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Skin Cancer Analysis with Deep Learning

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Abstract: Skin diseases are some of the most common diseases and are often difficult to diagnose than other diseases. Skin diseases may be caused by fungus, bacteria, allergic reaction, viruses, cancer etc. The technological advancement in laser diagnosis and Photonics based medical diagnosis has made it possible to diagnose the skin diseases much more quickly and accurately. But the cost of diagnostics is time-consuming and very expensive. Hence, we can use image processing techniques to help build automated preliminary detection system for such dermatological diagnostics.
Keywords: Deep Learning, Skin lesion, Image processing, MobileNet, Canny edge, Dermoscopy

I. INTRODUCTION

[9] In the year 2011-2015, a survey shows that a total of 20,270 patient visited the hospital 33,647 time to diagnose skin cancer. 9956 lesion samples were collected and 2763 confirmed cancer cases were recorded. This roughly counts to about 3.6 tests per person. It is estimated that every year 123,000 melanomas and 30,00,000 non-melanoma cases registered globally . A recent study reports 86 percent of melanoma and 90 percent of non-melanoma cases are induced by excessive exposure of ultraviolet rays. Making this disease common in equatorial regions of the world. [10]Moreover the cost of 215 melanoma diagnosis can go all the way up to $32,594 which mounts up to $151.6 per person which is significantly high. Additionally high-risk melanoma diagnosis costs another $73.4. For non-melanoma skin cancers (NMSC), the cost is $2469, with a NNS of 12.9 and a NNB of 1.6. These statistics suggest that the cost of skin disease detection grows higher with each failed attempt and the actual success rate can vary between 3-5 tests per person. Hence it becomes crucial to know what tests absolutely need to be performed and what can be left out. And to address this we can include a computerized preliminary test before the actual diagnosis begin. This computerized test can be achieved using image processing using specialized software to carry out such tasks.

This basically begins by taking a picture of the affected skin sample(lesion) and subjecting it to a camera to take the picture. The software suns in the system analyzing the image and it gives us the results of the tests. The output must be in a suggestion format where all possible matches may be listed out and the highest probability results must be emphasized to proceed with medical confirmation diagnosis. The extraction of features from the image plays a key role in helping to classify lesion samples. The software must be equipped with Computer vision techniques in order to enable such detections. Hence, This work contributes in the research of skin cancer diagnosis and detection. We have proposed an image processing and Deep Learning based model to detect skin diseases. Our proposed approach is easy to embed, fast and can be performed without the use of expensive and complex equipment. The system successfully detects 7 different types of skin cancers namely Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc).

II. BACKGROUND WORK

In [1], a system is proposed for the dissection of skin diseases using color images without the need for doctor intervention. The system consists of two stages, the first the detection of the infected skin by uses color image processing techniques, k-means clustering and color gradient techniques to identify the diseased skin and the second the classification of the disease type using artificial neural networks. The system was tested on six types of skin diseases with average accuracy of first stage 95.99% and the second stage 94.016%. In the method of [2], extraction of image features is the first step in detection of skin diseases. In this method, the greater number of features extracted from the image, better the accuracy of system.The author of [2] applied the method to nine types of skin diseases with accuracy up to 90%.Melanoma is type of skin cancer that can cause death, if not diagnose and treat in the early stages.

The author of [3], focused on the study of various segmentation techniques that could be applied to detect melanoma using image processing. Segmentation process is described that falls on the infected spot boundaries to extract more features.

The work of [4] proposed the development of a Melanoma diagnosis tool for dark skin using specialized algorithm databases including images from a variety of Melanoma resources.

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Similarly, [5] discussed classification of skin diseases such as Melanoma, Basal cell carcinoma (BCC), Nevus and Seborrheic keratosis (SK) by using the technique support vector machine (SVM). It yields the best accuracy from a range of other techniques. On the other hand, the spread of chronic skin diseases in different regions may lead to severe consequences.
Therefore, [6] proposed a computer system that automatically detects eczema and determines its severity. The system consists of three stages, the first effective segmentation by detecting the skin, the second extract a set of features, namely color, texture, borders and third determine the severity of eczema using Support Vector Machine (SVM). In [7], a new approach is proposed to detect skin diseases, which combines computer vision with machine learning. The role of computer vision is to extract the features from the image while the machine learning is used to detect skin diseases. The system was tested on six types of skin diseases with accurately 95%

III. MOTIVATION

By looking at the global and local statistics we wanted to reduce the difficulty and cost involved in skin cancer detection and treatment and skin disease in general. Our motive was inspired by the application of image proceeding in medical science and being able to develop a new way that could change the medical procedures and make them accurate and easy. We also intend to promote skin health and skincare to our people. We need to do this because skin diseases are chronic, their development and spread are often unpredictable. The diagnosis and treatment of a skin disease takes longer time and causes financial and physical cost to the patient. In general, most of the common people do not know the type and stage of a skin disease. Some of the skin diseases show symptoms several months later, causing the disease to develop and grow further. This is due to the lack of medical knowledge in the public. Sometimes, a dermatologist (skin specialist doctor) may also find it difficult to diagnose the skin disease and may require expensive laboratory tests to correctly identify the type and stage of the skin disease. The advancement of lasers and photonics based medical technology has made it possible to diagnose the skin diseases much more quickly and accurately. But the cost of such diagnosis is still limited and very expensive. Hence we as a team intend to create a much more efficient, quick and cost effective way to early detect skin diseases and help users to easily deal with them beforehand.

IV. OBJECTIVES

The goal is to make a simple model that can go from an image to a predict how likely different skin-diseases a person might have based on a picture of your skin. It is not optimised to completely replace medical systems but can act as a preparedness stage to find out what possible confirmatory tests need to be made thereby saving time and money.It is also a great example to learn how image processing works (and fails) in real conditions. Our project can be applied to software on mobile phones to classify objects. It can also be applied to medical image processing field where our program will reduce the noise and generates informational results. With the increase in the speed of processors, the future application of our project is not limited to a particular field but in the entire field of intelligent image processing.

V. PROPOSED SYSTEM

There are two steps in our system that involve image manipulation/pre-processing and image analysis.
For the purpose of image manipulation, we use image pre-processing techniques such as Gaussian filtering and Thresholding. We also have an intermediate step where we use the manipulated image to get the canny edge diagram of the particular image. For the prediction and analysis of the image we use a Convolutional Neural networks on the canny edge diagram and the rgb image.

A. Dataset Introduction

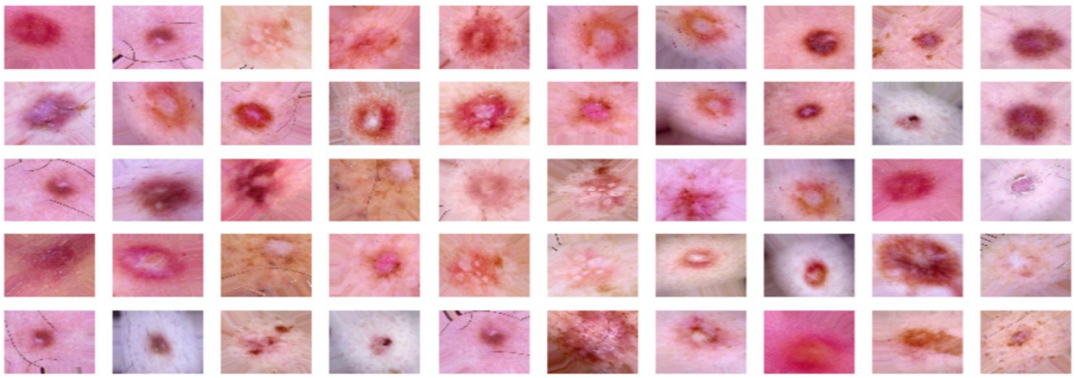


Fig. 1. Random sample of the Dataset containing 10000 skin lesion images from the HAM10000 dataset

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We have used the HAM10000 skin lesion dataset Training of neural networks for automated diagnosis of pigmented skin lesions is hampered by the small size and lack of diversity of available dataset of dermatoscopic images. To tackle this problem we have used the HAM10000 ("Human Against Machine with 10000 training images") dataset. The dataset consists of dermatoscopic images from different populations, acquired and stored by different modalities. The final dataset consists of 10015 dermatoscopic images which can serve as a training set for academic machine learning purposes. Cases include a representative collection of all important diagnostic categories in the realm of pigmented lesions: Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc).

B. Image Pre-proceesing

The Process of Canny edge detection algorithm can be broken down to 5 different steps:

1) Convert the image to Greyscale
2) Apply Gaussian filter to smooth the image in order to remove the noise.
3) Find the intensity gradients of the image.
4) Apply non-maximum suppression to get rid of spurious response to edge detection.
5) Apply double threshold to determine potential edges
6) Track edge by hysteresis Finalize the detection of edges by suppressing all the other edges that are weak and not connected to strong edges.

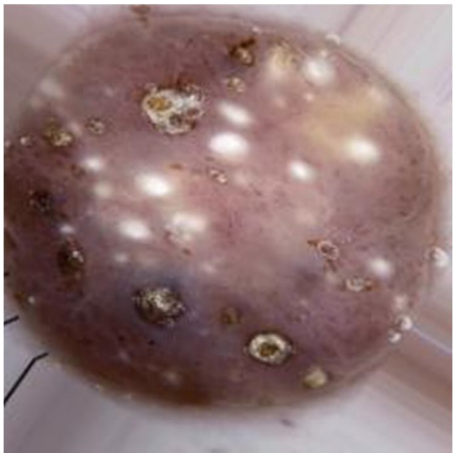


Fig. 2. Sample image of a Basal cell carcinoma disease.

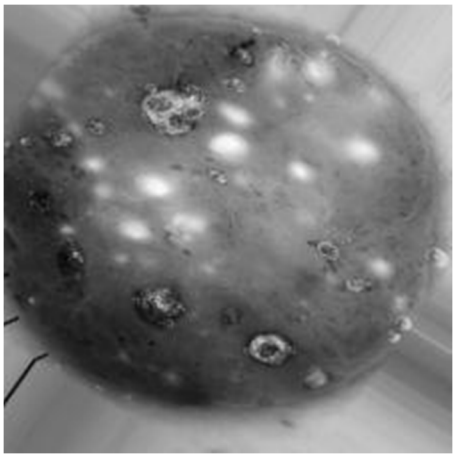


Fig. 3. Image obtained after applying Greyscale conversion for easier non-maximum suppression.

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a) *Gaussian filtering:* Since all edge detection results are easily affected by image noise, it is important to filter the noise to avoid false detection caused by noise. Hence we use image smoothening filters to remove unwanted noise. To smoothen the image, we have applied a Gaussian filter to fold with the image. This step will soften the image and will remove most interfering noises in the image and also reduce the effects of apparent noise in the edge detector The equation for a Gaussian filter kernel of size (2k + 1) × (2k + 1) is given by

$$G(x,y) = -\frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$$

The larger the size of the filter, the lower the detector's sensitivity to noise. In addition, the position error for detecting the boundary increases slightly as the size of the Gaussian kernel increases. a good size for most cases is a 5x5 filter, but this will depend on specific situations.

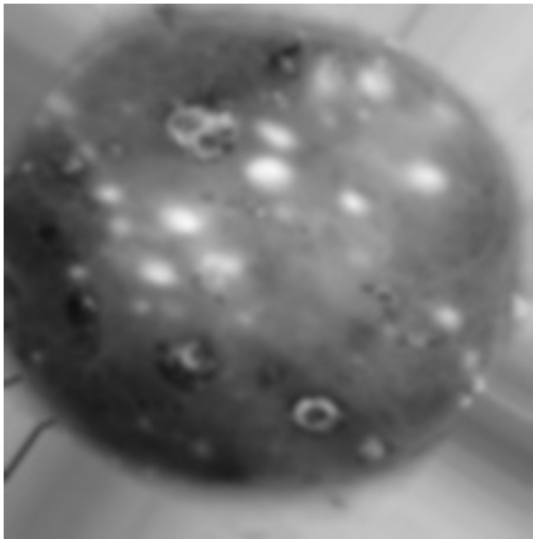


Fig. 4. Image obtained after applying Gaussian 5X5 filter results in a blurred image and enhanced gradient effect.

b) Finding intensity Gradients of the image: Image gradients are generally used to extract information from images. For this purpose, gradient images are created from the original image (usually by convolution with a filter, for example Sobel filter). Each pixel in a gradient image measures the change in intensity of the same point in the original image in a certain direction. In order to obtain the full range of directions, the gradient images are calculated in the x and y directions. Intensity gradients are most commonly used in edge detection algorithms. For a given image, pixels with high gradient values become possible edge pixels. The pixels in the direction of the gradient with the highest gradient values become edge pixels, and edges can be traced perpendicular to the gradient direction.

c) Non-maxium suppression: This algorithm is another part of edge detection. The image is traversed along the gradient direction, and if pixels are not in the local maxima region they are set to zero. This supresses all image information that is not part of local maxima.

d) Double tresholding: The double thresholding is used to refine edges detected by the non-maximum suppression. The remaining edge pixels after applying non-maximum supression provide a more accurate representation of real edges in an image. However, some of the edge pixels that remain may possibly be caused by image noise and color variations. In order to eliminate these scattered edge dots, we filter out edge pixels with a weak gradient value and keep the edge pixels with a high gradient value. This is done by applying double thresholding, by selecting high and low threshold values. If the inspected edge pixel's gradient value is higher than the max threshold value, it is set as a strong edge pixel. If the inspected edge pixel's gradient value is falls in the inclusive range of the maximum and minimum threshold values, it is set as a weak edge pixel. If the inspected edge pixel's value is lesser than the minimum threshold value, it will be suppressed. The two threshold will depend on the content of a given input image and its values are empirically determined.

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e) Edge tracking by hysteresis: After applying double thresholding the strong pixels are finalized and are part of the edge diagram, however, there is some debate on position of the weak edge pixels, since these pixels were neither extracted from the true edge, nor the noise/color variations. To get the final verdict for the weak edges, the weak edges formed by the noise/color variations should be removed. Generally a weak edge pixel formed by true edges is connected to a strong edge pixel while noise responses are unconnected. To track an edge connection, neighborhood analysis is used by inspecting a weak edge pixel and its 8-connected neighborhood pixels. If there is at least one strong edge pixel present in the neighborhood, the inspected weak pixel can be preserved.

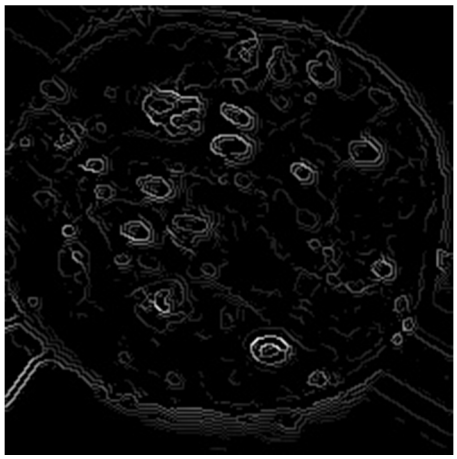


Fig. 5. Image obtained after applying (i) non-maximum suppression, (ii) Double Tresholding and (iii) Edge tracking by hysteresis results in formation of the canny edge diagram of Fig. 2.

C. Network Structure

The project uses 2 separate neural networks to conduct 2 separate analysis on 2 separate image sets. Both the networks are the 92 layer deep MobileNet Convolutional Neural network.

1) *MobileNet:* MobileNet is an efficient and portable CNN architecture that is used in real world applications. MobileNets primarily use depthwise separable convolutions in place of the standard convolutions used in earlier architectures to build lighter models.MobileNets introduce two new global hyperparameters(width multiplier and resolution multiplier) that allow model developers to trade off latency or accuracy for speed and low size depending on their requirements. MobileNets are built on depthwise separable convolution layers. Each depthwise separable convolution layer consists of a depthwise convolution and a pointwise convolution. Counting depthwise and pointwise convolutions as separate layers, a MobileNet has 28 layers.A standard MobileNet has 4.2 million parameters which can be further reduced by tuning the width multiplier hyperparameter appropriately. The size of the input image is 224 × 224 × 3.

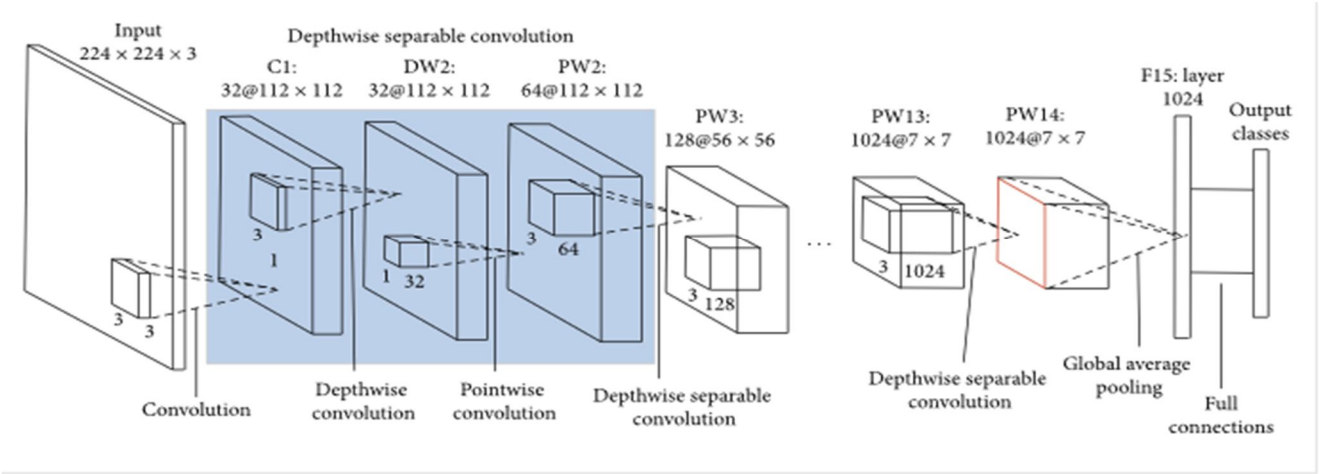


Fig. 6. [13] Architecture and functional segmentation of MobileNet

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Table 1. Layer-wise MobileNet network parameters

TYPE	STRIDE	KERNEL SHAPE	INPUT SIZE
Conv	2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw	1	3 × 3 × 32	112 × 112 × 32
Conv	1	1 × 1 × 32 × 64	112 × 112 × 32
Conv dw	2	3 × 3 × 64	112 × 112 × 64
Conv	1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw	1	3 × 3 × 128	56 × 56 × 128
Conv	1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw	2	3 × 3 × 128	56 × 56 × 128
Conv	1	1 × 1 × 128 × 256	56 × 56 × 128
Conv dw	1	3 × 3 × 256	28 × 28 × 256
Conv	1	1 × 1 × 256 × 256	28 × 28 × 256
Conv dw	2	3 × 3 × 256	28 × 28 × 256
Conv	1	1 × 1 × 256 × 512	14 × 14 × 256
Conv dw	1	3 × 3 × 512	14 × 14 × 512
Conv	1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw	1	3 × 3 × 512	14 × 14 × 512
Conv	1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw	1	3 × 3 × 512	14 × 14 × 512
Conv	1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw	1	3 × 3 × 512	14 × 14 × 512
Conv	1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw	1	3 × 3 × 512	14 × 14 × 512
Conv	1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw	2	3 × 3 × 512	14 × 14 × 512
Conv	1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw	2	3 × 3 × 1024	7 × 7 × 1024
Conv	1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool	1	Pool 7 × 7	7 × 7 × 1024
Fully Connected	1	1024 × 1000	1 × 1 × 1024
Softmax	1	Classifier	1 × 1 × 1000

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The MobileNet output is a 1000 class SoftMax classifier that is capable of predicting over 1000 different objects in an image. For our project we use only 6 of those 1000 classes to predict 6 of our categorized diseases.

Our project ustilizes 2 MobileNet simultaneously to achieve a confirming top 3 result. The networks can be called as Network A and Network B.

Network A is a mobileNet network that is trained using the edge diagrams of the images provided to it. The edge diagrams are produced using the canny edge detection algorithm.

Network B is also a MobileNet that is trained using the standard 224x224 RGB image.

To find the final detection result we calculate the softmax probability of the both the network A and Network B.

The final probability is calculated by taking the average probability of both the network outputs.

$$Prob(i) = \frac{Prob_a(i) + prob_b(i)}{2}$$

Where

Prob(i) is the final probability.

$Prob_a(i)$ is the probability output from Network A.

$Prob_b(i)$ is the probability output from Network B.

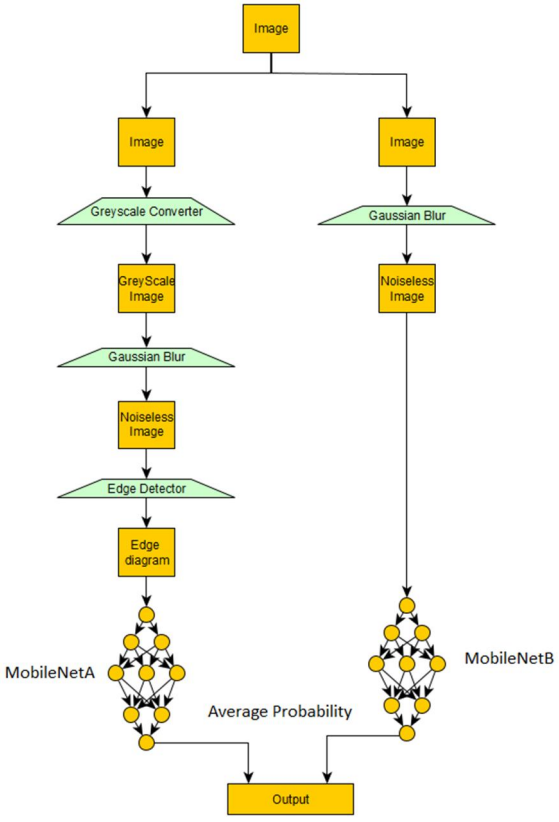


Fig. 7. Model flow diagram

The accuracy results for a single point prediction is close to 80.2% which makes it less ideal to predict the exact disease because of the 20% uncertainity which is beyond the accepted standards of medical diagnosis tests. Hence we have created a top 3 accuracy which gives us the 3 most probable diseases that can be possible based on the image. Further confirmatory tests may be required to find the exact disease but the number of tests is significantly reduced in the medical procedures.

The uncertainity rate of the 3 point prediction is less than 1.5% which makes it a very strong argument to accept the results.

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VI. METRICS OF TESTING

A. Multivariate Precision-Recall

In pattern recognition, information retrieval and classification , precision (also called positive predictive value) is the fraction of relevant instances among the retrieved instances, while recall (also known as sensitivity) is the fraction of relevant instances that were
retrieved. Both precision and recall are therefore based on relevance.

$$Precision = \frac{TP}{TP + FP}$$

$$Recall = \frac{TP}{TP + FN}$$

B. F1-Score

In statistical analysis of binary classification, the F-score or F-measure is a measure of a test's accuracy. It is calculated from the precision and recall of the test, where the precision is the number of true positive results divided by the number of all positive results, including those not identified correctly, and the recall is the number of true positive results divided by the number of all samples that should have been identified as positive. Precision is also known as positive predictive value, and recall is also known as sensitivity in diagnostic binary classification.

$$F_1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

C. Accuracy

The accuracy of a machine learning classification algorithm is one way to measure how often the algorithm classifies a data point correctly. Accuracy is the number of correctly predicted data points out of all the data points. More formally, it is defined as the number of true positives and true negatives divided by the number of true positives, true negatives, false positives, and false negatives.

$$Accuracy = \frac{Total\ number\ of\ correct\ predictions}{Total\ number\ of\ test\ data\ points}$$

D. Model Training Results Per Epoch

Prediction Accuracy report of Neural Network A (mobileNet for unchanged image)

Table 2. Single point prediction, top 2 prediction and top 3 Prediction accuracy of Network A

Epochs	Single prediction accuracy	Double prediction accuracy	Triple prediction accuracy
0	0%	0%	0%
5	49.45%	69.34%	83.52%
10	59.21%	81.58%	92.35%
15	69.36%	86.73%	95.27%
20	74.12%	90.87%	97.18%
25	76.60%	92.07%	97.79%
30	80.2%	93.75%	98.41%

Prediction Accuracy report of Neural Network B (mobileNet for Canny edged image)

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Table 3. Single point prediction, top 2 prediction and top 3 Prediction accuracy of Network B

Epochs	Single prediction accuracy	Double prediction accuracy	Triple prediction accuracy
0	0%	0%	0%
5	30.57%	51.21%	68.22%
10	36.32%	59.32%	74.71%
15	42.36%	63.21%	79.72%
20	51.12%	73.87%	82.18%
25	60.60%	79.07%	84.39%
30	73.2%	82.75%	89.41%

E. Model Test Results

Table 1. Model test results

Metric	value
Precision recall	0.92/1
F1 score	0.87/1
Accuracy	98.41%

VII. DEPLOYMEMT

A. Implementation

The Project has been developed using Python 3.8 using the anaconda data science environment. We have used Tensorflow 2.0 to carry out the deep learning functions and operations. Keras is used to develop and train neural networks. We have also used the Pillow library for image pre processing functionalities and also have developed a custom code to implement the canny edge detection algorithm. Numpy and Pandas Libraries were used to segregate and organize the data for the ease of network training and also for easy of understanding data. Duplicate images were also removed using the pandas library and data classes that were low on images were enriched using data augmentation.

B. Deployment

The Project has been Deployed using Django web development framework and the prediction model was developed using python Data science tools such as Jupyter notebook and SpyderIDE. The webpages were Constructed using HTML,CSS and Javascript and also Django template language is being used to merge the frontend and backend. The project is currently deployed in a local server under the address localhost:800/upload link.

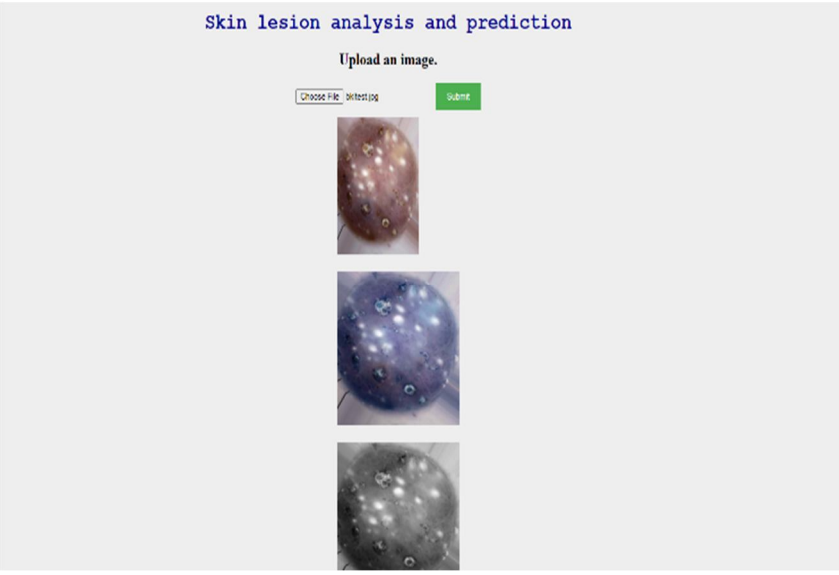


Fig. 7. Django website implementation screenshot- file upload also shows the preprocessing images including the canny edge image.

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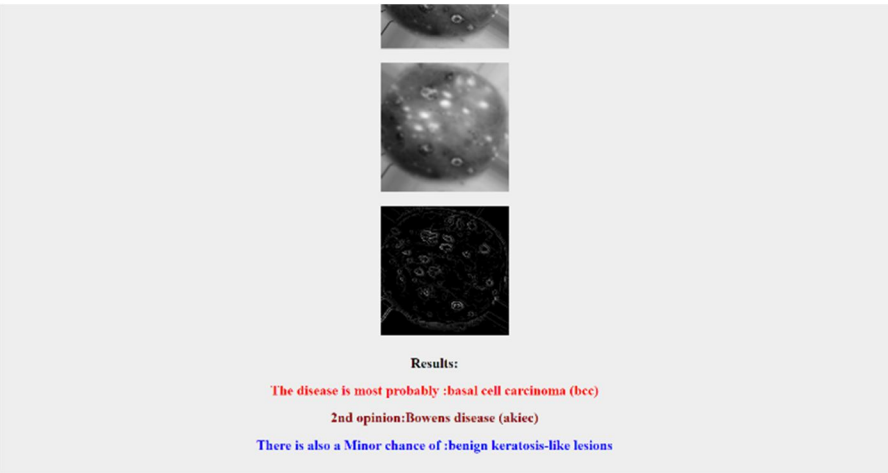


Fig. 8. Displaying top 3 predictions of the uploaded image.

VIII. CONCLUSION

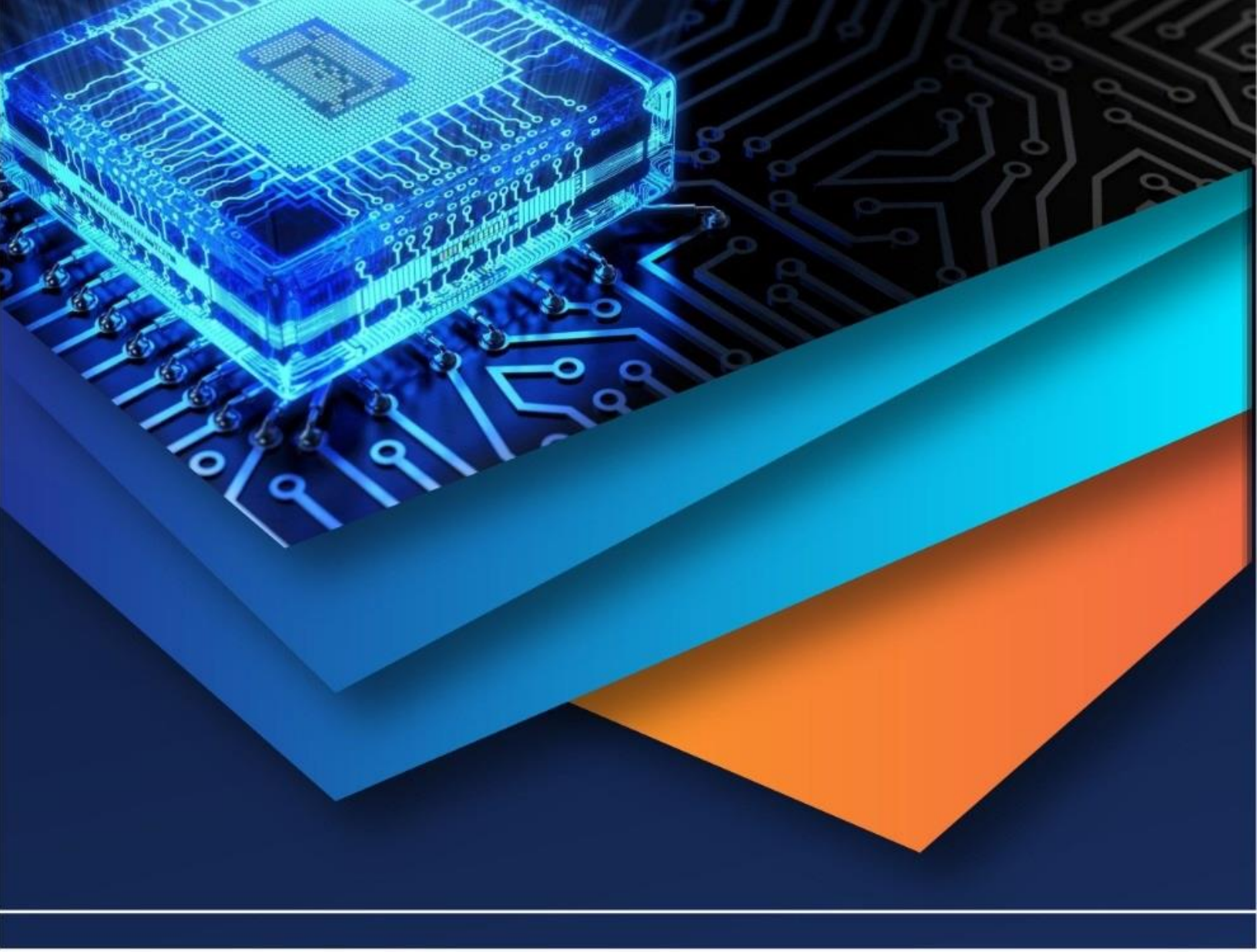
Detection of skin diseases is a very important step to reduce death rates, disease transmission and the development of the skin disease. Clinical procedures to detect skin diseases are very expensive and time-consuming. Image processing techniques help to build automated screening system for dermatology at an initial stage. The extraction of features plays a key role in helping to classify skin diseases.

We have successfully developed and constructed the model that helps us target the detection of 6 skin diseases namely Actinic keratoses and intraepithelial carcinoma / Bowen's disease (akiec), basal cell carcinoma (bcc), benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichen-planus like keratoses, bkl), dermatofibroma (df), melanoma (mel), melanocytic nevi (nv) and vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage, vasc).

REFERENCES

[1] Arifin, S., Kibria, G., Firoze, A., Amini, A., & Yan, H. (2012) “Dermatological Disease Diagnosis Using Color-Skin Images.” Xian: International Conference on Machine Learning and Cybernetics.
[2] Yasir, R., Rahman, A., & Ahmed, N. (2014) “Dermatological Disease Detection using Image Processing and Artificial Neural Network. “Dhaka: International Conference on Electrical and Computer Engineering.
[3] Santy, A., & Joseph, R. (2015) “Segmentation Methods for Computer Aided Melanoma Detection.” Global Conference on Communication Technologies.
[4] Zeljkovic, V., Druzgalski, C., Bojic-Minic, S., Tameze, C., & Mayorga, P. (2015) “ Supplemental Melanoma Diagnosis for Darker Skin Complexion Gradients.” Pan American Health Care Exchanges
[5] Suganya R. (2016) “An Automated Computer Aided Diagnosis of Skin Lesions Detection and Classification for Dermoscopy Images.” International Conference on Recent Trends in Information Technology.
[6] Alam, N., Munia, T., Tavakolian, K., Vasefi, V., MacKinnon, N., & Fazel-Rezai, R. (2016) “Automatic Detection and Severity Measurement of Eczema Using Image Processing.” IEEE.
[7] Kumar, V., Kumar, S., & Saboo, V. (2016) “Dermatological Disease Detection Using Image Processing and Machine Learning.” IEEE.
[8] Singh, N. (2018). MobileNet V1 Architecture. https://iq.opengenus.org/mobilenet-v1-architecture/.
[9] Matsumoto M, Secrest A, Anderson A, Saul MI, Ho J, Kirkwood JM, Ferris LK. Estimating the cost of skin cancer detection by dermatology providers in a large health care system. J Am Acad Dermatol. 2018 Apr;78(4):701-709.e1. doi: 10.1016/j.jaad.2017.11.033. Epub 2017 Nov 24. PMID: 29180093; PMCID: PMC5963718.
[10] Karimkhani C, Boyers LN, Dellavalle RP, Weinstock MA. J Am Acad Dermatol. 2015;72(1):186-187. http://www.jaad.org/article/S0190-9622(14)01999-9/fulltext
[11] Stewart BW, Wild C. International Agency for Research on Cancer, and World Health Organization. World cancer report 2014.
[12] Stern RS. Prevalence of a history of skin cancer in 2007: results of an incidence-based model. Arch Dermatol. 2010 Mar;146(3):279-82. https://doi.org/10.1001/archdermatol.2010.4
[13] Wei Wang, Yutao Li, Ting Zou, Xin Wang, Jieyu You, Yanhong Luo, "A Novel Image Classification Approach via Dense-MobileNet Models", Mobile Information Systems, vol. 2020, Article ID 7602384, 8 pages, 2020. https://doi.org/10.1155/2020/7602384

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