Figure. 10. The designed framework reached the mean accuracy value of 96.56% for C_{akiec}, 99.4% for C_{bcc}, 98.37% for C_{bkl}, 95.08%

Table.6 Classification results for each class

Class name	Precision	Recall	F1score
C_{akiec}	0.968	0.961	0.965
C_{bcc}	0.992	0.995	0.994
C_{bkl}	0.983	0.983	0.983
C_{mel}	0.961	0.938	0.949
C_{df}	0.988	0.984	0.985

C_{nv}	0.991	0.971	0.98
C_{vasc}	0.98	0.987	0.984
Mean	**0.980**	**0.974**	**0.977**

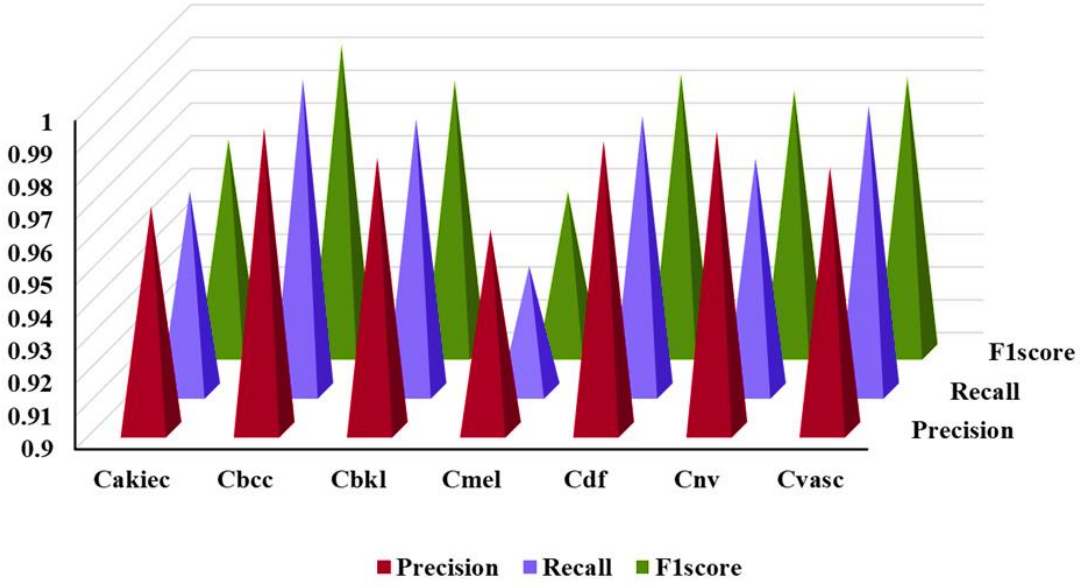


Figure.9 Class wise performance of the designed model

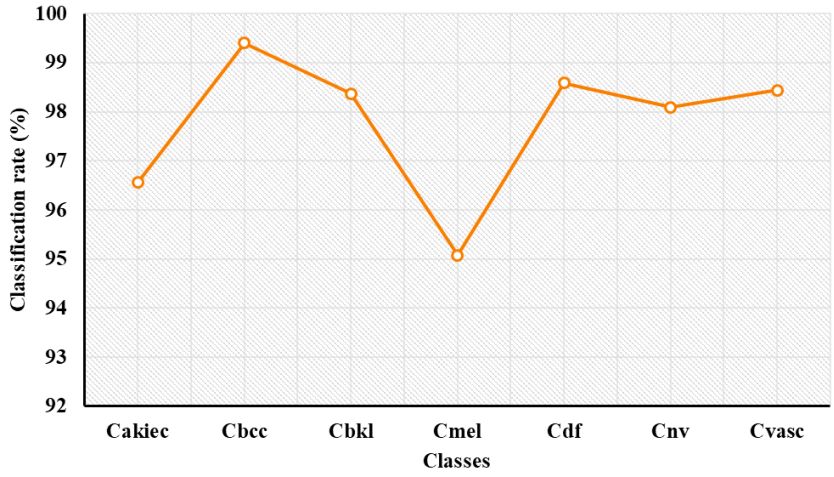


Figure.10 Obtained results of the designed model on the seven classes from HAM10000 dataset in terms of accuracy

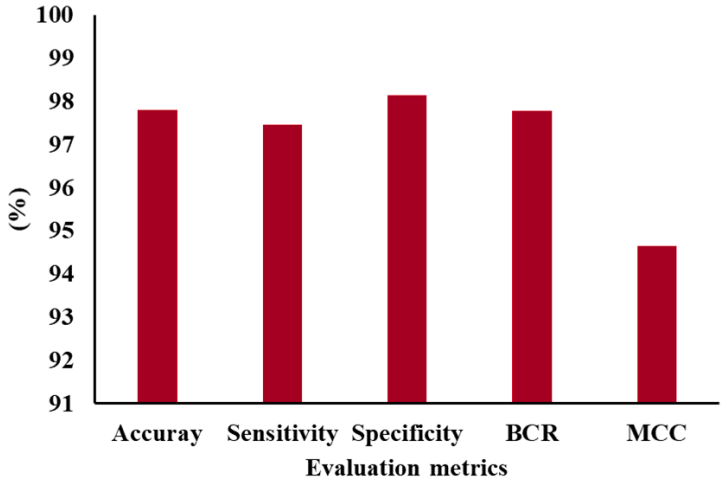


Figure.11 Efficacy of the introduced model

for C_{mel}, 98.59% for C_{df}, 98.09% for C_{nv} and 98.44 for C_{vasc}. The designed framework achieved the mean accuracy of 97.79%, which is proving the categorization power of the presented method. The classification performance of the introduced model is evaluated computing some metrics which are listed in Table.5 with 10-cross fold validation is graphically illustrated in Figure.11. It is found from the Figure.11 that the presented model provides excellent performance by registering ACC, SEN, SPE, BCR and MCR values are 97.79%,97.45%,98.13%,97.78% and 94.64% respectively.

4.3 Comparison with previous models

To prove the superiorpower, classification potential of the presented model is compared with the previous methods such as Dense Net 201 [1], Inception V3 [4],Wide-shufflenet [5],Mobile Net V2- LSTM [7],Efficient Net B4 [8], Ensemble [10],Dark Net 19 [11] and CNN-SVM [13]. Only the prevailing methods using HAM 10000 data for the experimentation is considered because the comparison between results is true and realistic. Table. 7 presents the comparison outcomes of the simulation results between the presented model and former methods.

Table.7 Performance comparison of different methods

Contributors	Network	SEN. (%)	SPE. (%)	ACC. (%)
Hemsi et al. [1]	DenseNet 201	84.8	85.3	91.73
Chaturvedi et al. [4]	Inceptionv3	89	90.1	91.56
Hoang et al. [5]	Wide-shufflenet	86.33	97.72	86.33
Srinivasu et al. [7]	MobileNet V2 -LSTM	92.24	95.1	90.21
Huang et al. [8]	EfficientNet B4	96	80.1	91
Shahin et al.[10]	Ensemble	80.1	83.2	89.9
Khan et al.[11]	Darknet 19	84.2	92.22	95.8
Hameed et al.[13]	CNN-SVM	67.2	97.2	90.1
Proposed		97.45	98.13	97.79

Hemsi et al. [1] adopted DenseNet 201 for skin disease diagnosis and yielded 91.73% classification accuracy with SEN. 84.8% and SPE. 85.3%. Chaturvedi et al. [4] investigated the power of Inception V3 for categorizing skin diseases and attained ACC. of 91.56%, SEN. of 89% and SPE. of 90.1%. Skin disease diagnosis using MobileNet V2 and LSTM [7] reported SEN., SPE. and ACC. values are 92.24%,95.1% and 90.21% respectively.Huang et al. [8] categorized skin diseases using EfficientNet B4 and attained SEN., SPE. and ACC values are 96%,80.1% and 91% respectively.Shahin et al. [10] developed an ensemble model to classify the skin diseases and achieved SEN. of 80%, SPE. of 83.2% and ACC. of 89.9%.Khan et al. [11] formulated Darknet 19 for skin disease diagnosis and obtained ACC. of 95.8% with 84.2% SEN., and 92.22% SPE. Skin disease classification based on CNN-SVM [13] gave 67% SEN.,97.2% SPE., and 90% ACC. From the comparison, it is quite clear that very few of the earlier methods [7] reported good results in terms of all metrics. Most of the methods failed to achieve better sensitivity [1] [3] [5] [11] [13]or specificity [8][10], while the introduced model achieves better results than that of other methods. The comparison results confirm the superiority of the presented model over the existing methods for skin detection. Pictorial representation of the Table.5 values is illustrated in Figure.12, Figure.13 and Figure.14 in light of specificity, sensitivity and accuracy respectively.

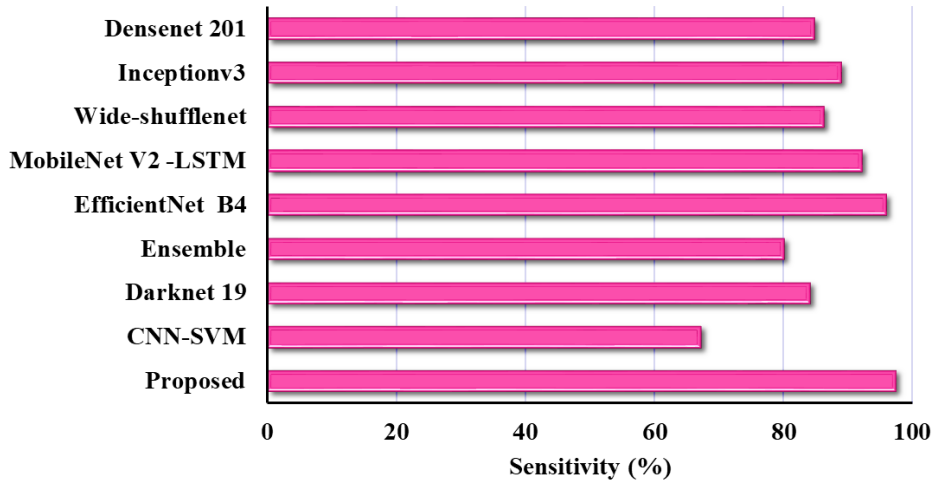


Figure.12 Performance comparison between the introduced model and the previous method in terms of sensitivity

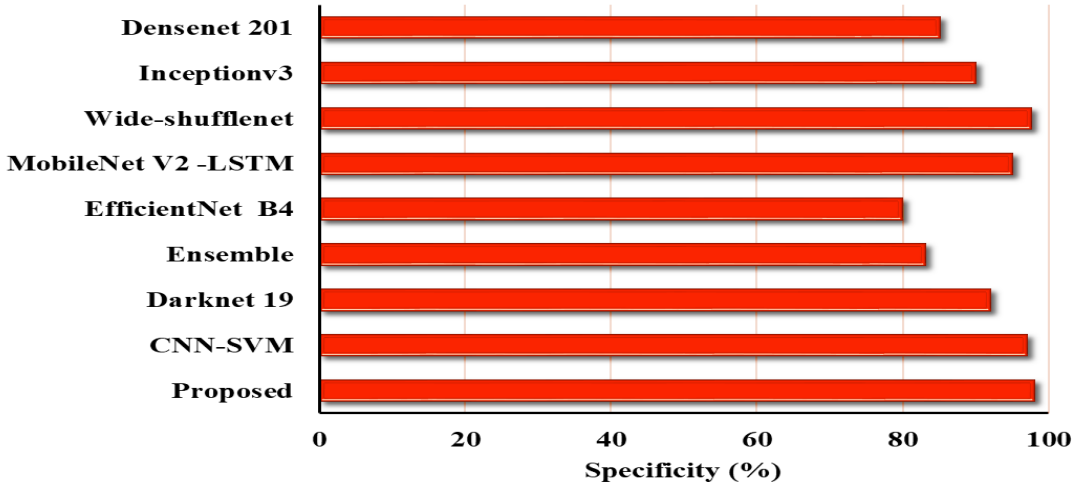


Figure.13 Performance comparison between the introduced model and the previous method in terms of specificity

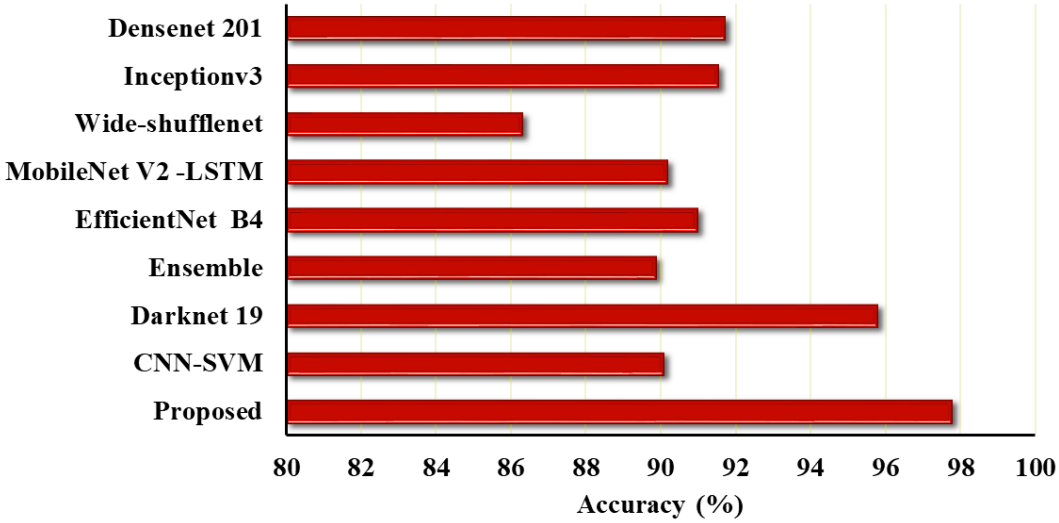


Figure.14 Performance comparison between the introduced model and the previous method in terms of classification rate

Computational cost analysis

Table.8 Comparison of computational cost

Contributors	Network	Time (s)
Hemsi et al. [1]	DenseNet201	105.23
Srinivasu et al.[7]	MobileNet V2 -LSTM	101.87
Hoang et al. [5]	Wide-shufflenet	114.17
Rathod et al. [14]	CNN	151.23
Harangi [15]	Ensemble	129.5
Proposed		99.01

Most of the former methods have reported better performance with high computational cost. Figure.8 compares the effectiveness of the presented model with the previous methods with respect to computation of the testing data. The introduced model is faster than the previous methods considered for comparison. Graphical representation of the Table.8 is evinced in Figure.15.

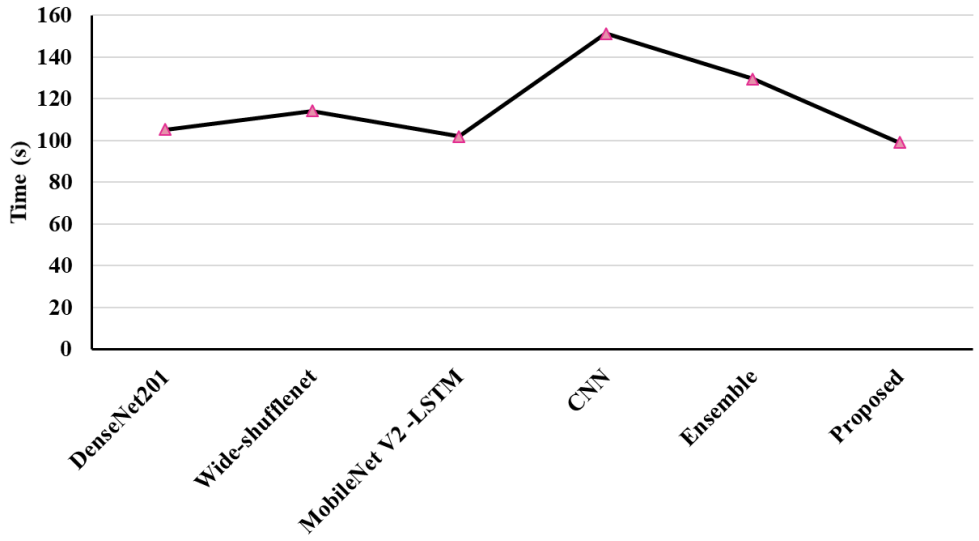


Figure.15 Comparison of computation time between the presented model and the earlier methods

5. CONCLUSION AND RECOMMENTATIONS

Multiclass skin diseases categorization is a tough task due to the lack of data availability and high interclass similarity.Dermatologists usually analyze and diagnose the skin cancer by visual scanning of images that is subjective time consuming and prone to errors. Henceforth, there is a need to develop a robust skin diagnosis model to classify skin disease. In recent investigation, DL based models have proven to be an efficient tool for skin disease classification. Categorization of multi class skin cancer on the basis of DL has been presented in this paper. Primarily, unprocessed images are subjected to some image processing techniques to remove unwanted data. Features are extracted and classified with the help of modified centerNet. Classification potential of the introduced model is validated using HAM10000 dataset. Experimental results proved that the presented model can efficiently classify skin diseases by registering mean accuracy of 97.79%. Further to this, effectiveness of the presented model is compared with other latest techniques to show its superiority where it has provided impressive results all of them. Future work will be concentrated in using metaheuristic algorithm to further improve classification rate.

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