Performance Analysis of Skin Cancer Detection Using GLCM and SVM

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Abstract.

Cancer of the skin is the most prevalent and destructive form of the disease in humans. The most dangerous kind of skin cancer is called melanomas. If it is caught in its early stages, it is very easy to treat. The biopsy technique is the formal approach that is used for diagnosing the presence of melanoma. This technique may be rather uncomfortable and requires a lot of time to complete the procedure. As a result of this research, a computer-aided detection method for the early diagnosis of melanoma has been developed. Within the scope of this research, an effective method of diagnosis is developed via the use of image processing methods and the Support vector machine (SVM) algorithms. The picture of the damaged skin is captured, and then it is subjected to a number of different pre-processing methods in order to provide an improved image and a smoothed image. After that, the image goes through a process of segmentation that uses morphological and thresholding approaches to separate the various components of the picture. The photos of the skin have had some crucial aspects of its texture, color, and form removed. For the purpose of extracting texture characteristics, the Gray Level Co-occurrence Matrix (GLCM) approach is used. The GLCM, color, and form characteristics that were retrieved are the ones that are used as input by the SVM Model. It determines if the photograph in question depicts a benign melanoma or a malignant melanoma. When we integrate and use the shape, color, and GLCM characteristics to the classifier, we are able to reach a high level of precision that is equal to 96 percent.

Keywords. Melanocytes, Support Vector Machine, Segmentation, Gray Level Co-occurrence Matrix.

1. INTRODUCTION

When it comes to humans, the skin is considered to be the most vital organ in the body. The muscles, bones, and internal organs that lie under the skin are shielded by the skin. The skin plays a very significant part in the overall defense mechanism of the organism against UV radiation. UV radiations released by the sun cause DNA in the cells of the skin to become damaged. These factors have the potential to be the origin of skin related disorders as well as malignancies of the skin. Melanin is found in skin cells and acts as a shield against the damaging effects of ultraviolet (UV) radiation. Since persons with light skin do not produce as much melanin in their skin, they are more susceptible to the damaging effects of ultraviolet (UV) radiation than those with dark complexion. Because of this, those with light skin are more likely to have been diagnosed with melanoma. Melanoma cancer is considered to be the most lethal kind of all skin diseases that may affect people. Malignant melanoma and benign melanoma are the two subtypes that may be assigned to the cancerous skin growth known as melanoma. Even though it has been revealed that only 4 percent of the people are affected with this malignant melanoma, it accounting for more than 70 percent of the fatality caused due to melanoma cancer [1].Malignant melanoma kind is among the worst and most deadly forms of skin cancers.

The human skin, which serves as both the body's covering and its main organ, is the body's largest organ. Up to 7 levels of ectodermal tissues may be found in skin, which serves as a protective barrier for the muscles, bones, ligaments, and internal organs that lie underneath it. The human skin has many important functions: it prevents harmful substances and bacteria from entering the bloodstream, it assists in maintaining the respiratory rate, and it enables humans to experience sensations of cold, heat, and touch. A skin lesion is the term used to describe an abnormality in one area of the skin in comparison to other areas of the skin. The infection that occurs either in or on the skin is the fundamental and primary cause of skin lesions. Primary skin lesions are those that are present at birth or develop over the course of a person's lifetime, whereas secondary skin lesions are those that are caused by improper treatment of primary skin lesions. Both types of skin lesions have the opportunity to enhance into skin cancer, and each year in the United States, upwards of three million people are diagnosed with some form of skin cancer. Every year in India, more than 5000 individuals are diagnosed with skin cancer, and over 4000 people lose their lives to the disease. Basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and melanoma are the three types of skin malignancies that may develop. Melanoma is the most dangerous kind. If a tumor is determined to be malignant, which is a very hazardous kind of skin cancer due to the fact that this tumor develops quickly and spreads to other places of the skin [3] [11] then the tumor is deemed to be cancerous. A benign tumor, on the other hand, is not a particularly hazardous sort of tumor since it grows but does not spear. Since the skin lesion is evaluated with the naked eye, where features cannot be detected accurately, manual identification of skin cancer is not particularly suited. This leads to maltreatment, which ultimately ends in death. Early stage discovery of accurate skin cancer may boost the likelihood of a patient surviving the disease. As a result, automated detection is more trustworthy, resulting in improved accuracy and efficiency.

Melanoma skin cancer might be healed if it has been recognized or successfully treated in really initial phases, so for the diagnosis to melanoma can indeed be supplied early date and will save this same person’s life, however if melanoma is detected during last phases, there are many more possibilities for such an illness to just go depth again into the epidermis. Melanoma skin cancer might be healed if it is recognized or successfully treated in really beginning phases, so for the diagnosis to melanoma can indeed be supplied previous period after it has progressed to this point, it will be far more difficult to cure. Melanocytes, which are found throughout the body, are the primary factor in what leads to the development of melanoma [1]. The biopsies taken from the patient are used in the official way of diagnosing skin cancer. This approach includes a procedure for removing a bit of human tissue from the body, after which the tissue will be examined further in a laboratory. To do this is by far the most difficult and agonizing task possible. For testing reasons, there will be a significant increase in the amount of time required. Both patients and their physicians need to devote more time to the testing process. The use of the biopsy approach is fraught with increased danger since there is a possibility that the illness may spread to other areas of the body.

The majority of scholars contributed to this investigation and suggested a number of different detecting methods. Melanoma, a kind of skin cancer, may be found using a method known as common identification, which consists of four key stages: pre-processing, separation, semantic segmentation, and classification [2] [12]. This approach is used to find melanoma. In order to get the area of interest, a method called segmentation first isolates the lesion from the surrounding skin. Because of its efficiency and ease of application, the GLCM approach has been used as the foundation for the feature extraction process of a significant number of computerized melanoma detection equipment.

This computer-based analysis will cut down on the amount of time spent detecting a problem while also improving its level of precision. Dermatological illnesses are high in complexity; as a result, diversity and a scarcity of knowledge is one of the most challenging problems for rapid, simple, and correct diagnosis. This is particularly true in developing nations and developed economies with inadequate healthcare budgets. Additionally, it is well knowledge that the early diagnosis of an illness in its early stages lowers the risk of the disease developing into a more severe condition. There are just a few environmental variables that have been shown to have had a significant role in the development of malignant melanoma skin disorders [1].

The biopsy is the standard diagnostic procedure for cancer. During a biopsy, afflicted somatic cells are extracted, and the resulting sample is submitted to the laboratory for examination. The procedure is laborious and takes a considerable amount of time. Therefore, an automatic software-assisted system is necessary in order to achieve accurate and rapid processing. Through the application of quantitative characteristics, it will provide enhanced comprehension of the aim. During this phase of the process, the characteristics of the cancerous area are collected, and a support vector machine (SVM) classifier is used to diagnose carcinoma. This method of diagnosis makes use of the photographs obtained during dermoscopy. After that, some image preprocessing is carried out to strengthen the standard and remove noise from the images, which is then followed by segmentation through the use of the thresholding approach. The GLCM approach is used [4] in order to extract the picture characteristics; the classifier is then provided with these extracted features as an input. Classifier will classify the picture that is provided as either malignant or non-cancerous, depending on the circumstances.

In this study, we tried out a whole new method for melanoma diagnosis when we got to the phase when we extracted features. By integrating a variety of different methods for the extraction of features, it is our hope to attain a relatively high level of accuracy in the categorization of melanomas. In this study, we evaluate feature extraction using texture, shape, and color, and then we classify the results to see which method yields the most accurate results. First, an SVM classifier is used to establish each method for feature harvesting, and then accuracy levels are determined for each method. Then, we used a support vector machine (SVM) to construct a classification algorithm, combining texture and shape information, and evaluated how accurate it was. In the end, we combined the different aspects of form, color, and texture in order to develop a classification algorithm and determine its correctness. In addition to this, using an analysis that is supported by an SVM classifier, we determine which method of extraction of features is the most practical and trustworthy for the identification of melanomas.

2. RELATED STUDY

In the subject of melanoma skin cancer detection, there have been many investigators working. They used a broad variety of computer vision methods, such as image analysis, separation, semantic segmentation, and picture categorization, among other machine vision. These methodologies have been used in a variety of other research articles as well.

The risk of death from skin cancer is among the highest of any malignancy. It is expected to spread to other parts of the body if the first symptoms are ignored and the condition is not properly evaluated and treated. Additionally, it takes place when the tissue is exposed to sun's rays, mostly because of the fast proliferation of skin cells during this time. In order to reduce the amount of time and effort required, as well as the risk to human life, early identification definitely requires the use of a reliable computerized method for the recognition of skin lesions. Graphics rendering and learning techniques are both components of the method that has been shown to be effective in the treatment of skin cancer. An automated method for the categorization of skin cancers was proposed by the author in [5]. In this particular investigation, nine distinct forms of skin cancer were identified and categorized. Observations are also made about the performance and efficiency of deep convolutional neural networks (CNN). Through the use of the Convolution Neural Network, the goal is to construct a model that not only detects skin cancer but also categorizes it into a number of different subtypes. Graphics rendering and deep learning are both concepts that are used in this form of diagnosis. The quantity of pictures has also been increased thanks to the use of a variety of strategies for image enhancement. In conclusion, the strategy known as transfer learning is used in order to further increase the accuracy of the classification jobs. The suggested CNN approach demonstrates an accuracy of around 79.45 percent, with a weighted mean accuracy of around 0.76, a weighted mean recall of around 0.78, a weighted mean f1-score of around 0.76, and so on.

Melanoma is the most lethal kind of skin cancer; nevertheless, if it is detected at an early stage, there is an extraordinarily elevated potential of the treatment that may reach up to 99.2 percent. Despite a decade of work put into employing technology, manual inspection by a dermatologist is still the primary and most trusted procedure that is employed up to this day. As a result, because limited number of dermatologists available, it is hard to undertake preventative monitoring on those who are at the greatest risk for early detection. Deep Convolutional Neural Networks (DCNNs), which have exhibited a significant advance in automated skin lesion categorization, are crucial for improving diagnostic performance across a mass population that has limited access to experts [6]. Website builder dermoscopy photography with incorporated artificial intelligence (AI) is a technology that has the potential to become accessible in the future for the study of skin lesions. As a consequence of this, the artificially

intelligent plug-in has the potential to act as facilitators for the dermatological community. In this research, we discuss the outcomes of our inquiry into the use of deep convolutional neural networks (DCNNs) for automated melanoma zone segmentation in dermoscopy pictures.
The likelihood of effective treatment of cancer may be increased by early and correct diagnosis of the disease. The most serious kind of cancer is malignant skin cancer, which is prevalent all over the globe and is becoming more common as time passes. Within the cancer varieties, malignant skin cancer is the most common form. Applications of computer assisted diagnosis are used in the process of categorizing various skin malignancies. Dermoscopy pictures obtained from the ISIC repository are utilized in this work to construct a dataset with two classifications; this dataset is then used to categories benign and malignant forms of cancer. In addition, the categorization score is anticipated to improve as a direct consequence of the early detection of the condition [7]. In order to accomplish this goal, several image preprocessing procedures, including color clarity, edge recognition, and noise removal, are used to dermoscopy pictures collected from the dataset. Following this operation of processing, the InceptionV2 computational intelligence network is used so that the processed photos may be classified.
Because of its prevalence and high mortality rate, melanoma of the skin necessitates the development of a detection technology that is both precise and effective in order to facilitate early clinical condition. Artificial Intelligence (AI) enhanced detection approaches strive to accomplish this objective while cutting down on the time and money required by conventional methods. In [8,] the author demonstrates how to enhance performance above single classification techniques by using a half as good learning strategy that is trained using weighted losses. The ensemble approach reduces over-fitting that occurs as a result of imbalanced data in the dataset. As a result, it was able to get a score of 0.591 on the Balancing Multi-class Accuracy test without identifying any unknown classes. During the testing phase, the algorithm was enhanced by adding the suggested CS-KSU module collection. This allowed for the identification of the existence of pictures that belonged to new classes. A score of 0.544 was achieved for the Area under the ROC Curve (AUC) when the extended procedure was applied to the unknown class. The efficiency of our algorithm is comparable to that of the most advanced methods now available for completing this assignment.
Melanoma is the most aggressive and potentially lethal type of skin cancer. Nevertheless, differentiating melanoma tumors from other types of skin lesions, such as non-melanoma lesions, has proven to be a difficult process. In the past, several computer-aided diagnostic and monitoring techniques have been built specifically for the purpose of carrying out this activity. Their performance has been hindered as a result of the complicated distinctive attributes of the skin lesion pictures, which include in homogeneous elements and hazy borders. These qualities have prevented them from reaching their full potential. In the article [9], the author presents a technique based on deep neural networks that overcomes these restrictions for the automated identification and classification of melanoma lesions. For the purpose of making learning and feature extraction more effective, an improved encoder-decoder system has been proposed [13] [14]. These mechanisms bring the conceptual level of the transceiver convolution layers closer to something like the digital converter convolution layers. In order to classify melanoma lesions in a pixel-by-pixel manner, the system incorporates a multi-stage and multi-scale technique, as well as a softmax classifier. Based on the findings obtained from pixel-wise classification, we develop a brand new technique that we name the Lesion-classifier. This technique is used to conduct the categorization of skin conditions into melanoma and non-melanoma.
Because it enables physicians to get rapid recognition for worrisome lesions via their cellular telephones, the field of mobile tele-dermoscopy contributes to the development of patients' medical management. Even for highly trained medical professionals, identifying skin cancer using dermoscopy photos may be a challenging process because of the intrinsic heterogeneity that exists in the presentation of skin lesions. Recent developments in photo editing using Deep Convolutional Neural Networks (CNN) have prompted a large number of scientists to employ CNN for the categorization of skin lesions. These scientists came to the conclusion that CNN worked just as well as experienced dermatologists. In this study, we made use of a dataset that consisted of 48,373 dermoscopy photos obtained from three separate archives and certified by qualified dermatologists. These images were categorized by the archivists. In [10], the author used transfer learning to manually train a resource-constrained CNN model dubbed MobileNetV2 for binary categorization of skin conditions into benign and malignant classifications. The predictive model achieved a total accuracy of 91.33 percent, with a batch size of 32 being used in the training process [15].

3. METHODOLOGY

Detecting the presence of malignant melanoma cells in an image using SVM-based methods is known as melanoma skin cancer detection. Here, SVM and GLCM techniques are employed to develop the algorithm. Additionally, certain chosen form and color characteristics are retrieved from the skin photos using the GLCM approach. To classify the data, all of the retrieved characteristics are pooled and fed into an SVM. Computer vision approach SVM is used for supervised learning models with associated. Figure 1 depicts the suggested methodology's key phases.

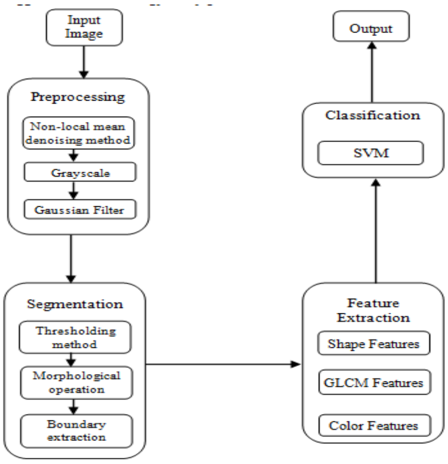

Figure 1: Methodology

3.1. Input Images

For the purposes of this investigation, the skin photos were obtained from the ISIC online collection. The collection of photographs pertaining to skin cancer may be found inside this internet repository. In order to establish an accurate method for the identification of melanoma and to minimize the number of fatalities that are caused by melanoma, the ISIC melanoma detection-based initiative was initiated. This ISIC dataset may include as much as 23,000 photographs. Within the scope of our investigation, we gathered a total of 600 pictures and used them for both training and testing purposes.

3.2. Image pre-processing.

The primary objective of feature pretreatment is to improve picture quality in addition to preparing for further treatment. This is accomplished by eliminating undesired elements from the foreground of digital mammograms. In order to get rid of the sounds and the elevated elements, the filtering were used.

3.2.1. Process of removing hair and noise.

The primary goal of this method is to remove undesirable sound and hair from skin pictures. The most difficult part of this investigation is determining which characteristics are true and which are the result of unwanted noise. A pixel's value may vary in a random way. The Non-local mean denoising approach is being used in our work to eliminate undesirable features from skin images. A denoised picture is shown in Figures 2 and 3 as compared to an original image.

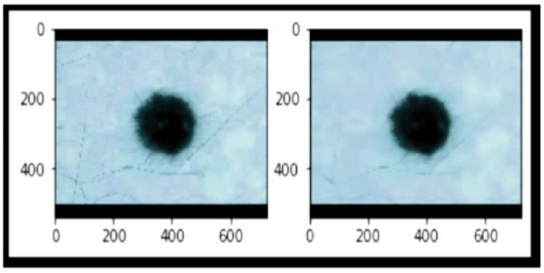

Figure 2: Noise eliminated

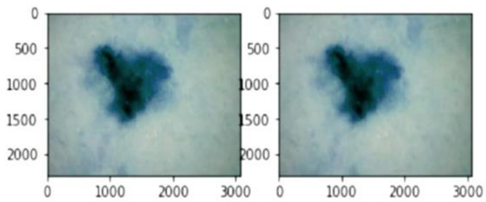

Figure 3: Noise eliminated

3.2.2. Conversion of RGB to Grayscale

The only information that is included in a grayscale picture is the brightness. The beam of energy corresponding to each data point in the grayscale picture may be thought of as a number. A grayscale picture provides a distinction between the various levels of brightness. The only thing that the grayscale picture measures is the amount of light. In the methods that we have provided, the color photographs are converted to grayscale before being saved. This is done because processing grayscale images is simpler and more efficient than processing colored ones. After that, we deploy a grayscale conversion technique to the pictures that are now free of noise. The picture in grayscale is shown in Figure 4.

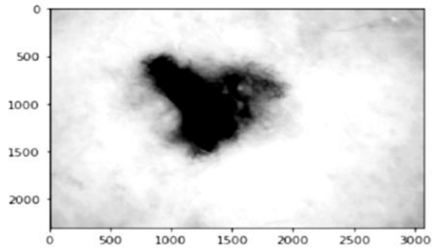

Figure 4: Sample Grayscale Skin Image

3.2.3. Applying Gaussian filter

A picture may be blurred using the Gaussian smoothing technique. The confidence interval of the Gaussian distribution is employed in the calculation of the filtering degree that is desired. The output that is provided by the Gaussian filter is a cumulative total of each pixel's neighboring pixels, with the averaged giving more consideration to the worth of the pixel intensities that are located in the centre of the image. In the approach that we have described, the grayscale pictures are given a Gaussian filter treatment in order to smooth them out. Figure 5 displays the picture after going through the Gaussian filter.

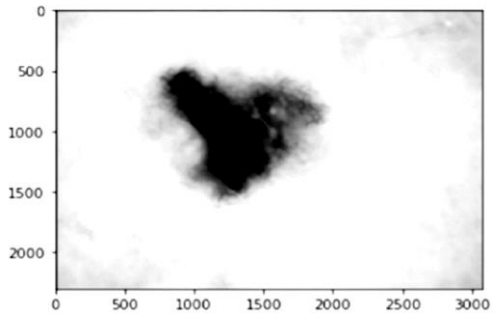

Figure 5: The filtering was done using a Gaussian distribution.

3.3. Segmentation

The procedure of fragmentation is used in order to obtain the area of interest (ROI) from the skin magnetic image. In ROI, all of the pixels have the same characteristics. In the system that we have provided, we are using two different methods for the segmentation: step. (1) An adaptive version of Otsu's thresholding approach applied to a picture (2) Filling up the gap by means of a morphological procedure. Figure 6 displays the picture after it has been divided.

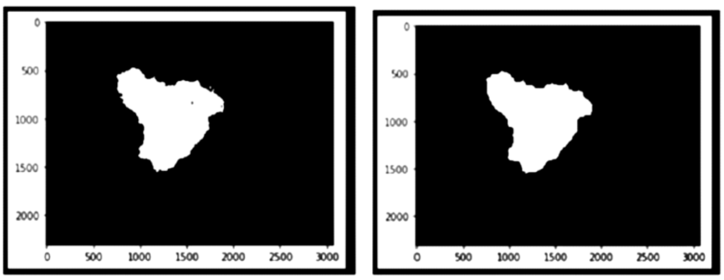

Figure 6: Sample threshold image & hole filled

In the last step of the classification stage, contours are used so that we can determine the border of the lesion portion. In order to assess the features of the form, boundary separation is necessary. The completed result can be seen in Figure 7, which was generated by the classification stage.

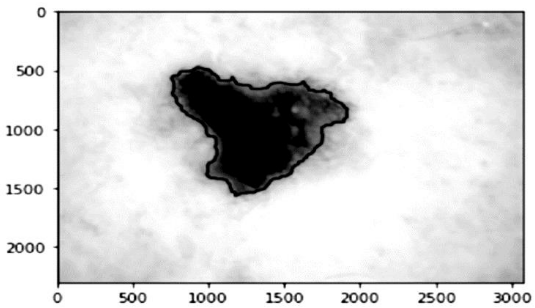

Figure 7: Retrieved picture of the boundary

3.4. Feature Extraction

The process of collecting data from the targeted skin picture involves many steps, one of which is edge detection. In the course of our research, we have identified a number of singular and distinct characteristics that set malignant melanoma apart from benign melanoma. In the approach that we have provided, the analysis of the texture characteristics was carried out using the

GLCM methodology, and in addition to that, we are recovering the color and form data. Following that, we aggregate them, and use them for the goal of categorization.
The GLCM approach is the surface data analysis method that we have chosen to use in the architecture that we have suggested. The grayscale picture is used as the input here. As input is provided, the grayscale picture is shown. The number of grey levels corresponds directly to the quantity of multiple rows that the GLCM matrix has. It is utilized for the goal of feature extraction since it is a method that maps these probabilities. There are Contrasting, Connectivity, Volatility, and Inverted Differentiation moments that may be obtained from the extraction of features from GLCM.

3.4.1. Shape Features

The Boundary roughness index, Anomalous index, Circumference index, and size index are the four shape features that are evaluated from the bruise in a binary picture.

3.4.2. Color Features

Within the scope of our investigation, we computed the mean as well as the sample variance for the RGB streams for color characteristics.
The purpose of image retrieval is to minimize the original picture information source by determining particular values or characteristics that aid to categories distinct photographs from each other and. This is accomplished via the method used to measure certain variables or characteristics.

3.5. Classification

The next phase is the categorization of pictures, which identifies melanoma as either benign or malignant depending on the appearance of the tumor. The classifier is used to distinguish melanoma photos from other types of images that do not include the disease. It's possible that using an SVM classifier would be desirable to simplify the categorization process significantly. After collecting a set of skin data, one then predicts, for every number of inputs, to which of the two groups the collected data should go. The support vector machine (SVM) generates a hyper plane that separates 2 categories with a significant space somewhere between. In the context of our research, sensory evaluation features, in addition to the results obtained of GLCM, are provided to SVM classifier. This includes taking testing and training data, as well as clustering data, in order to produce a classification model the source skin image and determine whether or not it contains melanoma.

4. RESULTS AND DISCUSSIONS

When compared to the conventional biopsy procedure, the diagnostic methodology that we have presented is quite effective. In this particular research Endeavour, both the financial investment and the amount of time necessary for the melanoma diagnosis procedure were significantly reduced. Techniques relating to machine learning and image processing are included into the approach for the purpose of diagnosing skin cancer. The support vector machine (SVM) method was used in order to perform accuracy tests on the skin lesion disease picture.

Image ID	Area	Perimeter	Diameter	Abnormality	Irregularity	Circularity
1	249592.0	2115.02	563.73	1482.95	1.43	17.92
2	93053.0	1308.95	344.21	893.34	1.47	18.41
3	168088.5	1827.99	462.62	1155.51	1.58	19.88
4	175778.0	1791.63	473.083	1232.90	1.45	18.26
5	534159.0	3277.70	824.69	2047.91	1.60	20.11

TABLE 1: The outcomes of the form feature extraction process

The SVM algorithm was used in order to improve the efficiency as well as the precision of the melanoma detection process. In the first step of the aforementioned system, form characteristics are extracted. The following shape characteristics are derived from this: area, perimeter, abnormality, irregularity, circularity, and diameter. Table 1 contains the characteristics of five photos that were selected at random.After the form characteristics have been extracted, they are fed into a SVM in order to identify the pictures using varied size test data. Table 2 details the performance of the different train to test ratios with regard to the various shapes attributes.

Train to Test ratio	Accuracy
5:5	85%
6:4	83%
7:3	84%
8:2	84%
9:1	87%

TABLE 2: The accuracy of various train-to-test ratios using shape features

Then, we use solely the GLCM selected features from epidermis pictures for categorization purposes. These are the GLCM characteristics: Brightness, Linkage, Inverted Differential Times (IDT), and Disorder Features of five photos randomly selected are shown in Table 3.

Image ID	Contrast	Correlation	IDT	Entropy
1	4.3229	0.9946	0.5962	8.8114
2	5.7088	5.7088	0.5050	9.4623
3	6.7545	0.9950	0.5216	9.1870
4	5.4357	0.9945	0.5318	9.0827
5	23.3354	0.9844	0.3676	10.2662

TABLE 3: GLCM feature extraction results

Table 4 presents the results of the difference train test ratio along with GLCM characteristics.

Train to Test ratio	Accuracy
5:5	82%
6:4	84%
7:3	84%
8:2	87%
9:1	89%

TABLE 4: Accuracy for varying training to testing ratios using texturing attributes

Geometry and GLCM characteristics are then combined, and SVM is used to classify. Table 5 summarizes the results of the differential train test ratio using geometry and GLCM characteristics.

Train to Test ratio	Accuracy
5:5	87%
6:4	85%
7:3	87%
8:2	88%
9:1	91%

TABLE 5: An accurate train ratio test using a combination of form and texture characteristics has been developed.

Afterwards when, we integrate the characteristics of form, color, and GLCM, and then we apply those characteristics to an SVM classifier to generate the model. Table 6 contains the results of the differential train test ratio using shape, color characteristics, and GLCM characteristics.

Train to Test ratio	Accuracy
5:5	85%
6:4	88%
7:3	90%
8:2	91%
9:1	96%

TABLE 6: Combination of form, color, and GLCM characteristics for varied train test ratios

According to the chart that was just presented, the high accuracy achieved by utilizing only the GLCM feature is 89% when the ratio of training data set to test data is 90% to 10%. The highest level of accuracy is obtained, when the GLCM features and Shape features are combined. This degree of precision is achieved when the ratio is 90%:10%. We were able to create an SVM model with an accuracy of 96 percent by combining the GLCM, Shape, and Color features. This was achieved with a train-to-test ratio of 9:1 percent. The conclusion of our investigation is shown in Table 7.

Feature Extraction	Accuracy
Shape	87%
Texture (GLCM)	89%
Texture & shape	91%
Texture, shape & color	96%

TABLE 7: The Planned Study's Findings as Summarized

When we merged and applied the shape, color, and GLCM data to the classifier, we were able to determine which model had the highest level of accuracy again for process as a whole. On the basis of the findings presented above, we are able to draw the conclusion that the efficiency of the classification algorithm is dependent on the number of characteristics that are applied towards the SVM. The larger the amount of characteristics will give the higher level of accuracy.

5. CONCLUSION AND FUTURE SCOPE

The purpose of this research is to develop a technique for accurately detecting melanoma, which is a kind of skin cancer, such that it may be readily classified as either benign melanoma or malignant melanoma based on the input picture. When the GLCM approach with color and shape characteristics are coupled for the extracting the features, the suggested system achieves a high accuracy of 96 percent. Because it does not include any discomfort or time constraints, this procedure is superior to the biopsy method in terms of efficacy and comfort for both patients and medical professionals. We searched the web data repositories, but we were unable to find any photographs of people with dark complexion to use in the implementation. However, the darkish skins are essential for the ongoing work and experimentation that will be done with the research.

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