



Detection of Melanoma from Skin Images Using a Multiple Extraction and Support Vector Machine (SVM)

Sukanya S T¹, Dr. S. Jerine²

Research Scholar, Computer Applications, NICHE, Kumarakovil, India¹

Associate Professor, Software Engineering, NICHE, Kumarakovil, India²

Abstract: Digital Image Processing (DIP) plays an important role in the process of segmentation and classification of biomedical images. The detection of melanoma from skin images is the most widely used in biomedical imaging applications. In this paper, a new algorithm for the detection of melanoma from digital images using multiple extraction capabilities with a support vector machine (SVM) for very precise classification. To train SVM, more characteristics such as color, texture, and statistical characteristics are taken into account. To increase the sensitivity of the classification, feature extraction is performed in the RGB (red, green and blue) and HIS (hue, intensity, saturation) color domains. Two separate modules for training and testing are performed with sample data collected with the help of medical experts. To separate the skin region, a song-based segmentation technique is used in the gray scale component of the input image. The proposed method is tested with various images which are collected from different patients from different locations. From the validation of the result, it is clear that the proposed algorithm can provide a maximum precision of 95%, which is the best compared to conventional classification algorithms

Keywords: Melanoma, RGB, HIS, Support Vector Machine, Structural characteristic, Statistical characteristic.

I. INTRODUCTION

Cancer is a collection of diseases that includes unusual cell development with the possibility of attacking or spreading to different organs in the body. These present themselves differently from cancers of the good heart, which do not spread. Possible signs and side effects include a lump, strange death, delayed hacking, unexplained weight loss, and stool adjustment. While these side effects can manifest as cancer, they can have other causes as well. Over 100 types of cancer affect people. Skin cancer is the strange growth of skin cells. [1] It forms regularly on skin exposed to the sun. Regardless, this normal type of cancer can also occur on areas of the skin that are normally not exposed to daylight. There are three main types of skin cancer, basal cell carcinoma, squamous cell carcinoma and melanoma. Skin cancer mainly develops on the scalp, face, lips, ears, neck, chest, arms and hands, and on the legs in women. For example the palms of the hands, under the fingernails or toes and the genital area.

Skin cancer affects people of all skin tones, including those who have a darker appearance. By the time melanoma occurs in people with dark complexions, it is inevitable that it will occur in areas that are not usually exposed to the sun, such as the palms of the hands and the soles of the feet. Non-melanoma skin cancer responds constantly to treatment and sometimes spreads to other skin tissue. Melanoma is riskier than most of the different types of skin cancer. If not recognized early, it is quickly attacked by nearby tissues and spreads to different parts of the body. A formal determination strategy for the detection of skin cancer is the biopsy technique. [2] A biopsy is a technique to remove a piece of tissue or sample cells from the tolerant body so that it can be very well studied in a research facility. It is a clumsy strategy. The biopsy method is boring even for tolerant people like a specialist as it requires some investment for testing. A biopsy is completed by expelling skin tissue (skin cells) and this example is experimenting with the research facility's test arrangement. It is plausible to spread the disease to another part of the body. It's more dangerous. As the number of patients increases, it becomes more and more difficult for radiologists to complete the indicative procedure in the limited time available. The inspiration for this work is to help radiologists increase the speed of rapid and accurate detection of skin cancer using Deep Learning (DL)

Early detection of skin cancer is a basis for improving outcomes and is associated with 99% in general endurance (GE). %. However, with proper progress and reasonable evaluation, current electronic innovation could improve the accuracy of the demonstration. There is no doubt that the artificial intelligence (AI) algorithms that sort photos of lesions have recently been shown to be equipped to sort melanoma with a virtually identical degree of skill as dermatologists.



For some time now, the question of the characterization of skin diseases has also been at the center of the concerns of the group of people with artificial intelligence. Robotic ulcer placement can both aid clinicians in their daily clinical schedule and enable fast, modest, and life-saving access to analysis, even outside of the doctor's office, by creating apps on mobile phones. [4] Prior to 2016, generally continued to examine the old-fashioned AI work process: pre-processing, segmentation, feature extraction, and ranking. Either way, a high level of explicit user skill is required, especially for feature extraction, and determining sufficient features is very tedious. [5] Similarly, errors and data loss in the main phases of management affect the quality of the arrangement. For example, a poor segmentation result regularly requires poor results in feature extraction and, therefore, low clustering accuracy.

Considering each of the above mentioned cases, recognition of skin cancer using SVM is proposed. This procedure uses an advanced method of handling images and SVM for grouping. [6] This procedure has boosted the early identification of skin cancers and does not require the application of oil to the skin to obtain clear, crisp images of moles. In that sense, it's also a faster and cleaner approach. Anyway, mainly due to its greater amplification, detecting skin cancer using SVM can prevent unnecessary removal of beautifully harmless moles and skin lesions. The remainder of the article is organized as follows: Section II examines related work. Section III explains the proposed segmentation model. Section IV presents a detailed analysis of the results. Section V concludes the work

II. RELATED WORKS

Ho Tak Lau, Adel Al-Jumaily proposed an Automatically Early Detection of Skin Cancer Study Based on Neural Network Classification, in which, an automatically skin cancer characterization framework is created and the relationship of skin cancer image crosswise over various kind of neural network are contemplated with various kinds of preprocessing. The gathered images are feed into the framework, and crosswise over various image handling strategy to improve the image properties. [7] At that point the normal skin is removed from the skin affected area and the cancer cell is left in the image. Valuable data can be separated from these images and pass to the classification system for training and testing. The recognition accuracy of the 3- layers back- propagation neural network classifier is 89.9% furthermore, the auto-associative neural network is 80.8% in the image database that incorporates dermoscopy photograph and a digital photograph

Mahmoud Elgamal proposed an automatic skin cancer images classification technique, the basic concept is similar to the previously mentioned study, the difference is which includes three stages, namely, feature extraction, dimensionality reduction, and classification. In the first stage, we have gotten the features related to images utilizing discrete wavelet transformation. In the subsequent stage, the highlights of skin images have been decreased using principal component analysis to the more essential features. In the classification stage, based on supervised machine learning has been developed. The primary classifier based on feed-forward back-propagation artificial neural network and the subsequent classifier dependent on a k-closest neighbor. [8] The classifiers have been utilized to classify subjects as normal or abnormal skin cancer images. Order with an achievement of 93% also, 93.5% has been gotten by the two proposed classifiers and respectively.

There is a proposal on Methodology for diagnosing skin cancer on images of dermatologic spots by spectral analysis was by Esperanza Guerra-Rosas and Josué Álvarez-Borrego. This depends on utilizing Fourier spectral analysis by using filters such as the classic, inverse and k-law nonlinear. [9] The sample image was acquired by a quantitative measurement and another spectral technique is created to acquire a quantitative estimation of the complex pattern found in cancerous skin spots. At long last, a spectral index is determined to get a range of spectral indices characterized by skin malignant growth. The result will appear atan accuracy level of 94.5%.

A new advanced method on Detection and Analysis of Skin Cancer from Skin Lesions was proposed by Nidhal K. [10] EL Abbadi and 2Zahraa Faisal images are filtered to remove undesirable particles, at that point another technique for programmed segmentation of lesion territory is done dependent on Markov and Laplace filter to identify lesion edge, trailed by convert picture to YUV shading space, U channel will be processed to remove thick hair and concentrate lesion region. Finding skin cancer accomplished by utilizing ABCD rules with a new strategy for deciding asymmetry dependent on the rotation of lesion and divide lesion to two sections horizontally and vertically at that point check the number of pixels confounded between the two sections based on union and intersection between the two parts. A new strategy to decide the quantity of the number of colors based on the suggestion of color regions for each color shade was suggested in this paper.

A Deep learning-based skin lesion diagnosis was proposed by D.A. Gavrilov, N.N. Shchelkunov, A.V. Melerzanov. State-of-the-art solutions in the field of image processing and machine learning allow creating intelligent



systems based on artificial convolutional neural network exceeding human's rates in the field of object classification, including the case of malignant skin lesions. [11] This proposal presents an algorithm for the early melanoma diagnosis based on artificial deep convolutional neural networks. The algorithm proposed allows reaching the classification accuracy of melanoma at least 91%.

An innovative study on Automating Skin Disease Diagnosis Using Image Classification was conducted by Damilola A. Okuboyejo, Oludayo O. Olugbara, and Solomon A. [12]Odunaike. Which focused on designing and modeling a system that will collate past Pigmented Skin Lesion (PSL) image results, their analysis, corresponding observations and conclusions by medical experts using prototyping methodology? The information will be used as a library. A part of the system would use computational intelligence techniques to analyse, process, and classify the image library data based on texture and possibly morphological features of the images. Trained medical personnel in a remote location can use mobile data acquisition devices (such as cell phone) to generate images of PSL, supply such images as input to the proposed system, which in turns should intelligently be able to specify the malignancy (life-threatening) or benign (non-threatening) status of the imaged PSL.

Automated detection of non-melanoma skin cancer using digital images mainly based on Computer-aided diagnosis, but its application to non-melanoma skin cancer (NMSC) is relatively under-studied. The study by Arthur Marka, Joi B. Carter, Ermal Toto & Saeed Hassanpour is aiming to synthesize the research that has been conducted on automated detection of NMSC using digital images and to assess the quality of evidence for the diagnostic accuracy of these technologies. [13] The method follows Eight databases were searched to identify diagnostic studies of NMSC using image-based machine learning models. Two reviewers independently screened eligible articles. The level of evidence of each study was evaluated using a five-tier rating system, and the applicability and risk of bias of each study were assessed using the Quality Assessment of Diagnostic Accuracy Studies tool.

III. PROPOSED SYSTEM

The proposed system has two phases namely the Training and testing phase. In the training phase, the images are undergoing several steps they are normalization, image enhancement, image segmentation, and feature extraction. Fig.1 shows the proposed system.

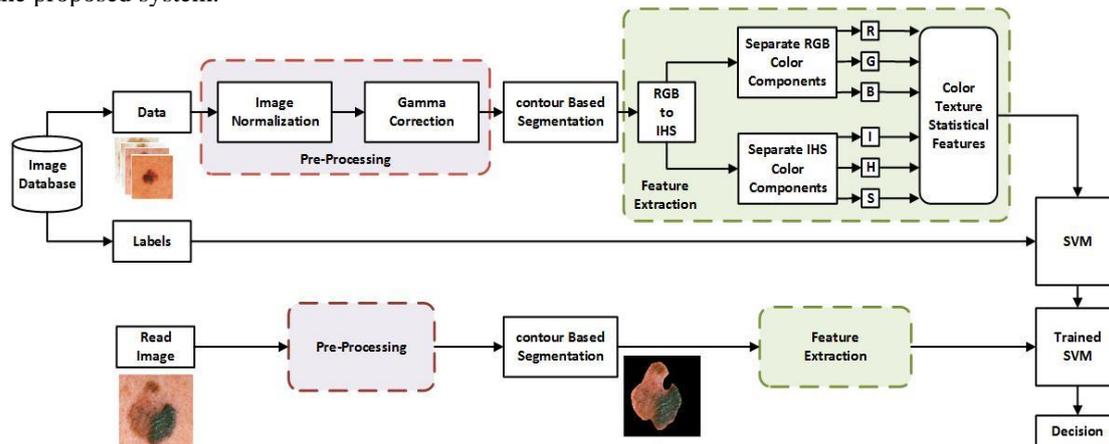


Fig.1. Block Diagram

A. Preprocessing

In image processing, standardization is a procedure that changes the extent of pixel intensity. Standardization is in some cases called differentiate extending or histogram extending. In increasingly broad fields of information handling, for example, computerized signal preparing, it is referred to as powerful range expansion. The motivation behind powerful range extension in the different applications is, for the most part, to bring the picture, or another kind of sign, into a range that is increasingly natural or typical to the faculties, henceforth the term standardization. Frequently, the inspiration is to accomplish consistency in a powerful range for a lot of information, flag, or pictures to stay away from mental interruption or exhaustion. [14] For instance, a paper will endeavor to make the entirety of the pictures in an issue share a comparative scope of grayscale.

Normalization convert k dimensional gray image $P: \{M \in F^i\} \rightarrow \{J, \dots, K\}$ with intensity values into a new image $P_{new} : \{M \in F^i\} \rightarrow \{J_{new} \dots \dots, K_{new}\}$.



The linear normalization of a gray image is given by the following formula.

$$P_{new} = (P - J) \frac{K_{new} - J_{new}}{K - J} \tag{1}$$

a. Gamma Correction

Gamma correction, or regularly basically gamma, is a nonlinear activity used to encode and interpret luminance or tristimulus values in video or still picture systems. [14] Gamma correction is, in the least complex cases, characterized by the accompanying force law articulation:

$$I_{out} = KI_{in}^{\gamma} \tag{2}$$

Where, the non-negative genuine info esteem I_{in} is raised to the poweryand duplicated by the consistent K , to get the yield esteem I_{out} . In the regular instance of $K = 1$, information sources and yields are commonly in the range 0–1.

b. Contour Based Segmentation

An active contour or snake is a curve defined in an image that is allowed to change its location and shape until it best satisfies predefined conditions. It can be used to segment an object by letting it settle much like a constricting snake around the object boundary. A snake C is usually modeled as a parameterized curve $C(s) = (x(s), y(s))$, where the parameter s varies from 0 to 1. So, $C(0)$ gives the coordinate pair $(x(0), y(0))$ of the starting point, $C(1)$ gives the end coordinates, and $C(s)$ with $0 < s < 1$ gives all intermediate point coordinates. The movement of the snake is modeled as an energy minimization process, where the total energy E to be minimized consists of three terms:

$$E = \int E(C(s)) ds \tag{3}$$

$$= \int E_i(C(s)) + E_e(C(s)) + E_c(C(s)) ds$$

The term E_i is based on the internal forces of the snake; it increases if the snake is stretched or bent. The term E_e is based on external forces; it decreases if the snake moves closer to a part of the image, we wish it to move to. For example, if we wish the snake to move to edges, we may base this energy term on edginess values. [15] The last term E_c can be used to impose additional constraints, such as penalizing the creation of loops in the snake, penalizing moving too far away from the initial position, or penalizing moving into an undesired image region. For many applications, E_c is not used, i.e., simply set to zero. Common definitions for the internal and external terms are:

$$E_i = c_1 \left\| \frac{dc(s)}{ds} \right\|^2 + c_2 \left\| \frac{d^2c(s)}{ds^2} \right\|^2 \tag{4}$$

$$= -c_3 \|\nabla f\|^2$$

Where the external term is based on the assumption that the snake should be attracted to edges of the original image f . By using other external terms, we can make use of different image features, making the snake follow ridges, find corner points, etc. The constants c_1 , c_2 , and c_3 determine the relative influence of each term on the movement of the snake. [15] Fig.2 shows the object image and snake evaluation towards the object. The first one shows the initial snake position and in further images shows the further evaluation of snake towards object boundary. In the last image snake completely tracks the object boundary which gives the shape of the object perfectly.

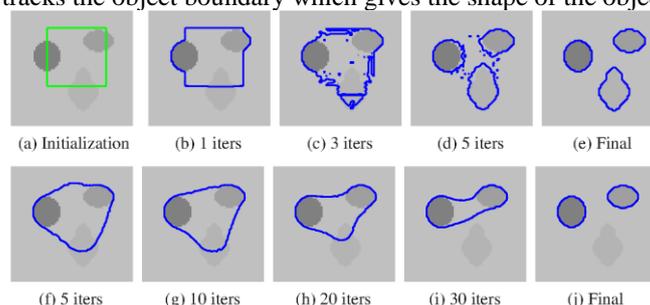


Fig 2. Contour Based Segmentation



c. IHS Color Feature

The Intensity-Hue-Saturation (IHS) transformation decouples the intensity information from the color carrying information. The hue attribute describes a pure color and saturation gives the degree to which pure color is diluted by white light. This transformation permits the separation of spatial information into one single intensity band. There are different models of IHS transformation. The models differ in the method used to compute the intensity value. Smith's hexacore and triangular models are two of the more widely used models. The hue and saturation values are computed based on a set of complex equations.

While converting color from RGB to IHS following transform is used.

$$\begin{bmatrix} I \\ V_1 \\ V_2 \end{bmatrix} = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ -1/\sqrt{6} & -1/\sqrt{6} & 2/\sqrt{6} \\ 1/\sqrt{6} & -2/\sqrt{6} & 0 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (5)$$

$$S = \sqrt{V_1 + V_2} \quad (6)$$

$$H = \tan^{-1} \left(\frac{V_2}{V_1} \right) \quad (7)$$

The advantage of the IHS is that large volumes of data can be processed quickly and sharp images are generated. The disadvantage is that it might result in a spectral distortion from the original multispectral image.

d. Color feature

Color is a significant and the most straight-forward element that people see when seeing a picture. The human vision framework is progressively delicate to color data than dim dimensions so the color is the primary competitor utilized for highlight extraction. A color histogram is one normal technique used to speak to the color substance.

RGB color space is the most widely recognized one utilized for pictures on PC since the PC show is utilizing the mix of the essential colors (red, green, blue) to show any apparent color. Every pixel on the screen is made out of three which is animated by red, green and blue electron gun independently. [16].

In any case, RGB space isn't perceptually uniform so the color separate in RGB color space does not compare to color divergence in observation. [19] Along these lines we like to change picture information in RGB color space to other perceptual uniform space before highlight extraction. In our method, the RGB components of the image are extracted separately.

B. Texture Feature

a. Local Binary Patterns (LBP):

LBP is a sort of visual descriptor utilized for characterization in PC vision. LBP operator is frequently utilized to the grayscale picture, where a code is performed for every pixel. But in our proposed system the LBP operator is used for color image for that initially the R, G and B component of the image is extracted separately and stored in a matrix after that the LBP is applied to the R, G, and B components separately. For instance, when thinking about a cell of 3x3 pixels, the focal pixel is looked at to neighbor pixels. Any order of pixels is conceded, be that as it may, thus the begin is the upper left pixel, when utilizing clock-wise course. In the event that the estimation of the center pixel is littler than or on the other hand equivalent to the estimation of the neighbor then an "1" will be taken into the record, generally a "0" is considered. [17] [19] The resulted value is a binary number that is associated with a pattern. A weight is doled out to every digit of the got double number and a comparing thing can be determined.

b. Compound Local Binary Pattern (CLBP)

The original LBP operator discards the magnitude information of the difference between the center and the neighbor gray values in a local neighborhood. As a result, this method tends to produce inconsistent codes. [18] One example is shown in Figure 3. Here, the 8-bit uniform LBP code (11111111) corresponds to a flat area or a dark spot at the center pixel [16], which is not correct in this case. As the LBP operator considers only the sign of the difference between two gray values, it often fails to generate appropriate binary code. Being motivated by this, we propose CLBP, an extension of the original LBP operator that assigns a 2P-bit code to the center pixel based on the gray values of a local neighborhood comprising P neighbors. Unlike the LBP that employs one bit for each neighbor to express only the sign of the difference between the center and the corresponding neighbor gray values, the proposed method uses two bits for each neighbor in order to represent the sign as well as the magnitude information of the difference between the



center and the neighbor gray values. Here, the first bit represents the sign of the difference between the center and the corresponding neighbor gray values like the basic LBP pattern and the other bit is used to encode the magnitude of the difference with respect to a threshold value, the average magnitude (M_{avg}) of the difference between the center and the neighbor gray values in the local neighborhood of interest. [19] The CLBP operator sets this bit to 1 if the magnitude of the difference between the center and the corresponding neighbor is greater than the threshold M_{avg} . Otherwise, it is set to 0.

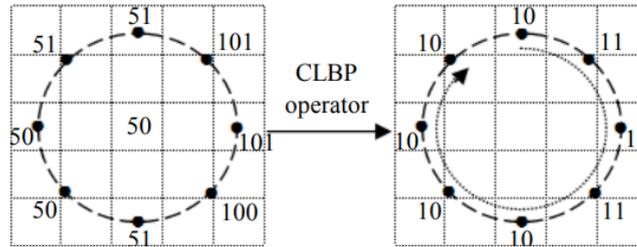


Fig 3. Illustration of the basic CLBP operator. Here, the generated CLBP code is 101111110101010.

Thus, the indicator $s(x)$ of (2) is replaced by the following function:

$$s(i_p, i_c) = \begin{cases} 00 & i_p = i_c < 0, |i_p - i_c| \leq M_{avg} \\ 01 & i_p = i_c < 0, |i_p - i_c| > M_{avg} \\ 10 & i_p = i_c \geq 0, |i_p - i_c| \leq M_{avg} \\ 11 & \text{Otherwise} \end{cases} \quad (8)$$

Here, i_c is the gray value of the center pixel i_p is the gray value of a neighbor, and M_{avg} is the average magnitude of the difference between i_p and i_c in the local neighborhood.

C. Statical Feature

a. Mean

Mean is the average of all pixels of an image. The arithmetic mean filter, otherwise called averaging filter, works on a sliding 'm×n' window by ascertaining the normal of all pixel esteems inside the window and supplanting the middle pixel esteem in the goal picture with the outcome. Its numerical definition is given as pursues as given by

$$MEAN = \frac{1}{mn} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j) [19] \quad (9)$$

b. Standard Deviation (Std):

It is the most widely used measure of variability or diversity used in statistics. As far as picture handling it indicates how much variety or "scattering" exists from the normal (mean, or anticipated esteem. [19] A low standard deviation demonstrates that the information directs incline toward being very near the mean, while elevated expectation deviation shows that the information calls attention to spread out over an enormous scope of qualities. Mathematically standard deviation is given by

$$\check{f} = \sqrt{\frac{1}{mn-1} \sum_{(r,c) \in W} \left(g(r,c) - \frac{1}{mn-1} \sum g(r,c) \right)^2} \quad (10)$$

A standard deviation filter calculates the standard deviation and assigns this value to the center pixel in the output map. As it has the capability in measuring the variability, it can be used in edge sharpening, as intensity level gets changes at the edge of the image by a large value. Standard deviation filters can be useful for radar images. The interpretation of radar images is often difficult: you cannot rely on spectral values because of backscatter (return of the pulse sent by the radar). This often causes a lot of 'noise'. By using a standard deviation filter, you may be able to recognize some patterns.



c. Variance

Variance is used to classify into different regions by calculating how each pixel varies from the neighboring pixel (or center pixel) and is used in classify into different regions. [19]

$$\text{VARINACE} = \frac{1}{MN} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i, j) - \bar{f}(i, j) \quad (11)$$

Where, $\bar{f}(i, j)$ is the mean of the image block

d. Kurtosis

$$\begin{aligned} \check{f}(x, y) & \quad (12) \\ &= \frac{\frac{1}{mn-1} \sum_{(r,c) \in W} \left(\frac{1}{mn-1} \sum_{(r,c) \in W} g(r, c) - \frac{1}{mn-1} \sum_{(r,c) \in W} g(r, c) \right)^4}{\frac{1}{mn-1} \sum_{(r,c) \in W} \left(\frac{1}{mn-1} \sum_{(r,c) \in W} g(r, c) - \frac{1}{mn-1} \sum_{(r,c) \in W} g(r, c) \right)^2} \end{aligned}$$

In statistics, kurtosis [9] is a measure of the shape of the probability distribution of a real-valued random variable. [14] It is closely related to the fourth moment of a distribution. A high kurtosis is distribution has longer, fatter tails, and often (but not always) a sharper peak. A low kurtosis distribution has shorter, thinner tails, and often (but not always) a more rounded peak. Mathematically kurtosis is given as follows

e. Support Vector Machine

In AI, SVM are coordinated learning models that ought to have related learning figuring should use the data and see structures for portrayal and backslide examination SVM can perform either straight or non-direct arrangement. Shows how basic leadership is performed in SVM. In supervised training, the preparation information comprises an arrangement of preparing cases, where every illustration is a couple comprising of information and expected yield esteem. [20] A regulated learning algorithm investigates the preparation information and after that predicts the right classification forgiven informational index input. For example, the teacher teaches the student to identify orange and lemon by giving some features of that. Next time when the student can see lemon or orange can easily classify the object based on his gaining from his educator, this is called directed learning.

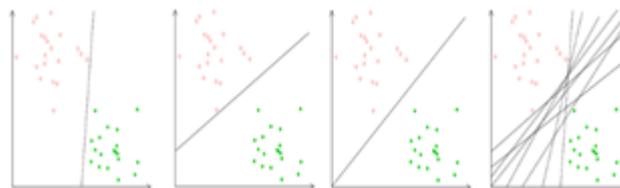


Fig 4. Support Vector Machine

One can perceive the article just if it is lemon or orange, yet if the given inquiry was grapes the understudy can't recognize it The Margin of a quick classifier has the width by which the length of the purpose of imprisonment can be reached out before hitting the information explanations behind a substitute course of action. The line is protected to pick having the most astounding edge between the two datasets. The information focuses which lie on the edge are called Support Vectors. The subsequent stage is to discover the hyperplane which best isolates the two classes.

SVM plays out this by taking an arrangement of focus and part them utilizing diverse application-particular scientific recipes. From that, we can locate positive and negative hyperplane. Fig 4. Shows how support vectors are represented in SVM. The numerical equation for discovering hyperplane is

$$(p, q) + r = +1(\text{positive labels}) \quad (13)$$

$$(p, q) + r = -1(\text{negative labels}) \quad (14)$$

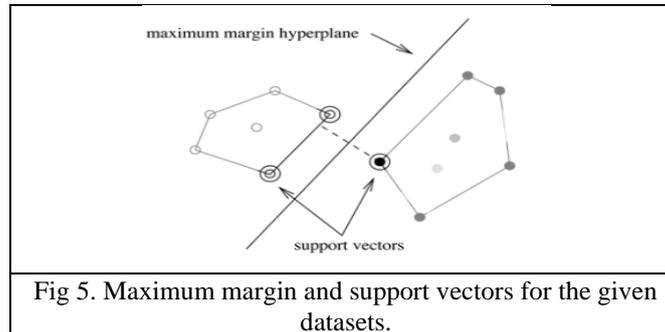
$$(p, q) + r = 0(\text{hyper labels}) \quad (15)$$

We can find the values of P and r using the above equation and linear algebra. Thus, we get the answers for p and r with a margin value of $2\sqrt{(k.k)}$. The margin is calculated as follow

$$\text{Margin} = 2/2\sqrt{(k.k)} \quad (16)$$



In SVM, this model to categorize new data. With the above functional solutions and calculated marginal value, new data can be categorized into a different category level. The following figure demonstrates the margin and SV for linearly separable data.



IV. RESULT AND DISCUSSION

The proposed skin cancer detection model is implemented in MATLAB 2019a in an i5 system with 4 GB RAM. In this work, we have used the PH² database. Performances of the model are measured in terms of Total Accuracy (TAcc), sensitivity (San), specificity (Spec), Positive Predicted Value (PPV) and Negative Predicted Value (NPV). For the analysis purpose, our method is analyzed with the existing methods. The resultant graphs with respect to detection performance are given below. Additionally, Fig 6 shows the sample images used in the Image retrieval model.

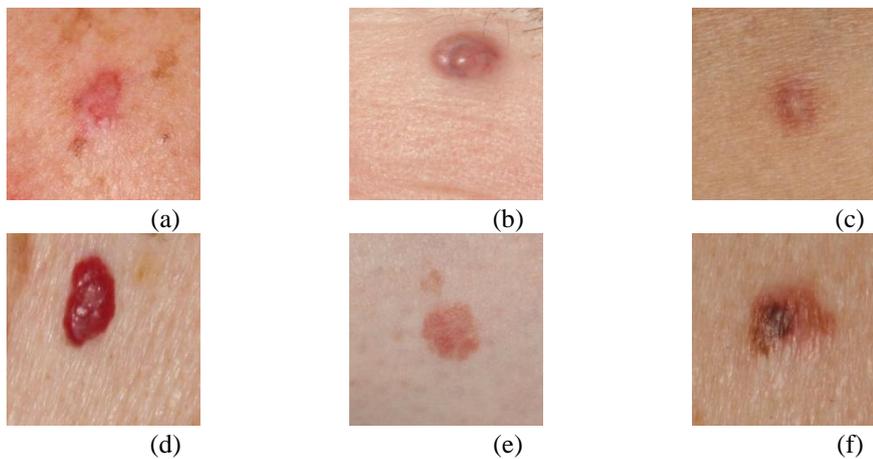


Fig 6. (a)-(f) Sample input images

A. Dataset

This image database contains a total of 200 dermoscopic images of melanocytic lesions, including 80 common nevi, 80 atypical nevi, and 40 melanomas. The PH² database includes medical annotation of all the images namely medical segmentation of the lesion, clinical and histological diagnosis and the assessment of several dermoscopic criteria. The assessment of each parameter was performed by an expert dermatologist.

B. Evaluation Metrics

a. Accuracy

Accuracy of a system is defined as the ratio between a number of correct predictions to the total number of predictions. Table –I show that the proposed system yields high accuracy rather than the other methods.

$$\text{Accuracy} = \frac{Tp + Tn}{(TP + TN + FP + FN)} \quad (17)$$

**b. Sensitivity**

Sensitivity is defined as the ability to respond to affective changes in the input data. From the table, it is clear that our proposed method has more sensitivity than the other existing methods.

$$\text{sensitivity} = \frac{T_p}{T_p + F_n} \quad (18)$$

c. Specificity

Specificity is defined as the ability of a system to correctly segment the images is called specificity. The proposed system produces the maximum specificity of 91.

$$\text{specificity} = \frac{T_n}{T_n + FP} \quad (19)$$

d. Positive predictive value

Positive predictive value is the probability that subjects with a positive screening test truly have the disease.

$$PPV = \frac{\text{number of True Positive}}{\text{number of Positive Calls}} \quad (20)$$

e. Negative predictive value

Negative predictive value is the probability that subjects with a negative screening test truly don't have the disease.

$$NPV = \frac{\text{number of True Negative}}{\text{number of Negative calls}} \quad (21)$$

C. Results

Color is the most important feature of the colored image, and when you deal with colored images to extract some information the image must be split the colored image according to its type of representation (e.g. RGB or HSV, etc.) to process the pixel intensity values. Fig.7. shows the separated Red Component (a), Green component (b), Blue Component (c) in RGB color space and Hue Component (d), Saturation component (e) and Intensity Component (f) in HIS color space.

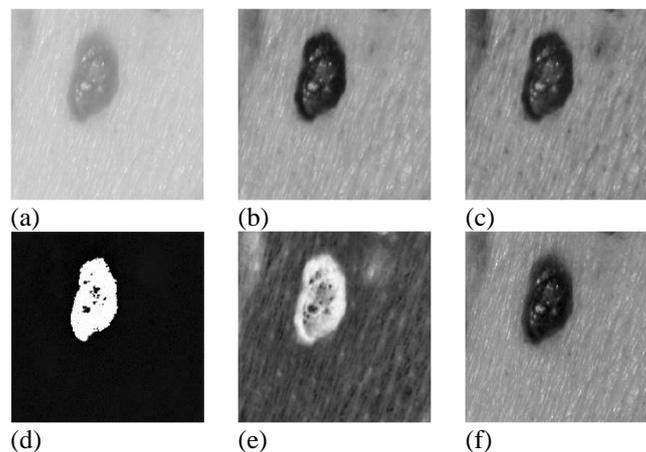


Fig 7. (a) Red Component, (b) Green component, (c) Blue Component, (d) Hue Component, (e) Saturation component, (f) Intensity Component

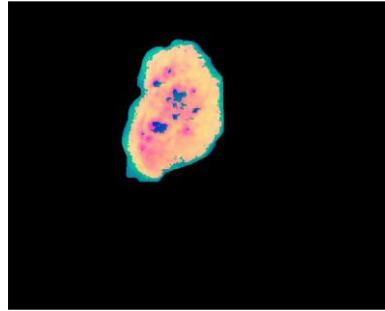


Fig 8. HIS color component of Segmented image

Table I. shows the segmentation performance of the proposed method for the input melanoma images our proposed method is compared with another existing method. Among all the method proposed method performs better than other methods. Fig.8. shows the segmented input images which have melanoma.

TABLE I. SEGMENTATION PERFORMANCE

Methods	Sen	Spec	PPV	NPV	Tacc
[20]	84	72	70	87	77
[31]	82	71	67	85	76
ANN	80	69	68	84	75
Prop	93	91	93	23	95

V. CONCLUSION

In this paper, a highly accurate Melanoma Detection and classification are performed by using multiple feature extraction and SVM classifier. The input image is preprocessed by using normalization to scale the image. Adaptive gamma correction is applied to improve the contrast of the image. Multiple feature extractions such as color, texture and statistical features are estimated to train the support vector machine. Training and testing are performed separately by using collected sample data. From the evaluation result, it is clear that the proposed algorithm obtained the highest accuracy of 95% percentage it is higher when compared to the conventional algorithms.

REFERENCES

- [1]. Habif TP. Premalignant and malignant nonmelanoma skin tumors. In: Clinical Dermatology: A Color Guide to Diagnosis and Therapy. 6thed. St. Louis, Mo.: Saunders Elsevier; 2016
- [2]. Niederhuber JE, et al., eds. Melanoma. In: Abeloff's Clinical Oncology.
- [3]. 5th ed. Philadelphia, Pa.: Churchill Livingstone Elsevier; 2014.
- [4]. Alfred, Naser, and Fouad Khelifi. "Bagged textural and color features for melanoma skin cancer detection in dermoscopic and standard images." Expert Systems with Applications 90 (2017): 101-110.
- [5]. Maron, Roman C., Michael Weichenthal, Jochen S. Utikal, Achim Hekler, Carola Berking, Axel Hauschild, Alexander H. Enk et al. "Systematic outperformance of 112 dermatologists in multiclass skincancer image classification by convolutional neural networks." European Journal of Cancer 119 (2019): 57-65.
- [6]. Tan, Teck Yan, Li Zhang, Siew Chin Neoh, and Chee Peng Lim. "Intelligent skin cancer detection using enhanced particle swarm optimization." Knowledge-Based Systems 158 (2018): 118-135.
- [7]. Kaur, Prabhpreet, Gurvinder Singh, and Parminder Kaur. "Intellectual detection and validation of automated mammogram breast cancer images by multi-class SVM using deep learning classification." Informatics in Medicine Unlocked (2019): 100151.
- [8]. Automatically Early Detection of Skin Cancer: Study Based on Neural Network Classification Ho Tak Lau, Adel Al-Jum
- [9]. Mahmoud Elgamal, AUTOMATIC SKIN CANCER IMAGES CLASSIFICATION, (IJACSA) International Journal of Advanced Computer Science and Applications, Vol. 4, No. 3, 2013
- [10]. Esperanza Guerra-Rosas¹, and Josué Álvarez-Borrego³, Methodology for diagnosing of skin cancer on images of dermatologic spots by spectral analysis
- [11]. Nidhal K. EL Abbadi and Zahraa Faisal, Detection and Analysis of Skin Cancer from Skin Lesions, International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 19 (2017) pp. 9046-9052
- [12]. DEEP LEARNING BASED SKIN LESIONS DIAGNOSIS, D.A. Gavrilov ^{1*}, N.N. Shchelkunov ¹, A.V. Melerzanov ¹ The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XLII-2/W12, 2019 Int. Worksh. on "Photogrammetric & Computer Vision Techniques for Video Surveillance, Biometrics and Biomedicine", 13–15 May 2019, Moscow, Russia
- [13]. Damilola A. Okuboyejo, Oludayo O. Olugbara, and Solomon A. Odunaike, Automating Skin Disease Diagnosis Using Image Classification, Proceedings of the World Congress on Engineering and Computer Science 2013 Vol II WCECS 2013, 23-25 October, 2013, San Francisco, USA
- [14]. Arthur Marka, Joi B. Carter, Ermal Toto & Saeed Hassanpour Automated detection of nonmelanoma skin cancer using digital images: a systematic review <https://bmcmimedimaging.biomedcentral.com/articles/10.1186/s12880-019-0307-7>
- [15]. Lee, Dong-U., Ray CC Cheung, and John D. Villasenor. "A flexible architecture for precise gamma correction." IEEE Transactions on Very Large-Scale Integration (VLSI) Systems 15, no. 4 (2007): 474-478.



- [16]. Caselles, Vicent, Francine Catté, Tomeu Coll, and Françoise Dibos. "A geometric model for active contours in image processing." *Numerische mathematik* 66, no. 1 (1993): 1-31.
- [17]. Barbu, T. U. D. O. R., A. D. R. I. A. N. Ciobanu, and M. I. H. A. E. L. A. Costin. "Unsupervised color-based image recognition using a LAB feature extraction technique." *Buletinul Institutului Politehnic Iași, Universitatea Tehnică "Gheorghe Asachi 57* (2011): 33-41.
- [18]. Vatamanu, Oana Astrid, et al. "Content-based image retrieval using local binary pattern, intensity histogram and color coherence vector." 2013 E-Health and Bioengineering Conference (EHB). IEEE, 2013.
- [19]. Sliti, Oumaima, Habib Hamam, and Hamid Amiri. "CLBP for scale and orientation adaptive mean shift tracking." *Journal of King Saud University-Computer and Information Sciences* 30.3 (2018): 416-429.
- [20]. Hlaing, Chit Su, and Sai Maung Maung Zaw. "Tomato Plant Diseases Classification Using Statistical Texture Feature and Color Feature." In 2018 IEEE/ACIS 17th International Conference on Computer and Information Science (ICIS), pp. 439-444. IEEE, 2018.
- [21]. Tong, Simon, and Edward Chang. "Support vector machine active learning for image retrieval." *Proceedings of the ninth ACM international conference on Multimedia*. ACM, 2001.

BIOGRAPHY



Sukanya S T, received BCA degree in Computer Applications from Manonmanium Sundaranar University Tirunelveli in 2014, Received Master Degree in Master of Computer Applications from Anna University Chennai in 2016, and received his Master of Philosophy Degree in Noorul Islam University in 2017. Presently working as an Assistant Professor in MCA Department of the Narayanaguru College of Engineering, TamilNadu, India, and Pursuing Ph.D in Noorul Islam Centre for Higher Education. Her Research Interest includes Data Mining, Image Processing and Neural Networks.



Dr. S. Jerine, Received B. Sc degree in Computer Technology from Manonmanium Sundaranar University Tirunelveli, in 2003. Received M. Sc degree in Computer Technology from Anna University in 2005. Received M.Phil degree in Computer Science from Madurai Kamraj University in 2008. Received Ph.D. degree in computer science from Noorul Islam Centre for Higher Education in 2018. Currently working as an Associate Professor in the department of Software Engineering at Noorul Islam Centre for Higher Education. Research interests include Wireless Networks, Network Security and Image Processing