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Literature Survey on Skin Cancer Detection Using Raspberry Pi and Deep Learning

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Abstract— *A growing variety of metabolic and genetic abnormalities which are being linked to cancer, are lethal. Body could become infected with cancerous cells, threatening human life. Squamous and basal cell carcinomas, as well as the clinically aggressive melanoma, is the most common cause of death from skin cancer. Skin cancer screening is therefore necessary. This study aims to survey the methods used for the detection of skin cancer and to examine if it has been implemented using portable hardware for the same. Skin lesions in this dataset must range from benign to malignant, nonmelanocytic to melanocytic malignancies. This paper compares various existing methodology for skin cancer detection. This survey paper also finds out that there is no handheld gadgets proposed and designed for the early detection of skin cancer.*
Keywords— *Deep learning, Machine learning, Handheld device.*

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I. INTRODUCTION

The skin is made up of the epidermis, dermis, and subcutaneous tissues. It has muscles, nerves, lymphatic vessels, and circulatory system that allow it to sweat, sensethe outside temperature, and protect the body. The skin, which covers the whole body is capable of shielding multiple organs and structures from exterior dangers such as purposeful skin damage, viruses, and people's immune functions. Skin can stabilise the function of the skin barrierby minimizing the loss of lipids and moisture from the dermis and epidermis. Despite its defensive and insulatingcapabilities, skin is still not indestructible because it is constantly transformed. The epidermis, or top layer of skin,is composed of three types of cells: BASAL cells- which give skin its round form, SQUAMOUS cells- which are flat and scaly on the surface, and MELANOCYTES- which provide colour of skin and protect it from injury.

Melanoma, the fatal skin cancer disease, is responsible for the majority of skin cancer fatalities in many countries.Despite the fact that people with darker skin tones are agedbetween 20 to 30 are more likely to develop melanoma than individuals with lighter skin, it has been determined that individuals with darker complexions either have agreater or less risk of mortality for particular kinds of melanoma. Early detection and correct diagnosis are required to determine viable cancer therapy.

The survival probability drops to 20% if it spreads to other parts of the body. The dermatologist's knowledge is frequently required for accurate diagnosis. Dermatologistswho have had training on the different lesions characterized by melanomas are prepared to offer an accurate diagnosis. Diagnosing melanoma can be difficult given that there is no inherent difference between skin lesions and skin tissue, malignant and non-melanoma skin lesions are visually similar, and there are additional criteriato consider. Pathologists will surely benefit from the establishment of a robust and reliable detection technique for skin malignancies, such as system that can continuously assess skin lesions. This is especially important at a time when knowledge is limited. Furthermore, using such automated diagnostic technologies can dramatically reduce skin cancer mortality,which benefits both the healthcare system and patients.

There are many classic machine learning algorithms which estimates and performs skin cancer classification. But these methods are useless in clinical practise for complex diagnostic needs. Typically, conventional machine learning approaches for skin cancer detection which require collecting properties from skin-disease photos and then categorising the collected features. When working with high-resolution photos with millions of pixels, deep learning model frequently result in considerable computing expenses and extra training time. In addition to that, numerous sounds will be produced as aconsequence of the diverse settings. As a result, the consistency and generalization capacity of these methods must also be considered. There have been a number of studies detailing advancements in the classification of skin cancer, have specifically analysed the frontier challenges in the classification of melanomas, such as the domain adaptation, data imbalance and limitation efficiency ofmodel, and model robustness.

The Section II outlines the general methodology followed in skin cancer detection and Section III provides an examination of related works on skin disease detection. Section IV encapsulates the findings of the study.

II. DESIGN FLOW

Dermoscopy is a non-invasive skin visualisation method thatuses optical magnification. Human vision diagnosis, on the other hand, is rather subjective, lacking in precision and repeatability. Subjectivity is not a restriction of computerized dermoscopy image analysis systems. These methods enable to employ a software like an independent variable diagnostic approach, which might be utilized for pre-screening patients by inexperienced operators and assisting professionals.

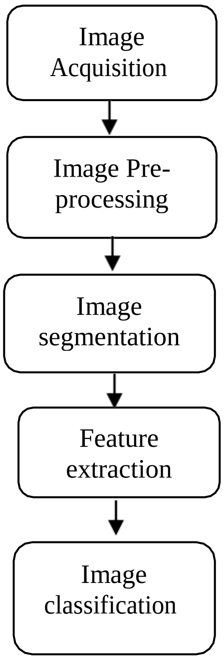

Fig. 1: Methodology Block Diagram

A rich feature set that can be retrieved from the source images must be defined. The gathering of suspicious skin pictures is the first step in the cancer detection technique. Feature extraction is a pre-processing procedure in which gathered information is cleaned and formatted and Cancer detection can be accomplished using a machine learning or deep learning classification methods. Different algorithms and methods will be used and the results are compared in each and every stage.

III. LITERATURE REVIEW

Hossam and Asmaa [1] their study specifies, a threshold- based automatic approach named sparrow search algorithm (SpaSA) which is utilized for detection, classification, and segmentation. To fulfil this task many deep and machine learning architectures and algorithms have been presented. Support vector machines, recurrent neural networks, fuzzy C-means and deep neural networks are examples of segmentation methods. This paper majorly contributed on presenting the taxonomy of skin diseases and segmentation techniques such as U-Net, swin U-Net and U-Net++ etc. andalso emphasis on the classification techniques and hyperparameter optimization process. Furthermore, dataset collection, pre-processing, segmentation phase, learning and optimization, are discussed. Additionally, the research madethe case that it is crucial to detect early signs of new skin growth, a suspicious change in an already-existing mole or nevi, and a sore that doesn't heal within two weeks. There is a guide to the common melanoma symptoms known as the ‘‘ABCDE’’ rule. where A is for asymmetry, B is for border, C is for color, D is for diameter and E is for evolving.

Gray level co-occurrence matrix was used to extract texture features, energy, entropy, contrast and inverse difference moment from segmented images. A fuzzy clustering algorithm was used to extract features from the input images, and Gabor filters were used to extract features like size, color, and texture. Additionally, previously used deep learning models that indicated accuracy and the dice coefficient were reviewed.

The data set summary used is represented in the table 1.1 shown below

Dataset	**Images**
ISIC 2019/2020	25,331 -2019 11,449 - 2020
HAM10000	10, 015
Images of Skin diseases	27, 153
Images of Skin cancer segmentation,classification	10, 015

Dataset with scripting language python and python packages such as tensorflow, keras-unet-collection, keras, NumPy, Scikit-Learn, OpenCV, Pandas, SciPy, and Matplotlib and optimization environment with the help of Google Colab and Intel(R) Xeon(R) CPU at 2.00 GHz, Tesla T4 16 GB GPU with CUDA v.11.2, and 12 GB RAM the following outcomes were attained. The U-Net++ model with DenseNet201 as the support provided the best results for the "Skin cancer segmentation and classification" dataset in terms of loss, IoU, AUC, F1-score, accuracy, and Dice values. The best model in terms of AUC value, however, was the attention U-Net model. Regarding the "PH2" dataset, the attention U-Net using DenseNet201 as a foundation was the best model in terms of loss, F1, IoU, accuracy, and dice values. The "Swin U-Net" model, however, performs the best in terms of specificity, accuracy, and squared hinge values. The greatest reported overall accuracy from the applied CNN trials is 98.83% by the MobileNet pre-trained model for the " HAM10K" dataset.

The goal of future research is to improve the performance of the skin cancer segmentation phase while also evaluating thesystem with more datasets that will become accessible.

Yinhao Wu, Bin Chen et.al [2] proposed a detection and prediction of skin cancer and have used a created PH2 dataset to aid in the development of segmentation and classification methods. It contains 200 dermoscopy color images of three types of skin diseases. PH2 is commonly used as a testing dataset skin disease detection algorithm. And also, some other data set includes, The MED- NODE Dataset3 collected by the Dermatology department of the UMCG, collection includes 170 digitized photos of melanoma and nevi cases. It comprises 10,015 dermoscopic photos of pigmented skin lesions with seven typical disorders, The Derm7pt dataset comprises around two thousand clinical and color dermoscopy pictures of skin diseases. The BCN200005 dataset, is part of an ISIC archive that includes over thirteen thousand representative dermoscopic images from clinical fraternities around the world.

The study provides an in-depth examination of the most current deep learning-based skin cancer categorization algorithms. Then, in the skin cancer classification of image as numerous frontier difficulties such as data imbalance, model robustness, data limitation, domain adaptability, and model efficiency, then follow related remedies. The bootstrap technique enables to arbitrarily choose the training pictures for the network and reduce the repetitions. Experiments revealed that this technique outperformed other techniques SVM. Then a basic CNN network was created to detect skin cancer. Input photos is pre-processed to remove noise. Then the process is fed to CNN model and finally, the results of the experiments revealed that CNN is efficient than other categorization methods.

Doaa Khalid et.al [3] have used a dataset for the study comprising images by ISIC, 2022. This dataset is classified as two categories: the benign and the malignant. Transfer learning networks are a type of machine learning in which a model developed for one task and is used for another. It is typically employed when a researcher lacks sufficient data to train on. However, the problem with the data may be solved by augmenting the data or providing new data. The fundamental reason for the requirement for transfer learning is because melanoma and benign lesions seem quite similar, making it difficult to identify them apart and categorize them.

Xception and MobileNetV2: The Xception architecture is an extension to the Inc architecture. In place of the traditional Inc modules, depth-separable convolutions are used. The Xception net records cross channel correlation. This net, like the Xception net, employs depth wise separable connections.

The deeper CNNs that employ skip connections include DenseNet121, ResNet50 and EfficientNet. The ResNet algorithm is based on two simple design ideas. For the same output map size, layers have an equal number of filters. DenseNet-121 is made up of four Average Pools and 120 Convolutions. Effective Net uses a mechanism known as compound coefficient to scale up models quickly and easily. Compound scaling, as opposed to random scaling, employs a predefined set of scaling factors to uniformly scale each dimension. The figure 3.1 diagrammatically depicts the suggested technique. Researchers have developed increasingly complex CNNs in recent years to better address computer vision difficulties. TensorFlow and a DL framework created by Google is utilized in this study.

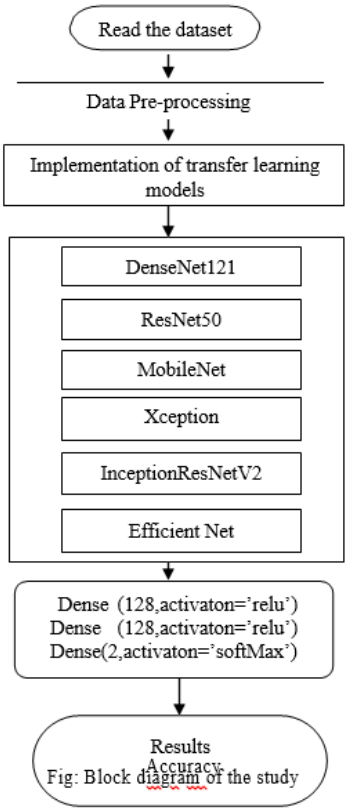

Fig. 2: depicts the suggested technique

In this discussion above, we used the precision, specificity, recall, and precision metrics to determine the score. The class of plus points and the class of minus points. The validity of the models was calculated using multiple equations and was compared.

Below Table 1 summary of the comparison of six models

Model	Accuracy (%)	Precision (%)	F1-score(%)	Specificity (%)
ResNet50	98.1	97.8	98.1	97.8
Xception	99.1	98	99	98.6
MobileNetV2	99.4	99.4	99.4	99.4
InceptionResNetV2	98.45	98.6	98.4	98.7
EfficientNet	98.5	98.7	98.5	98.75
DenseNet121 Model	99.6	99.7	99.5	99.7

Viswanatha Reddy Allugunti [4] used two different deep learning methods. Lesion Indexing Network and Lesion Feature Network. A deep learning method which uses two networks to obtain segmentation and classification results. Aheat map is used to deduce the lesion index calculation unit, which is then used to adjust the coarse classification findings. It is observed that a basic CNN can handle the limitations in retrieving dermoscopic characteristics. The author used ISIC 2017 dataset.

To train CNN, the author used a dataset, which is two orders of magnitude larger than the previous datasets, which had 2,032 pathologies.

A technique that uses transference learning and a Google Network that has already been trained was introduced by M.
A. Kassem and colleagues. For the ISIC 2019 Challenges Data Set, this methodology was developed. The proposed method is capable of accurately identifying all eight different types of lesions. The specificities, precision, sensitivity, and precision of the proposed techniques were evaluated, and their respective values were 97 percent, 94.92 percent, 79.8 percent, and 80.36 percent.

D. T. Mane, claim that customized CNN layers that display the network dynamics have been created. There are 80,000 possible Marathi numerals, however only 70,000 are utilized in classes, while the other 10,000 are only used in tests. Kfold cross validation was employed to evaluate the CNN's performance, and it achieved an accuracy rate of 94.93% on average for the test data sets. Using CNN that has been customized, high-level attributes can be derived from the images.

Table 2: Dataset description

Type	Number of images
Superficial spreading melanoma	936
Nodular melanoma	756
Lentigo maligna melanoma	783

Models were tested after they had been trained. The computation of the performance was done using the confusion matrix. Elements of the confusion matrix are used to imply both intended and actual classifications. Two classes correct and incorrect are produced as a result of the classification procedure. By examining the four key case studies listed below in order to calculate the prediction:

- The percentage of positives that are detected ismeant by the term "true positive".
- False negative indicate that they are described asbeing inaccurate.
- True negative measures the attacks and identifiesthe percentage of false positives.

CNN classifier's modular and hierarchical structure not only outperforms machine learning approaches, but it alsoreduces computing work necessary. One of the limitations isthat it is tested on a single dataset.

Walaa Gouda et.al [5] deep-learning approach, CNN was utilized in this study to recognize the two major types of skin cancers, malignant and benign, utilizing the ISIC-2018 dataset.The photographs were initially edited and enhanced with ESRGAN. During the preprocessing stage, the images were normalised, enhanced, and scaled. Skin lesion photographs might be diagnosed using a CNN approachbased on accumulation of results obtained over many iterations. Later, for fine-tuning, many transfer learning models were applied, including Inception Resnet, Resnet50, and InceptionV3.

The proposed technique proved successful in simulation using ISIC-2018 skin lesion dataset. The CNN model had anaccuracy rate of 83.2%, compared with Resnet50 - 83.7%, InceptionV3 - 85.8% and Inception Resnet - 84% models.

Augmentation

Upgraded pictures with accompanying masks such as brightness, rotation, shifting, reflection, and scaling were created for each image in the collection. The low quality of raw lesion pictures provided by electronic detectors limits detection and evaluation. There were 1440 benign and 1197 malignant training photos in all. Following augmentation, there were 1760 benign and 1773 malignant pictures. Oversampling on the malicious pictures was used to correct the uneven distribution of classes.The result of the picture augmentation procedure after various augmentation settings have been applied.

Data Preparation

Due to the small pixel dimensions of certain photos in the dataset, the image capture factor may vary and all images will need to be scaled. This can drastically change the brightness and size of the image. Each acquisition techniquehas its own criteria, so a collection of lesion images can contain a wide range of images. To ensure that the data wereconsistent and free of noise, the pixel intensities of all photographs within the range were standardized [1, 1]. Normalizing with the equation made the model lesssensitive to small changes in body weight and could beimproved. Image, Minimum, Normalize, and Maximum are represented by Inorm, MaxI, and MinI, respectively.

To demonstrate the performance of the proposed DL system and compare the results with the existing state-of-the-art, they performed parameter tuning and experimental metrics simulations using the ISIC-2018 dataset. The recommended training set was an 80% randomized array of lesion pictures. This set was used for all testing. Throughout the learning phase, 10% of the data was utilized for verification. Load pairs with the highest accuracy values were kept. The Adam optimizer was used to pre-train the proposed architecture on the ISIC-2018 dataset. It applies a learning rate approach that reduces the case where learning remains static over longperiods of time.

Devised a technique for swiftly and correctly identifying both benign and malignant kinds of cancer by evaluating photographs of skin lesions. The proposed method employs image enhancing techniques to increase the brightness of the lesion picture and eliminate noise. To minimise overfitting and overall functionality of the recommended Deep learning. Resnet Inception and Resnet50, InceptionV3, weretrained on the top edge of pre-processed medical images of lesions. The performance of the proposed system was evaluated using the ISIC-2018 lesion image dataset. The Inception model has accuracy rate (85.7%) in the suggested technique. This study's originality and contribution include the use of ESRGAN as a pre-processing phase.

M. Krishna Monika et.al [6] The dull razor approach is used to terminate all unwanted hair particles from the skin lesion, followed by the Gaussian filter for picture smoothing. The Median filter is used for preserving and noise filtering the lesion's margins. Because color is a key factor in determining the kind of malignancy, color based k means clustering is used during the segmentation phase. Asymmetry, Border, Color, Diameter, and Gray Level Cooccurrence Matrix are used to extract statistical and textural features. The experimental study is carried out using the ISIC-2019. Multi class Support Vector Machine was used for classification, and the accuracy is around 96.25%.

The suggested method makes use of a dataset made up of high-resolution dermoscopic pictures.In numerous ways, the picture capture process must be non-uniform. Thus, the primary purpose of the preprocessing stage is to improve picture attributes like quality, clarity, and so on by deleting or minimizing undesired components of the image or backdrop. picture enhancement, Grayscale conversion, and noise reduction are the key phases in preprocessing. In this suggested approach, all photos are first transformed to grayscale. Then, for picture improvement and noise reduction, two filters Gaussian filter and the median filter are utilized.

The Dull Razor Method is used in conjunction with filters toremove unwanted hair from skin lesions. Picture enhancement aims to improve image quality by improving visibility. Most skin lesions are composed of body hair, which might be an impediment to attaining high accuracy during categorization. So, in order to eliminate the undesirable hair from the photos, the dull razor procedure is utilized. The Dull Razor approach primarily accomplishes the following tasks. It detects the position of a hairs on the skin lesion by applying the grayscale morphological operation. After detecting the position of the hair pixel, it checks the form as either lengthy or thin architecture and then replaces that hair pixel by utilizing bilinear interpolation. Finally, it smoothens the substituted hair pixelusing the adaptive median filter.

Clustering methods are classified as unsupervised algorithms, yet they are comparable to classification of algorithms.These are mostly utilized with unlabeled data. The essential phases in this technique are as follows:

a) choosing the number of clusters
b) Selection of a random k-point and can be considered as centroids.
c) Assigning each data point to the closest centroidfor the construction of clusters.
d) Assigning the data points to the new nearest centroid again. If any reassignments is required, continue the operation until the value k is reached

Texture characteristics are categorized as first, second, or third order in statistical texture analysis. The findings are obtained at various locations of the photos in relation to one other. The GLCM approach is a technique for obtaining statistical texture properties of second order. The computation is carried out by GLCM by taking into account two pixels at a time, known as the reference and surrounding pixels. It is described using a matrix, where the number of grey levels in a picture is equal to the number of rows and columns.

MSVM is a component of the Support Vector Machine that is used to solve multiclass issues. SVM is a fairly exact implementation approach. SVM is based on the decision planes idea, which divides things into multiple classes. It establishes the capability control and so determines the decision bounds.

Several variables are contributing to a rise in the global rate of skin cancer incidents. As a result, early diagnosis is critical in both detection and treatment. Thus, this study describes a strategy based on the MSVM classification, which employs two successful approaches for feature extraction known as ABCD and MSVM. The attained accuracy is around 96.25%. The suggested approach classifies skin tumours using eight different categories in order to achieve high accuracy and precision.

Vijayalakshmi M M [7] The approach of removing noiseand then feature extraction is used in this work. The image is passed into the after noise removal classifier for the disease prediction process and additional feature extraction. The majority of earlier articles concentrated on feature extraction before moving on to illness prediction.The use of computer vision techniques has been extensively discussed in earlier publications. It is clear that the publishers have used image processing methods to complete the preliminary assignment.

The model is divided in three phases:

Phase-1: Dataset collection for the 1st model is done bygathering photos from the ISIC dataset. Also includes preprocessing the photos, which entails removing hair, glare, and shading.

Phase-2: consists of segmentation and feature extraction, with three different approaches of segmentation being investigated. A, B, and C are the three Otsu segmentation methods, while D is the water shed segmentation method. Color, shape, size, and texture are extracted as features.

Phase-3: they have trained their model, SVM, Back Propagation Algorithm, and CNN on the dataset that was collected, then model was tested.

Architecture:

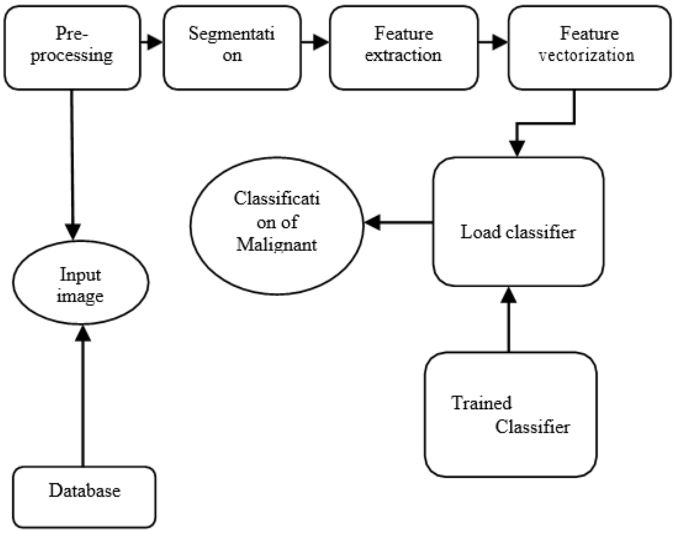

Fig. 3: ArchitectureNeural Networks :

When designing a neural network, we do not know the accuracy of the weights. So if the model errors out on large values, give it random weights first. Therefore, you should change the value to minimize the error value using back propagation algorithm.

- Minimum Error – Checks if errors are minimized
- Update the parameters – Update the parameters if the error is too large. Then check for errors again.
- Once the error is minimized, the model can begiven some inputs and then outputs will begenerated.

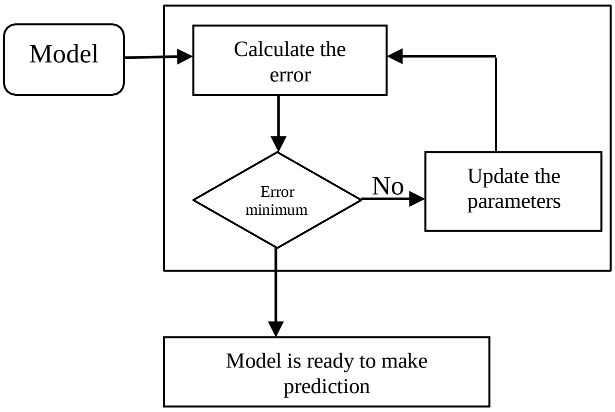

Fig. 4: Neural network

Support Vector Machine:

SVM is an algorithm mainly used to classify data into different classes. SVM uses hyperplanes that act like decision boundaries between different classes.

Convolution Neural Network:
CNNs are class of neural networks that is the artificial neural network (ANN),it is also referred as ConvNet or CNN, most commonly used to analyze the visuals of images, which is used in this setup.

Li-sheng Wei et.al [8] The proposed methodology to skincancer recognition.
(1) Processing
(2) Feature extraction
(3) Classification

The identification of skin diseases.Image processing:
In this work, three prevalent skin conditions paederal dermatitis, herpes, and psoriasis are chosen as the primary research objects.

First, because noise constantly has a negative effect on the source images used to gather samples of the skin epidermis, median filtering is required to denoise the images in order to lessen the effect that irrelevant background has on skin segmentation and identification. A common technique for removing "salt-and-pepper" noise from an image is to usethe +e median filter.

The primary principle of the median filter algorithm is to iteratively replace each grey value in the signal with the median of its nearby grey values. The "window" slides over the entire signal, grey value by grey value, and is referred to as a pattern of neighbors. The original photographs are denoised and their characteristics are improved using the median filtering technique.
where height and width each represent height and width of the original image, while height(new) and width(new) refer to height and width of the rotated image and θ is the angle needing rotating.
The corresponding coordinates of image is$(x_0 - x_{\square 1}) = (x_1 - x_{\square 2}) \times \cos\theta - (y_1 - y_{\square 2}) \times \sin\theta$ $(y_0 - y_{\square 1}) =$
$(x_1 - x_{\square 2}) \times \sin\theta - (y_1 - y_{\square 2}) \times \cos\theta$
where $x_{\square 1}$ and $y_{\square 1}$ are the center coordinates of the original image, $x_{\square 2}$ and $y_{\square 2}$ are those of the modified image; x_0 and y_0 are the original coordinates, and x_1 and y_1 are transformed ones. Then, the sampling transformation image is processed using the above distance transformation, which is frequently used to transform binary images and also useful for theextraction of skeleton.

This study offers a strategy based on the MSVM classification, which employs two effective approaches for feature extraction known as ABCD and MSVM. The attained accuracy is around 96.25%. The suggested approach classifies skin tumors using eight different categories in order to achieve high accuracy and precision.

IV. CONCLUSION AND FUTURE WORK

In this paper, it can be observed that many work has already been established about the comparative study of different algorithm and methods applied in detection of various stages of skin cancer. But there is no mention about any handheld device as an end solution to the early diagnosis of skin cancer, still many algorithms and methods are yet to be tested on different hardware devices.

In future, a handheld, portable, easy to use hardware solution can be made as a commercial product and can assistas a primary opinion on the suspected skin lesion.

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