CHAPTER 3

SUPPORT VECTOR MACHINE APPROACH

3.1 Introduction

In our research work, the role of Support Vector Machine is classifying the skin Melanocytes. Before the classification process established the images are should be preprocessed and it will be help full for the classification accuracy. So that the image preprocessing steps is important, this process is used to removing the irrelevant and noise information from the image which helps to improve the overall efficiency of the skin cancer detection process [78]. Then the general noise removal processing steps such as image acquisition, image resizing, noise removal, hair removal, segmentation, feature extraction and classification are shown in Fig 3.1. Once the preprocessing done, the extracted features are used as an input to the SVM classifier for skin cancer classification.

Figure 3.1 Processing Steps of Image Preprocessing
3.2 Preprocessing Process

The preprocessing steps are involved in following manner such as Image Acquisition, Image Resizing, Hair removing, Filtering and finally Segmentation.

3.2.1 Data Acquisition

In this research work, the skin images have been collected from the International Skin Imaging Collaboration data set [79]. The data set capture the photography of the skin for detecting the skin cancer to reduces the melanoma morality rate. The collected skin cancer sample dataset images are shown in Fig 3.2.

The dataset includes 557 cutaneous melanocytic lesions from adults (>=18 years of age) with either a definitive histopathology diagnosis (for excised lesions) or a documented history of being clinically through review of serial clinical images acquired at least 6 months apart. Lesions were excluded from the dataset if there were equivocal histopathology, unacceptable image quality, or if the lesions were located on the face, acral or mucosal sites. The collected images have been used to process by using the several steps for detecting the skin cancer which is explained as follows.

Figure 3.2 Skin Cancer Images
3.2.2 Resizing and Color Transmission

Image resizing is also referred as the image scaling which helps to change the resolution of the collected skin cancer image [80]. During the resizing process, the graphic primitives and pixels information are enhanced without affecting the quality of the original image. In this research work, the collected skin images are resized into 512*512 images and the sample resized images are shown in Fig 3.3

The resizing process enhances the pixel value size without affecting the quality of the captured skin image. The collected Skin images are an RGB color which is difficult to process while detecting the skin cancer. So, initially, the RGB color images are transformed into the grayscale image [81] which performs better than the color image. The grayscale image consists of black, white and in-between gray colors. In that combination, the black pixel has (0,0,0) values, the white pixel has (255,255,255) values and the gray pixel has (127, 127, 127) Medium values. Then the grayscale value is computed by using the weighted average of this red, green and blue value.

![Original Skin Image](image1)

![Resized Skin Image](image2)

**Figure 3.3 Resized Skin Image**
The grayscale weighted average grayscale is estimated by eqn (3.1). The color has been transferred which is shown in Fig 3.4. Further, it also helps to analyze the each and every pixel value with effective manner.

\[
Grayscale = 0.2989 \times Intensity(r) + 0.58701 \times Intensity(g)0.1140 \times Intensity(b) \\
........ \quad (3.1)
\]

3.2.3 Hair Removal using Dull Razor method

The next important process is hair removal because the entire skin is covered by hair and that has different color, texture, and orientation which reduce the efficiency of the skin cancer detection process. In addition, the hair corrupted the pixel information easily. So, the hair has been removed by applying the Dull Razor and Pixel Interpolation technique which successfully analyzes and removes the thick dark, replace the hair pixels by the neighboring non-hair pixels and smoothing the location with effective manner [82]. Initially, the location of the hair has been identified and the pixel interpolation method examines the images and generates the two-dimensional images of the part of the human body [83].
The created two-dimensional picture comprises of lines which have been changed over into the transmitted space this can be a greatly valuable device in picture preparing on the grounds that it is useful for the recognition and evacuation of lines in a picture [84], for example, may be when hairs ought to be expelled in a skin picture. The hair has been identified by applying the average filter and morphological operator [85]. Average filter is a low pass filter and is considerably easy for de-noising the images. The function of average filter is computed as

\[ g(x, y) = \frac{1}{M} \sum_{(x,y) \in S} f(x, y) \]  

(3.2)

Where \( S \) denotes neighborhood of pixel \((x,y)\) and \( M \) denotes the number of pixels in neighborhood \( S \).

**Step 1:**

It recognizes the dark hair locations by a formalized gray-scale morphological closing operation. Closing operation simply defined as dilation after erosion process utilizing the same structuring element for both processes. The main input of this process is a given image is to be a structuring element and closed. The process of a gray level dilation followed by gray level erosion is defined as Gray level closing.

\[ f \cdot b = (f \oplus b) \ominus b \]  

(3.3)

**Step 2:**

In the eqn (3.3) is used to differentiate the hair pixels shapes as long and thin structure and substitutes the verified pixels by a bilinear interpolation. Fig 3.5 shows the effects of filling in closing gaps and holes which describe as closing operation.
Figure 3.5 Closing Operation

Step 3:

After that star, the smooths operation for replaced hair pixels with an adaptive median filter is defined as,

$$f_{(i,j)}^{(n)} = f_{(i,j)}^{(n-1)} \quad if \quad |X_{n}^{(n-1)} - m_{ij}^{(n-1)}| < T$$

$$\ldots \ldots \quad (3.4)$$

Where, T is defined as the pre-defined threshold value. The impulse detection process senses the noise even at great exploitation level setting which means here use the flag matrix value as 1 wherever noise occurs. Final Dull Razor Filter operation results are shown in Fig 3.6
3.2.4 Noise Removal using Gaussian Filter

The next important step is noise elimination because the capture skin image consists of unique ID, dataset details, created details, license code, age details, malignant detail and unstructured Meta data information which reduces the efficiency of the further noise removal process [86]. The noise present in the image has been removed by applying the Gaussian filter. It is one of the effective noise removal methods which analyze each and every pixel present in the image by using the Gaussian function. The Gaussian function minimizes the rise and fall of the step function input value.

Initially, the Gaussian noise in the images has been analyzed independently because of the fluctuations and color changes issues. While other distributions are possible, the Gaussian (normal) distribution [87] is usually a good model, due to the central limit theorem that says that the sum of different noises tends to approach a Gaussian distribution. Not only that but also Gaussian noise represents statistical noise having Probability Density Function (PDF) equal to that of the normal distribution, which is also known as the Gaussian distribution. Then the probability distribution of the pixel value is estimated as follows,
This process is repeated to eliminate the Gaussian noise because it is used as additive white noise to generate additive white Gaussian noise. The noise removed skin cancer image is shown in Fig 3.7.

\[
\eta (X_t, \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t - \mu)^T \Sigma^{-1} (X_t - \mu)}
\]  

...(3.5)

Figure 3.7 Noise Removed Skin Images

3.2.5 Image Segmentation

According to the noise and unwanted hairs are successfully removed which helps to enhance the efficiency of the system. The next step is image segmentation which divides the images into multiple regions by analyzing the pixels present in the image [88]. During the image segmentation process, it has been divided according to the texture, color, and other important details. Each pixel is examined about the particular concept and the similar pixels are grouped together which used to determine the boundaries of the affected part and region of the image. The segmentation has been done by analyzing the edges of the image. Edges of the image consist lot of useful information which helps to examine the features in the next step with effective manner [89].
The Edge-Based Technique which is segmented based on specific edge regions by finding the edge pixels and which is connected by using contours [90]. Basically, the boundaries are characterized by the edge, the edge is gratefully helpful in the process with boundaries and regions and as an edge point is a transition given gray level skin image which is liked with a point. Typically, the edges happened on the boundary between two different kinds of regions. Here have to consider the gradient point in the edge direction which is pixel’s intensity is increases rapidly [91]. The sample segmented image is shown in Fig 3.8.

\[
\nabla f = \left[ \frac{\partial f}{\partial x}, \frac{\partial f}{\partial y} \right] \quad \text{.................(3.6)}
\]

The edge strength is provided by the gradient magnitude

\[
\|\nabla f\| = \sqrt{\left(\frac{\partial f}{\partial x}\right)^2 + \left(\frac{\partial f}{\partial y}\right)^2} \quad \text{.................(3.7)}
\]

The gradient direction is computed by using the equation

\[
\theta = \tan^{-1}\left(\frac{\frac{\partial f}{\partial y}}{\frac{\partial f}{\partial x}}\right) \quad \text{......................(3.8)}
\]

According to the gradient magnitude and direction, the skin edges are continuously examined. From the extracted information, the similar pixels are grouped and segmented with effective manner.
3.3 Feature Extraction

Feature extraction is the process of extracting useful information from the image [92]. This information is used to further pattern recognition and classification process. Traditional method of feature identification is scoring method, and the score will be calculated by Total Dermoscopy score (TDS).

Figure 3.9 Skin Melanoma and its Features

In our research work, the essential features are extracted of Melanocytes like Asymmetry, Border irregularity, Color change, Diameter, Evolving using the Gray Level Co-occurrence (GLCM). These basic features are how typically appears are shown in Fig 3.9. So, the features are extracted from the resulting segmented image by using GLCM method [93,94]. This matrix is the texture measurements of the image which is used to extract the important information such as basic features and also the contrast, correlation, homogeneity and energy
3.3.1 Asymmetry

Asymmetry is the significant features for understanding the correct shape with the help of symmetry, which is very helpful in pattern analysis [95]. In case, the shape is totally symmetrical means which ratio is defined as 0. As these asymmetries are increases means the ratio is closer to 1. Asymmetry Index is defined by using the eqn (3.9)

\[ AI = \frac{\Delta A}{A} \times 10 \] ........................(3.9)

Where, \( A \) is defined as the area of the whole given skin Image. \( \Delta A \) is defined as the region difference between lesion area and total image. For example, if the image has the area size \( A \) is 4.4 and region difference between the lesion area and whole image \( \Delta A \) is 0.24 then applying the values to the Asymmetry Index equation \( AI = \frac{0.24}{4.4} \times 100 \) and the output of AI is 5.4545

3.3.2 Border irregularity

The skin segmentation is tending to have irregular borders with not chased sharp edges. Melanocytes area tends to have smooth borders [96]. The Irregularity Index is defined as a perimeter (P) and function of area (A) is defined as follows

\[ IR = \frac{4\pi a}{p^2} \] ........................(3.10)

Example, if the area \( A \) of the image is 5943 and the perimeter \( P \) is 290 means the irregularity Index (IR) or Border Irregularity is

\[ BI = \frac{4 \times \frac{22}{7} \times 5943}{290 \times 290} = 1.12 \]

3.3.3 Color Changes

Basically, color features are defined as standard deviation, skewness and mean and these features are obtained by utilizing Color Moment (CM) descriptor
\[ \mu_i = \frac{1}{N} \sum_{j=1}^{N} f_{ij} \] \hspace{1cm} (3.11)

\[ \sigma_i = \left( \frac{1}{N} \sum_{j=1}^{N} (f_{ij} - \mu_i)^2 \right)^{\frac{1}{2}} \] \hspace{1cm} (3.12)

\[ \gamma_i = \left( \frac{1}{N} \sum_{j=1}^{N} (f_{ij} - \mu_i)^3 \right)^{\frac{1}{3}} \] \hspace{1cm} (3.13)

where ‘i’ is the color value of the \( i^{th} \) color component of the \( j^{th} \) image pixel and \( N \) is the total number of pixels in the image. \( \gamma_i, \sigma_i, \mu_i (i = 1, 2, 3) \) defined as the skewness, standard deviation and mean of each channel of given image respectively. The values are applied to the appropriate formula and the values are obtained and output values are 1.0722

3.3.4 Diameter

Diameter is the process of straight line pass through the segmented region having the endpoints lies on the circle. Diameter is calculated as follows,

\[ D = 2r \] \hspace{1cm} (3.14)

\( D \) represents as the diameter; \( r \) is the radius of the segmented region. For example radius \( (r) \) of the image region value is 0.325 means then \( D = 2 \times 0.325 \)

\[ \text{Diameter (D)} = 0.650 \]

3.3.5 Evolving

Evolving is another skin feature which helps to examine, how the shape of the particular mole has been changed. The changes may be measured in terms of using the color, shape, elevation and other symptoms. In addition to this various features are derived from the segmented images for improving the cancer classification process which is explained as follows. The effective features are extracted which are fed into feature selection process which is done by information gain entropy method.
3.3.6 Contrast

Contrast is the process of separating the darkest area and brightest area which is analysis by using eqn (3.16).

\[ contrast = \sum_{i,j=0}^{n-1} P_{ij} (i - j)^2 \quad (3.15) \]

Where, i, j are the darkest and brightest area

3.3.7 Homogeneity

It is also called as inverse difference moment, which is measuring the compactness of distribution of Gray Level Co-occurrence matrix elements into main diagonal. The homogeneity is measured by using eqn (3.16)

\[ Homogeneity = \sum_{i,j=0}^{n-1} \frac{P_{ij}}{1+(i-j)^2} \quad (3.16) \]

3.3.8 Correlation

Correlation is the relationship between the two variables which is calculated by using eqn (3.17)

\[ correlation = \sum_{i,j=0}^{n-1} P_{ij} \frac{(i-\mu)(j-\mu)}{\sigma^2} \quad (3.17) \]

Where \( i - \mu \) is one variable, \( j - \mu \) is another variable

3.3.9 Energy

It is the squared element in the Gray level co–occurrence matrix which is measured by the eqn (3.18)

\[ Energy = \sum_{i,j=0}^{n-1} (P_{ij})^2 \quad (3.18) \]
3.4 Optimum Feature Selection using Information Gain and Entropy

In the previous stages, more than nine features are used for classification of Melanocytes. But only four features are used to skin Melanocytes classifications which contain the sufficient information for the process. The features are selected by the Information Gain and Entropy method [97] and it is known as Optimum features. This method examines the features extracted from the previous stage according to similarity measures. The similar values are estimated in the homogeneous manner.

\[ H = -\sum_{i=0}^{n-1} p_k \log_2 p_k \]  

With the help of the each feature entropy value, information gain value is calculated,

\[ \Delta H = H - \frac{m_L}{m} H_L - \frac{m_R}{m} H_R \]

Where, H is the entropy value; m is the number of instances.

The estimated information gain entropy value used to determine the decision value of the above extracted features. According to the process of Asymmetry, Border irregularity Color change and Diameter feature are chosen as optimum features which are used to detect the skin Melanocytes with effective manner. These four optimum features are used for as the input of classifiers. The extracted features related output value is shown in the Table 3.1.
Table 3.1 Selected Optimum Features

<table>
<thead>
<tr>
<th>S.No</th>
<th>Input Images</th>
<th>Input ABCD Features</th>
</tr>
</thead>
<tbody>
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<td></td>
<td></td>
<td>Asymmetry</td>
</tr>
<tr>
<td>1</td>
<td><img src="image1.png" alt="Image" /></td>
<td>5.5223</td>
</tr>
<tr>
<td>2</td>
<td><img src="image2.png" alt="Image" /></td>
<td>5.5365</td>
</tr>
<tr>
<td>3</td>
<td><img src="image3.png" alt="Image" /></td>
<td>3.5239</td>
</tr>
<tr>
<td>4</td>
<td><img src="image4.png" alt="Image" /></td>
<td>2.562</td>
</tr>
<tr>
<td>5</td>
<td><img src="image5.png" alt="Image" /></td>
<td>5.321</td>
</tr>
<tr>
<td>6</td>
<td><img src="image6.png" alt="Image" /></td>
<td>4.355</td>
</tr>
<tr>
<td>7</td>
<td><img src="image7.png" alt="Image" /></td>
<td>3.987</td>
</tr>
</tbody>
</table>
3.5 Classification using Support Vector Machine

Support Vector Machine (SVM) is introduced by Russian Scientist Vladimir Naumovich Vapnik in 1962 [98]. The researcher developed classifier is one of the supervised learning methodologies which utilize the hyper plane for classifying the retrieved skin feature. This method effectively analyzes the features in the linear space with the help of the hyper plane and classifies the features into normal and abnormal skin that is identified by labeling +1 and -1. This process is called as the linear classification that is shown in Fig 3.10

The class H1 does not separate the two classes; H2 separates but with a very thin margin between the classes and H3 separates the two classes with much better margin than H2. Thus the hyper plane creates the border between two different classes that is namely known as maximum-margin hyper plane or linear classifier or maximum margin classifier. Further, the Support Vector Machine method has been worked in both linear and non-linear way to analyze the features from the dimensional space.

3.5.1 Linear Model

The Support Vector Machine method separates the data by determining the hyper plane [99]. Let as consider $W$ is the hyper plane and $b$ is the displacement of the origin data. Then the input feature is determined by using as follows,

$$D(x) = W \cdot x - b$$  \hspace{1cm} (3.21)

Where,

$$x \in \begin{cases} A & \text{if } D(x) > 0 \\ B & \text{if } D(x) < 0 \end{cases}$$  \hspace{1cm} (3.22)
Based on the input feature estimation, the hyper plane is determined,

$$\frac{D(x)}{||W||} \quad \text{..........................}(3.23)$$

In the eqn (3.23), is the opposite signs which is belongs to the different sets when both inputs are belongs to the opposite sides of the hyper plane separation which is represented as follows,

$$w.x - b = 1 \quad \text{..........................}(3.24)$$

$$w.x - b = -1 \quad \text{..........................}(3.25)$$

Based on the hyper plane in the linear model, the output of that is relevant group is estimated as,

$$y_i = \begin{cases} +1 & \text{if } x_i \in A \\ -1 & \text{if } x_i \in B \end{cases} \quad \text{..........................}(3.26)$$

According to the output estimation process, the training data’s present in two groups is linearly separable with effective manner. The distance between the hyper plane. The linear separable based Support Vector Machine classification only fit for the defined dimensional space which is difficult to process while using the dynamic dimensional space for this issue, the non-linear separable based SVM classification is used which is explained as follows,
3.5.2 Non-linear Model

There are some difficulties present in the linear separable Support Vector Machine model is resolved by using the non-linear based classification which was introduced by the Isabelle Guyon, Bernhard Boser and Vapin in 1992 [100]. They introduced a new method which works better in high dimensional feature space with the easiest way by modifying the quadratic programming to the feature space transform function which provides the better result. Then the support vector decision function is defined as follows,

\[ D(x) = \sum_{i=1}^{p} \alpha_i y_i K(x_i, x) - b \] ........................(3.27)

So, in this work, the extracted skin features are fed into the non-linear support vector machine which separates the normal and abnormal feature with the help of the hyper plane and radial basis kernel function. The kernel function is calculated as, and it’s denoted as the Squared Euclidean distance between feature space.

\[ K(x, x') = \exp\left(-\frac{||x-x'||^2}{2\sigma^2}\right) \] ..........................(3.29)

3.6 Result of Support Vector Machine Classifier

The result of the Support Vector Machine Classifier is shown in Table 3.2. Its clearly shows the input of the classifier and the output values of the classifiers. The four optimum features are the input of the Support Vector Machine. In this table the output values are be ' 0 ' or ' 1 '. The output value ' 0 ' indicates the inputs has non - Melanoma i.e non cancerous and the output value ' 1 ' indicates the input image has Melanoma i.e cancerous.
### Table 3.2 Result of SVM Classifier

<table>
<thead>
<tr>
<th>S.No</th>
<th>Asymmetry</th>
<th>Border Irregularity</th>
<th>Color</th>
<th>Diameter</th>
<th>Output</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>5.5223</td>
<td>0.4857</td>
<td>1.0722</td>
<td>0.5506</td>
<td>0</td>
</tr>
<tr>
<td>2</td>
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<td>0.4674</td>
<td>1.0718</td>
<td>0.5726</td>
<td>1</td>
</tr>
<tr>
<td>3</td>
<td>3.5239</td>
<td>0.7705</td>
<td>1.080</td>
<td>0.6175</td>
<td>1</td>
</tr>
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<td>4</td>
<td>2.562</td>
<td>0.7212</td>
<td>1.0371</td>
<td>0.8526</td>
<td>0</td>
</tr>
<tr>
<td>5</td>
<td>5.321</td>
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<td>1.024</td>
<td>0.468</td>
<td>0</td>
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<td>6</td>
<td>4.355</td>
<td>0.753</td>
<td>1.065</td>
<td>0.56812</td>
<td>1</td>
</tr>
<tr>
<td>7</td>
<td>3.987</td>
<td>0.652</td>
<td>1.246</td>
<td>0.6432</td>
<td>0</td>
</tr>
</tbody>
</table>

### 3.7 Performance Analysis

Performance analysis examines the excellence of the preprocessing, segmentation, and feature extraction and classification process. The effectiveness is tested by running the algorithm in MATLABRa2013 tool and the efficiency is determined by using the following performance metrics [101].

### 3.8 Performance Metrics

The performance of the proposed system is analyzed with the help of the objective base quality measures such as Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Structural Correlation (SC), Normalized Correlation (NC) and Average Difference (AD), Sensitivity, Specificity and Accuracy [102].
3.8.1 Mean Square Error (MSE)

It measures the average of the square error [103] which means calculating the error amount by the pixel value of the original image differs from the image during the noise estimation process.

\[
\text{Mean Square Error} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (f(i,j) - f'(i,j))^2
\]

...(3.30)

The eqn (3.30) \( f(i,j) \) represented as the original image and \( f'(i,j) \) denoted as the noise estimated image. M is the height of the image and N is the width of the image.

3.8.2 Peak Signal to Noise Ratio (PSNR)

Peak Signal to Noise Ratio is the performance metric measures which are used to identify the quality of the original image which justifies the similarity between the original and noise image [104].

\[
\text{Peak Signal Noise Ratio} = 20 \log_{10} \left( \frac{255}{\sqrt{\text{MSE}}} \right)
\]

............(3.31)

Mean Squared Error which computes the difference between the actual value and the estimated value and then the advantage of the PSNR metric is the easiest computation.

3.8.3 Structural Correlation (SC)

Structural Correlation estimates the similarity between the original and noise estimated images [105]. This measure effectively compares the total weight of an original image to that of a coded or given.
3.8.4 Normalized Correlation (NC)

Normalized Correlation (NC) measures the similarity between the original image and noise image which is calculated by [106]

\[
\text{Normalized Correlation} = \frac{\sum_{i=1}^{M} \sum_{j=1}^{N} (f(i,j) - f'(i,j))^2}{\sum_{i=1}^{M} \sum_{j=1}^{N} (f(i,j))^2}
\]  

……(3.33)

Where, \( f(i,j) \) represents original image and \( f'(i,j) \) represents the noise estimated image, \( M \) is height of the image and \( N \) is the width of the image.

3.8.5 Average Difference (AD)

Average Difference (AD) is the important metrics which is used to identify the noise presents in the image [107]. The lower value of the AD means, the images having the reduced noise and it is computed by the following,

\[
\text{Average Difference} = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} (f(i,j) - f'(i,j))
\]  

……(3.34)

3.8.6 Efficiency

The last metric is efficiency which is used to determine the percentage of accuracy attains while segmenting, feature extraction and classification process.
3.8.7 Sensitivity

Sensitivity is a measure used to how the proposed system correctly classifies the skin cancer with efficient manner. The sensitivity is,

\[
\text{Sensitivity} = \frac{\text{True Positive}}{(\text{True positive} + \text{False Negative})} \quad \ldots \ldots \ldots (3.35)
\]

3.8.8 Specificity

Specificity measure how the proposed system correctly identify the negative classifiers during the skin cancer recognition process which is measured,

\[
\text{Specificity} = \frac{\text{True Negative}}{(\text{True negative} + \text{False positive})} \quad \ldots \ldots (3.36)
\]

3.8.9 Accuracy

Accuracy is a statistical measure which is used to analyze how well the binary classifier recognizes the skin cancer with optimized way. In addition, the accuracy is the proportion of the true results that include both true positives and true negatives among the total number of cases examined.

\[
\text{Accuracy} = \frac{\text{number of true positive} + \text{number of true negative}}{\text{number of true positive} + \text{false positive} + \text{false negative} + \text{true negative}} \quad .(3.37)
\]

The accuracy value also has been determined by the sensitivity and specificity values

\[
\text{Accuracy} = (\text{Sensitivity})(\text{Prevalence}) + (\text{Specificity})(1 - \text{Prevalence}) \ldots .(3.38)
\]

The excellence of the proposed noise removal, segmentation, and feature extraction and classification process is evaluated using the following implementation results.
3.9 Results and Discussion

The efficiency of the Gaussian filtering, edge detection technique and feature extraction process is applied to the International Skin Imaging Collaboration and Dermnet data set. The Peak Signal to Noise Ratio (PSNR) value of Gaussian filtering technique gives the better result in other methods such as Median filter [108], Weiner, Smoothing filter, Anisotropic filter [109,110]. The comparison of Peak Signal to Noise Ratio values are shown in Table 3.3

Table 3.3. Comparison of PSNR

<table>
<thead>
<tr>
<th>Methods</th>
<th>PSNR</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Filter</td>
<td>73.93</td>
</tr>
<tr>
<td>Weiner Filter</td>
<td>76.19</td>
</tr>
<tr>
<td>Smoothing Filter</td>
<td>82.43</td>
</tr>
<tr>
<td>Anisotropic Filter</td>
<td>84.30</td>
</tr>
<tr>
<td>Gaussian and Morphological filter with Dull Razor technique</td>
<td>94.22</td>
</tr>
</tbody>
</table>

In addition, the performance of the Gaussian and Morphological filter with Dull Razor technique based noise removal method is analyzed with the help of the following performance metric Table 3.4. It shows that the proposed method achieves the best result of various types of noises.
Table 3.4 Estimation of Quality Metric Parameters

<table>
<thead>
<tr>
<th>Methods</th>
<th>MSE</th>
<th>Structural Content</th>
<th>Normalized correlation</th>
<th>Average difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Filter</td>
<td>0.190</td>
<td>0.6498</td>
<td>1.0470</td>
<td>0.088</td>
</tr>
<tr>
<td>Weiner Filter</td>
<td>0.173</td>
<td>0.5563</td>
<td>1.0766</td>
<td>0.0763</td>
</tr>
<tr>
<td>Smoothing Filter</td>
<td>0.151</td>
<td>0.4357</td>
<td>0.9123</td>
<td>0.0619</td>
</tr>
<tr>
<td>Anisotropic Filter</td>
<td>0.139</td>
<td>0.3310</td>
<td>0.87896</td>
<td>0.0588</td>
</tr>
<tr>
<td>Gaussian and Morphological filter with Dull Razor</td>
<td>0.090</td>
<td>0.135</td>
<td>0.644</td>
<td>0.0245</td>
</tr>
</tbody>
</table>

After the Support Vector Machine classify the skin Melanocytes, the output values are evaluated by different performance matrix. Based on that Sensitivity, Specificity, and Accuracy are calculated. The performance of the Support Vector Machine is shown in Table 3.5 and the graphical representation also shown in Fig 3.11. Mean Square Error (MSE) of Support Vector Machine Classifier is 0.789.

Table 3.5. Performance of Support Vector Machine Classifier

<table>
<thead>
<tr>
<th>Performance Metrics</th>
<th>SVM Classifier</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>78%</td>
</tr>
<tr>
<td>Specificity</td>
<td>59%</td>
</tr>
<tr>
<td>Accuracy</td>
<td>81.33%</td>
</tr>
</tbody>
</table>
The efficiency of the system is examined with the help of the experimental results and discussions. Even though the Support Vector Machine method successfully recognizes the abnormal skin feature, the testing phase consumes more time which reduces the efficiency of the system. So, the derived features are fed into the k-Nearest Neighbor (k-NN) algorithm for classification.