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# Research on SVM and KNN Classifiers for Skin Cancer Detection

**A.Murugan, S.Anu H Nair, K.P. Sanal Kumar**

***ABSTRACT---Generally, a not unusual skin ailment in human disorder. In laptop imaginative and prescient applications, coloration is a sturdy indication for this sickness. This machine identifies pores and skin cancer based totally on the picture of the pores and skin. Initially, the skin image is filtered using filters and segmented Gausian the use of energetic contour segmentation. Segmented pix are fed as an input to the feature extraction. Pictures extracted classified the use of class strategies such as Support Vector Machine classifiers(SVM) and k Nearest Neighbor(kNN) classifiers. SVM classifier provided better results than kNN classifier***

***Keywords: Melanoma, Skin cancer, Gausian filter, Active contour.***

## I. INTRODUCTION

Cancer is a group of diseases which includes abnormal mobile growth that would spread and invade other elements of the frame. Symptoms that may be is a continual cough, unusual bleeding, lumps, and weight loss for no particular reason and adjustments in bowel moves. Because those symptoms imply most cancers, there can be other reasons for the disorder. There are extra than a hundred types of cancer that impacts the [1]. Although there are numerous sorts of most cancers, the most dangerous cancer is pores and skin most cancers. Skin cancer is a virus that affects the pores and skin. Skin most cancers can also seem as evil or a heart shape. Melanoma Benign moles only the arrival of the skin [2]. Malignant cancer is the advent of the wound that brought about bleeding.Malignant Melanoma is the most deadly kind of skin most cancers among all. Itascends of tumorousdevelopment in pigmented pores and skin. This is a lethal ailmentthatinitiates in melanocytes within the skin. Melanocytes are pigment that gives colour to the skin. [3] It typically starts as small lesions unfold later to different pores and skin areas. If skin cancer is diagnosed at an early degree, can purpose the patient's death. So early detection is one of the inevitable [4].

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There are different classes of pores and skin cancers occur in guys in girls. [5] Among the other lessons, each basal mobile and squamous mobile carcinomas arise more normally. Both varieties of cancers growth in frequency with age. Tumors are more not unusual in mild-skinned, blue or grey eyes, purple or blond hair, freckling, and Combustible man or woman, whereas, at the contrary, the tumor is quite rare in blacks and people greater intensely pigmented. Basal and squamous mobile tumors more regularly in outdoor people, together with farmers or sailors, employees inside the room. The majority of these tumors are caused by chronic sun exposure [6]. Squamous cell carcinoma is the less common of the two paperwork, however it's miles one closely associated with sun publicity. While the occurrence of both tumor improved as the lower in range, the rate of growth is steeper for squamous cellular carcinoma. Most deaths from each styles of skin cancer is caused by a spread of squamous cells, but usually best from squamous cellular carcinoma arising in the non-uncovered surface of the solar and may be due to different situations of exposure to the solar. Death of basal mobile carcinomas not often; simplest approximately four hundred cases of basal cell carcinoma metastasizing had been reported. Epidemiology of malignant cancer is tons distinct from different kinds of skin most cancers and is given in Figure 1.

A latitude gradient for melanomais proved in every usa with the very best area of sun exposure also be an area of high prevalence of cancer. More instances additionally seem to be approached in a mild-skinned, without problems sunburned humans. However, in comparison with basal mobile and squamous mobile carcinoma, the maximum concerned anatomic areas appreciably one-of-a-kind for melanoma, with regions less frequently exposed to sunlight, is likewise involved (the returned is the maximum commonplace site) [7].

**Figure. 1. Melanoma**

Computer-Aided diagnosis methods are better than the conventional Biopsy method. Computer-based skin cancer detection is more advantageous to patients, by which patients can identify skin cancer without going to the hospital or without the help of a doctor. It saves a lot of time for patients. This paper proposes a methodology that uses a CAD system to detect the type of skin cancer.

## II RELATED WORK

For the past few decades, many types of research have been developing different mythologies to detect cancer accurately. The methods use different pattern recognition techniques to detect cancer.One of them is Computer-aided diagnosis (CAD)[8] is one of the that detects the lesion

identification and the amount and quantification of the amount.Iyatomiet. al. Proposed an Web basically based

melanoma screening gadget. The proposed device the utilization of extraction calculations and neural classifier similartumor area arrange. Web servers can get admission to the photos transferred through dermoscopy and removes picture work extraction set of rules the utilization of the district 428 tumors, and neural network classifier is utilized to order sores. The creator utilizes photographs for their trials in 1258 and had an affectability of eighty five.9% and a particularity of 86.0%. [9] .Jaleelet., Al. Proposed a machine of PC helped discovery of pores and skin most tumors. In this works of art, Artificial Neural Networksare utilized for characterization of dangerous melanoma from considerate melanoma. GLCM division technique used to remove the areas of leisure activity. Precision of the proposed framework is 88% [10] .Oliveiraet. Al., Presented a fresh out of the plastic new system for extricating capacities from pictures of skin injuries by methods for asymmetry, outskirt, shading and surface assessment to analyze the kind of skin injury. This method is fundamentally founded on anisotropic dissemination get out, dynamic forms with out edges models and guide vector contraption.Theauthors claim that their proposed system gives accurate detection of skin cancer[11].Afifietet.,al.developed an optimized embedded SVM classifier for early detection of skin cancer using a minimum cost handheld device. The authors proposed a methodology involving hardware/software to know the melanoma discovery on a chip by employing the SVM classifier onto FPGA. The proposed design technology uses Ultra-Fast High-Level Synthesis. This technology gives a valid classification of melanoma on a chip. The fused methodology outcomes with an accuracy of 97.9% in the classification of the lesion [12].Murugan et., al. proposed a methodology for detecting skin cancer. For segmenting the lesion, they used the watershed algorithm, and the features are extracted using ABCD rule and GLCM. The extracted features are classified using KNN, Random forest and SVM. The SVM classifier produced the highest accuracy of 89.43% when the ABCD feature extraction is used [13].

## III PROPOSED COMPUTER-AIDED DIAGNOSIS

In the process of analyzing the infected area, the dermoscopic image is input. It is an imaging method thatinspects skin lesions using a dermatoscope. Diagnosing skin cancer comprises various stages. The stages are 1) image pre-processing which includes filtering and segmentation, 2) feature extraction, and 3) classification. In this paper, a novel model is proposed to detect skin cancer precisely, and the proposed model is shown in Figure 2. In this section, each step of the diagnosis process is discussed.

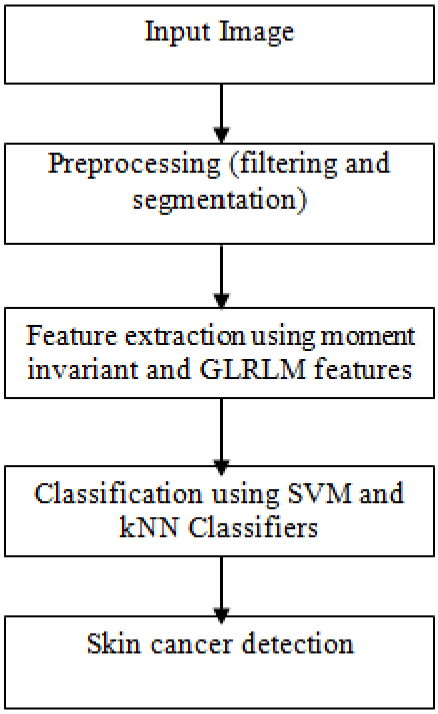


**Figure. 2: Block diagram of Proposed work**

*Image Pre-Processing*

In the pre-processing stage, improved picture first-class by using eliminating noise. Noise within the photo may be hair and bubbles. Because this sound reduce accuracy in classification. To put off noise within the picture, diverse filters used within the literature, such as median filter out, mean clear out, a Gaussian filter, adaptive median filter and adaptive clear out wiener for de-noising of various sounds which include Gaussian, salt and pepper, Poisson and speckle noise. In this paintings, a Gaussian filter out is used to take away noise inside the image.

*Gaussian Filter*

A Gaussian filter is used to smoothen the image to remove any artifact'snoise.In the Gaussian filters, in all dimensions, the same standard deviation is maintained. The Gaussian noise manipulates all the pixel values. The Gaussian Probability density function is used to value each pixel in the image[14].The outcome pixels of the gaussian filter is smoothed pixels according to the power-of-two Gaussian coefficients. The smoothing function can be expressed as in equation (1).

$$P_{smooth}(x,y)=(C_{normiA}+C_{normiB})[\sum_{i=-2}^{2}\sum_{j=-2}^{2}(C_{i,jA}+C_{i,jB})P_{raw}(x+i,y+j) \qquad (1)$$

where $P_{smooth}(x,y)$ and $P_{raw}(x+i,y+j)$ denotes the smoothed pixel and the raw pixel, respectively.

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$\sum_{i=-2}^{2}\sum_{i=-2}^{2}(C_{i,jA}+C_{i,jB})$ representsthe approximated Gaussian coefficient and $(C_{normlA}+C_{normlB})$ represents the normalized coefficient.

*Image Segmentation*

In this Segmentation stage, it separates the ROI image from the background. It is a region in which lesion is examined. The resultant of the step separates the cancerous portion of the image and the healthy portion of the image. There are four main types of segmentation methods, namely Threshold base, Region-based, Pixel-based and Model-based. In this work, the Active Contour [15]is used to separates the tumorous parts since it can preserve the local boundaries precisely.

*Active Contour*

Active contour [15] is an active model of segmentation that uses energy forces and segregates pixels for further processing. Contours are the boundaries of the image to be processed.It defines the Smooth structure in shut shape drawings and figures for the region. Form styles depict the limits of articles or various abilities of the image to shape a parametric bends or shapes. Model snake is one of the fiery form models, which are utilized in this work. Utilizing insignificant solidarity to glance through picture.The quality generally speaking lively snake model is the amount of inner vitality (Ein) which depends upon on the degree of spline identified with the state of the objective picture, the outside vitality (EEX), which incorporates an outer power given through the shopper and furthermore the power of different elements, and the vitality of the photo underneath thought (Ei) that convey significant records on the lighting of the spline speaking to the objective thing. The general quality set for the arrangement of the shapes inside the model of the snake is given by method for Equation 2.

$$E_{Tot}=E_{ex}+E_{in}+E_{i} \qquad (2)$$

Eindescribes inner strength, which defines Piecewise smoothness constraints in contour, where α decide how some distance snake might be extended and potential elasticity viable for a snake. β determine on the level of rigor to the snake. Internal strength is given by using equation 3.

$$E_{in}=\alpha\left|\frac{\partial v}{\partial s}\right|^{2}+\beta\left|\frac{\partial^{2}v}{\partial s^{2}}\right|$$

(3)

External energy constraint is specifically used to describe the snake near the minimum desired environment. This can be explained using a high-degree of interpretation and mutual.

$$E_{image}=w_{1}I(x,)+w_{2}\left|\nabla(x,y)^{2}\right|+\ldots \qquad (4)$$

Contour object of interest shown in the equation4 above, where w1 is referred to as a green way and w2 are known as the green edges. According to values higher than w1 and w2, which snakewill attuned to the dark pixel region in case of a great cost, and it goes toward a bright pixel when a terrible price. Representing the state of affairs with the help of snakes parametrically q (t) = (l (t), m (t)), we can write the practical strength as

$$E^{*}_{snake} = \int_0^1 E_{snake}\,(\mathrm{q(t)})^{ds} = \int_0^1 E_{int}(\mathrm{Q(T)}) + E_{image}(\mathrm{Q(T)}) + E_{con}(\mathrm{Q(T)})^{\ ds} \qquad (5)$$

where

$E_{int}$ --- Inside energy of the spline because of bowing

$E_{image}$ --- Rising to the image forces

$E_{con}$ --- Rise to the exterior constraint forces.

The interior spline energy is given as

$$E_{int} = (\alpha\ (t)\ |Q_t(T)|^2 + \beta(T)\ |\ Q_t(T)^2)/2 \qquad (6)$$

Where α (s) and β (s) are weights

The process decreases energy that is bound to existing contour as a sum of external energies and internal energies. Exterior energy expression is achieved as it is minimal at object boundary. Internal energy decides the shape of contour by controlling its curvature and shape regularity

## IV FEATURE EXTRACTION

The feature extraction starts after the pre-processing steps. After the pigmented lesion is segmented, necessary features have to be extracted to decide whether the lesion under consideration is benign or malignant. The features can be a collection of real numbers, and it characterizes a typical lesion. Researchers have introduced many feature extraction methods in the past few decades. In this work, three of such methods were used; they are the Moments Invariant features, Gray Level Run Length features, which discriminate tissue features accurately.

*Moments Invariants*

The first feature extraction method is the moment invariants (MIs),which is able to maintain the ability of moment invariants in providing unique and distinguishable features in a skin lesion. The MIs are well-known to be invariant are evaluated using central moments of the image function f(x, y) up to third order, which is used as features.[16]

Let M *X* M is 2 dimension moments of a dermoscopic image which has a gray function *f (x, y)*. Where the values of x and y are from 0 to M-1 i.e. (0, 1,….M-1),which is given as in eq.7.

$$m_{pq} = \sum_{x=0}^{x=M-1}\sum_{y=0}^{y=M-1}(x^p)\,.\,(y^q)\ f(x,y)\ \ p,q = 0,1,2,3\ \ldots \qquad (7)$$

The moments function *f (x, y)* transformed through a quantity *(a, b)* is given in eq. 8.

$$\mu_{pq} = \sum_x\sum_y(x+a)^{\,p}\ .\ (y+b)^{\,q}\ f(x,y) \qquad (8)$$

In accordance with the normalized central moments, which are invariant to order three, namely position of the object, the scale of the object and the object orientation. The seven moments are given in equation 9.

$$M_1 = (\eta_{20} + \eta_{02})$$
$$M_2 = (\eta_{20} + \eta_{02})^2 + 4\eta_{11}^2$$
$$M_3 = (\eta_{30} + 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2$$
$$M_4 = (\eta_{30} + \eta_{12})^2 + (\eta_{21} - \eta_{03})^2$$
$$M_5 = (\eta_{30} + 3\eta_{12})(\eta_{30} + \eta_{12})(\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 ] + (3\eta_{21} + \eta_{03})(\eta_{21} + \eta_{03}) [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 ]$$
$$M_6 = (\eta_{20} + \eta_{02}) (\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 ] + 4\eta_{11} (\eta_{30} + \eta_{12}) (\eta_{21} + \eta_{03})$$
$$M_7 = (3\eta_{21} - \eta_{03}) (\eta_{30} + \eta_{12}) (\eta_{30} + \eta_{12})^2 - 3(\eta_{21} + \eta_{03})^2 ] - (\eta_{30} + 3\eta_{12})(\eta_{21} + \eta_{03}) [3 (\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2 ] \qquad (9)$$

*Gray Level Run Length Matrix (GLRLM)*

The third feature extraction method used in this work is the Gray Level Run Length Matrix [19], which captures the roughness of texture in a way stated. A run is a series of consecutive pixels of the same intensity along with the appropriate linear position. Adequate texture tends to comprise a smaller runs with comparable intensity, while the uneven texture have long walk further with far different intensity [20]. From each matrix run-length, texture features statistics can be calculated and is given in the table 1.Here, seven features extracted using GLRLM.Table 1. The formula for GLRLM Features

| *Features* | *Formula* |
|---|---|
| *Short Run Emphasis* | $\dfrac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \frac{P(i,j\vert\theta)}{j^2}}{N_z(\theta)}$ |
| *Long Run Emphasis* | $\dfrac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} P(i,j\vert\theta)\, j^2}{N_{z(\theta)}}$ |
| *Gray Level Non-uniformity* | $\dfrac{\sum_{i=1}^{N_g} (\sum_{j=1}^{N_r} P(i,j\vert\theta))^2}{N_z(\theta)}$ |
| *Run length nonuniformity* | $\dfrac{\sum_{j=1}^{N_r} \left(\sum_{i=1}^{N_g} P\,(i,j\vert\theta)\right)^2}{N_z(\theta)}$ |
| *Run percentage* | $\dfrac{N_{z(\theta)}}{N_p}$ |
| *Low Gray level Run Emphasis* | $\dfrac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} \frac{P(i,j\vert\theta)}{i^2}}{N_z(\theta)}$ |
| *High Gray Level run Emphasis* | $\dfrac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_r} P(i,j\vert\theta)\, i^2}{N_z(\theta)}$ |

Once the features are extracted using moments invariants, GLRM, the feature values are used as an input to the classification.

## V CLASSIFICATION

In order to classify a test sample from the set of known classes, it is vital to use a classifier after the features are extracted and selected from the skin lesion.There are a number of classifiers used in the literature. For our experiments for the classification of the skin lesion, SVM and kNN are used in this paper. The classification algorithm is trained to predict diagnosis, and in this paper, we aim at distinguishing between melanocytic and non-melanocytic lesions as well as identifying more than one type of skin cancer.

*Support Vector Machines (SVM)*

SVM is a machine learning algorithm that works on the basis of statistical theory [22]. In the literature, compared with the other machine learning algorithms, SVM performs better or par with the other machine learning algorithms. SVM solves constrained quadraticto differentiate two classes, and the problem which has multiclass can also be solved.Building limiting boundaries in a dataset optimally, the SVM algorithm makes a right decision between two classes limits. SVM algorithm maximizes the margin between the datapoints and the hyperplanes. The algorithm for Support Vector Machine is given below

*Step 1. Divide the given data set into two set of data items having different class labels assigned to them*

*Step 2. Features and attributes are classified based on the labelled class*

*Step 3. Candidate Support Value Estimation*

*Step 4. While the instances value is not equal to null Repeat the following steps for all instances*

*Step 5. Support Value is equal to Similarity between each instance in the attribute Find Total Error Value*

*Step 6. If any instance is less than 0 then Estimate the decision value Decision value = Support Value/Total Error*

*Step 7. Repeat the above steps until empty*

*k-Nearest Neighbor (kNN classifier)*

K Nearest Neighbor is administered classifier. Here, the example insights is classed by means of greater part alright Nearest Neighbor class.

Steps in kNN classifier calculation:

example: enter

Yield: showing tests

Steps in kNN classifier calculation:

1. Allot an expense for k

2. Compute the hole among the investigate question and each article inside the thing of the preparation set.

Three. Select the article closest tutoring with perceive to the check object.

4. Select the greatness with the most extreme scope of coordinating things.

5. Rehash till a similar evaluation procured.

In our investigate, the element of the Euclidean separation is utilized

## VI. RESULTS AND DISCUSSIONS

The dataset used in this work to evaluate the performance of the classifier is Caucasian Collaboration International Imaging (ISIC) [23]. The number of pictures taken for the experiment is 1000 and 10-fold cross-validation is used in which all samples are trained and tested.

## VII. PERFORMANCE MEASURES

The following measurements are used to indicate the performance of the classifiers.*Accuracy*

Accuracy is obtained by correctly classified images divided by the classified images.

Accuracy=TP+TN/(TN+TP+FP+FN) (10)

where

Tp is the number of items correctly classified as positive class

Tn is the number of items correctly classified as negative class

Fp is the number of items wrongly classified as positive class

Fn is the number of items wrongly classified as negative class

*Sensitivity*

Sensitivity is obtained as correctly classified true positive rate divided by true positive and false negative samples.

Sensitivity=TN/(TP+FN) (11)

*Specificity*

Particularity is determined as accurately ordered genuine negative rate partitioned by the genuine negative and bogus positive examples. Results that are genuine negative are treated as blunders.

Specificity= TN/(TN+FP) (12)

Figure 3 and Table 2 shows Performance metrics for SVM and kNN classifiers using Moment invariant feature.

**Table 2. Accuracy,Sensitivity and Specificity of various classifiers for moment invariant feature**

| Classifier | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| SVM | 87.99 | 87.67 | 88.32 |
| KNN | 81.77 | 82.51 | 81.04 |

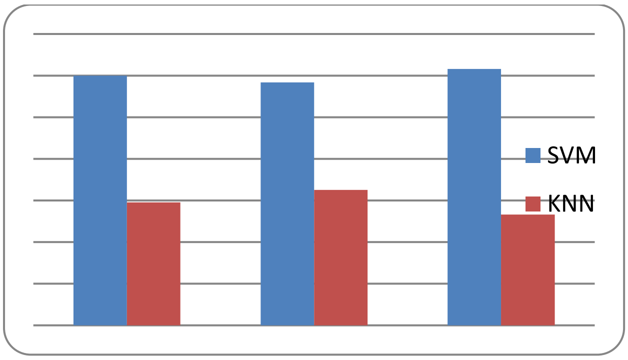


**Figure 3. Performance metrics for SVM and kNN classifiers using Moment invariant feature**

Figure 4 and Table 3 shows Performance metrics for SVM and kNN classifiers using GLRLM feature.

**Table 3. Accuracy, Sensitivity and Specificity of SVM and kNN classifiers for GLRLM feature**

| Classifier | Accuracy | Sensitivity | Specificity |
|---|---|---|---|
| SVM | 83.74 | 84.07 | 83.41 |
| KNN | 81.06 | 81.69 | 80.43 |

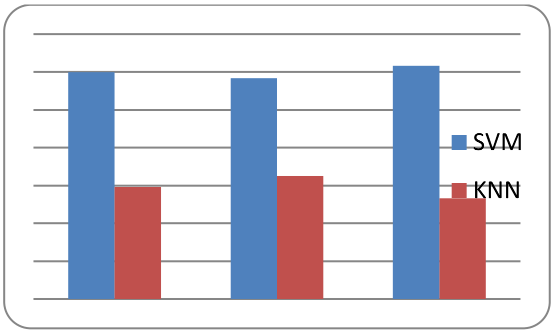


**Figure 4. Performance metrics for SVM and kNN classifiers using GLRLM feature**

It is evident from the results that the proposed system with the SVM classifier can accomplish the maximum sensitivity,specificity and accuracy as compared to kNN classifier used in this paper. The critical criteria to evaluate the performance of the classifier in detecting cancer are accuracy, specificity,and sensitivity. The proposed model with the SVM classifier also maintains a substantial score when compared to the kNN classifier. The accuracy obtained by SVM classifier is 89.5% and kNN classifier is 86.0%.

## VIII. CONCLUSION

In this paper, the skin cancer detection system using various classfier is proposed.The computer technology-based detection of Skin cancer is more beneficial to patients. In this paper, the diagnosing method uses an image processing methodology. The pre-processing of the identified skin region is done by the Gaussian filter and the active contour segmentation method is used to separate the affected area from the healthy skin. The unique features of the segmented images were extracted using moment invariant features and Gray Level RunLenth Matrix feature. These features help to classify the skin lesion under analysis is cancerous or Benign. Among the classifiers SVM outperforms than the other classifier KNN.

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