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A Comprehensive Evaluation of Skin Cancer Identification with Deep Learning Procedure using SVM & CNN

Dr. R. Vijayakumar Ph.D., Associate Professor[1],
vijayakumarr@mahendra.info

Dr. D. Chitra Ph.D., Professor[3]
chitravalli2000@gmail.com

M. Ajit[2]
ajitkumar6001@gmail.com
M.E. Communication Systems Engineering,
Department of Electronics and Communication Engineering,
Mahendra Engineering College, Tiruchengode Highway, Mahendhirapuri, Namakkal-637503.

Abstract—Skin is our biggest organ. The two-square-yard item weights six to nine pounds. The skin separates the body from its environment. The dermoscopy technique was developed to improve melanoma diagnosis. Dermoscopy, a non-invasive skin imaging technology, magnifies and lights a tiny area of skin to highlight spots. Skin diseases account for most global illnesses. This sickness is common, but identifying it requires a two-stage approach that successfully mixes Computer Vision with clinically verified histopathological findings. Before extracting features, the skin disease image is pre-processed. Step two is employing skin analysis histopathological characteristics to identify diseases with algorithms. The work focuses on two-classifier classification and feature extraction, such as: Support Vector Machine (SVM) and Convolutional Neural Network (CNN) classifiers. Statistics texture data is used to train the SVM Classifier to detect malignant skin lesions. Classification involves comparing each test set skin photo to the training set's. Training set images include healthy, malignant, and diseased skin. Lesion Image analysis systems use Melanoma criteria including colour, area perimeter, diameter, size, and shape to separate and feature pictures. Melanoma cancer lesion and non-melanoma image classifications use generated feature parameters. The result shows accuracy, sensitivity, and specificity. If integrated with deep learning technologies like CNN, the computer system can identify skin cancer better than experienced dermatologists. Based on this achievement, we enhanced our Deep Learning Architecture to categorize infected patient photos as benign or malignant. This strategy aims to reduce skin cancer deaths by improving early diagnosis and treatment. Also shown are efficiency, accuracy, and specificity. These two classifiers identify melanoma in adults and children based on age differences, and the best classifier provides complete findings.

***Index Terms*—Cancer Detection, Convolutional Neural Network, CNN, Classification, Melanoma, Support Vector Machine, SVM, Skin Cancer, Segmentation**

I. INTRODUCTION

There is a regular pattern to how cells in the human body normally divide and divide again. To ensure appropriate bodily function, its formation, functional period, and death should be in sequential order [1]. Diseases of all types are brought about when the natural order is upset. Cancer is one of the illnesses [2].

The human body has billions of cells, and cancer may start anywhere. When cancer cells invade neighboring tissues, it's because they began dividing uncontrollably in one area of the body [3][4]. In a typical human body, cells multiply and divide to meet the body's changing needs. As cells mature, age, or get damaged, they eventually die and are substituted by brand new cells. Once cancer develops, the methodical and exact process of cell splitting is destroyed. This leads to a dramatic increase in the cutoff for cellular abnormalities and damage. The process of cell death is necessary for cell survival, and the production of new cells is dependent on this process. If the cells aren't needed, they'll keep dividing uncontrollably, which might lead to tumor formation [5].

Cancer can cause either benign or malignant tumors. Malignant tumors are the most common type of tumors containing cancer cells. Cancer occurs when cells in a tumor metastasize, or when they invade healthy tissues in the area. When malignant tumors divide, some of the cancerous cells may travel to other areas of the body via the blood or lymphatic system, where they might start a new tumor far from their original location. Benign tumors, in contrast with malignant ones, do not metastasize or invade surrounding tissues. It is worth mentioning that benign tumors tend to be bigger. While malignant tumors occasionally regrowth after surgery is possible, benign tumors once removed cannot recur. A benign tumor in the brain poses an immediate and serious risk to human survival, in contrast to the vast majority of benign tumors found elsewhere in the body [6][7].

Sunlight, heat, damage, and infectious diseases (both bacterial and viral) are among things that the skin may shield the body from [8]. In addition to storing water and fat, the skin aids in keeping the body at a constant temperature. Skin cancer ranks highest among all cancers in terms of prevalence and is considered a critical public health concern. While sun exposure is the most common cause of skin cancer, it can begin anywhere on the body's surface. The skin is composed of many layers. The outermost layer of skin, called the epidermis, is typically where skin cancer begins. The following figure Fig.1 shows the Skin Cancer Image Samples

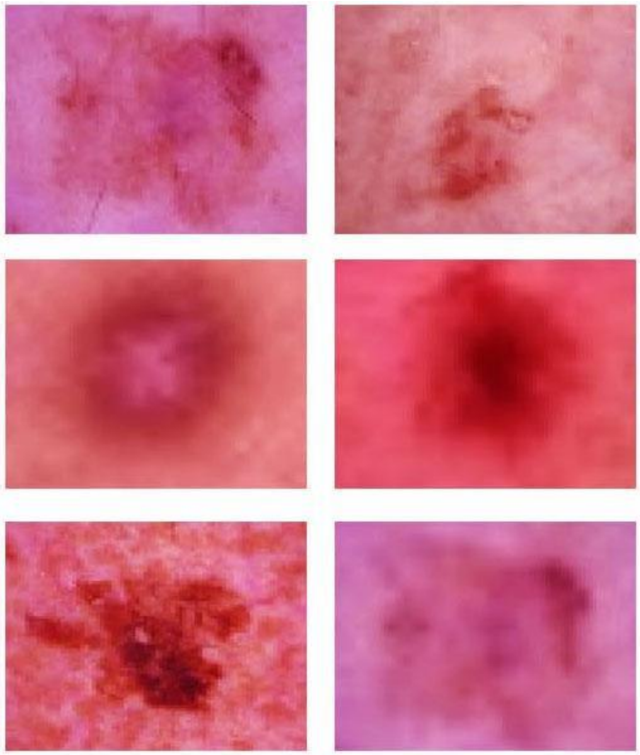


Fig.1 Skin Cancer Image Samples

Basal cell as well as squamous cell cancers of the skin was examples of non-melanoma skin cancers, one of several types of skin cancer. Not only does non-melanoma skin cancer respond well to therapy, it seldom spreads to other parts of the body. Among the many forms of skin cancer, melanoma poses the greatest hazard. Malignant skin lesions can be either melanocytic (like melanoma) or non-melanocytic (like basal cell carcinoma). Although it is rare, melanoma is the most aggressive and deadly form of skin cancer [9]. The likelihood of melanoma skin cancer metastasizing (invading other organs) increases if it is not detected in a timely manner.

(i) EPIDERMIS: Squamous cells, which are flat in structure, make up this layer, which serves as the outermost layer of human skin. Basal cells are the spherical cells that lie underneath the squamous cells. Melanocytic are the innermost cells of the epidermis, situated within the basal cells. Melanocytic produce the pigment (color) that is found in skin. Epidermal layers comprise the basale layer, which is the deepest, the spinosum layer, the granulosum layer, the lucidum layer, and the corneum layer, which is the most superficial. Keratinocytes, melanocytes, and Langerhans cells are the three primary cell types found in the epidermis.

(ii) DERMIS: Underneath the epidermis lies the dermis, the second primary layer of skin. It contains several cell types, including lymph tubes, blood vessels, and glands. There are glands that aid in skin drying, cooling, and sweetening, among others. Collagen, elastic tissue, as well as many extracellular components such as veins, lymph nodes, hair follicles, as well as glands makes up the dermis, a fibrous structure. The dermis helps in thermoregulation, in sensation, and providing support and protection to the skin as well as deeper layers.

The human skin consists of three distinct layers of tissue.

(a) The top layer Dermis called Epidermis

(b) The middle layer called Hypodermis
(c) The fatty or bottom layer

The dermis is composed of five layers: the basal, spinosum, granulosum, lucidum, and corneum layers. Nerve endings, sebaceous glands (sweat and oil glands), hair follicles, as well as blood vessels are all found in the dermis. The terminals of the nerves are sensitive to temperature, pressure, and pain. A greater density of nerve endings is found in some skin regions compared to others [10].

II. RELATED STUDY

As one of the leading cancer killers globally, skin cancer is among the worst forms of the disease [11]. Early detection of skin cancer can lower mortality rates. Despite its limitations, eye examination is still the primary method for diagnosing skin cancer. To aid dermatologists in the accurate and early detection of skin malignancies, solutions based on deep learning have been suggested. This literature review compiled the most current studies on deep learning for skin cancer categorization. Our review of the most popular deep-learning models as well as datasets of skin cancer classification is also available here [11].

With a sharp increase in occurrences globally, skin cancer is one of the most prevalent and deadly forms of cancer [12]. High death rates can occur from metastases if the disease is not detected in its early stages. If caught early, skin cancer is curable. Therefore, a primary focus of research is now the development of methods for the rapid and precise detection of these malignancies. Computational approaches to skin cancer identification and categorization have made use of a range of machine learning algorithms. Models and algorithms in machine learning can learn from information as well as make predictions on data that has never been seen before; this area of AI is known as machine learning. In order to identify skin cancer, doctors use the time-consuming and costly conventional biopsy approach. On the other hand, with the use of machine learning algorithms, cancer may be detected earlier, which reduces the burden on experts and improves the diagnostic accuracy of skin lesions. A critical evaluation of certain cutting-edge machine learning methods for skin cancer detection was provided in this paper. After compiling a number of researches, we compared the results of three popular methods for artificial neural networks: k-nearest neighbors, support vector machine, as well as convolution neural networks. We took a quick look at the pros and cons of each algorithm. The difficulties of skin cancer detection were brought to light, and potential areas for further study were suggested [12].

Melanoma has the highest mortality rate of any skin cancer kind [13]. For the objective of offering a supplementary viewpoint to specialists, several researchers have examined alternative techniques of spontaneous melanoma detection and diagnosis; nonetheless, individuals with an early diagnosis have a better prognosis. It has been challenging to construct models using available data due to the imbalance across classes. This work is evaluating the performance of machine learning algorithms with unbalanced basis training methodologies on the melanoma diagnosis issue. Two hundred dermoscopy images were used to extract skin lesion patterns using the ABCD rule and convolution neural network designs from VGG16, VGG19, Inception, as well as ResNet. The random forest classifier achieved a sensitivity of around 93% and a kappa value of 78% after utilizing attribute selection with GS using training data balancing utilizing the Synthetic Minority Oversampling Method with Edited Nearest Neighbor rule [13].

One of the most fatal forms of cancer in the world is melanoma [14]. In the absence of prompt medical attention, this skin cancer has the potential to metastasize. One of the best methods for detecting melanoma nowadays is classifiers based on Convolutional Neural Networks (CNNs). Recent deep convolutional neural network (CNN) methods for melanoma skin cancer detection and suspicious lesion investigation are detailed in this article. More than 36,000 photos culled from various databases were used to run the tests. With an accuracy as well as Area under Curve (AUC) over 99%, the top performing deep learning system obtains good ratings, according to the collected data [14].

In general, there are four main types of skin cancers: melanoma, basal cell carcinoma, squamous cell carcinoma, as well as Merkel cell cancer [15]. Skin cancer, namely melanoma, strikes a disproportionately large number of people compared to other forms of cancer. Skin cancer can be successfully treated and cured if caught and predicted early enough to prevent it from spreading to other parts of the body. Modern advances in machine learning as well as deep learning have led to the development of a reliable computerized diagnostic system that can aid doctors in making more accurate illness predictions and help patients proficiently recognize their symptoms. The current models use deep learning techniques to learn features from whole pictures, or they depend on algorithms for machine learning that can only choose features. Feature extraction and classification are accomplished using the suggested hybrid of machine learning classifiers and pre-trained convolution neural networks. The model becomes more accurate with this method. This study achieves an ultimate precision of 99.1 percent using a mix of VGG16 and XGBoost as both feature extraction and classifier. This is an improvement above previous efforts included in the literature review [15].

III. METHODOLOGY

With the use of forward chaining and depth first searches, identify specific skin conditions. Because a single skin illness can present in a variety of ways, it would be impractical to use a rule-based method to determine the kind of dermatological problem. We need a system that learns the fundamental pattern in skin disease, which can be inferred from the image and histopathological inputs, and then applies novel methods for image processing to analyze it and determine about the existence of skin cancer. A self-learning model that we developed would be the best option here because the problem we are attempting to resolve is probabilistic in nature. What make up human skin are its epidermis and dermis layers. A weakened immune system, allergies, viruses, and other pathogens can all lead to skin problems. Skin diseases are typically brought on by lax hygiene practices, germs, viruses, allergic responses, and a lack of immunity in the body. If dirtiness is the sole cause of skin diseases, then adopting better habits can save people from getting sick in the first place. This is particularly true in tropical countries like Indonesia, where excessive humidity fosters the growth of skin microorganisms. Another issue is that not everyone is aware of the best ways to treat or prevent skin problems.

With the advent of computerized diagnosis tools, the medical industry has undergone tremendous change, allowing both professionals and laypeople to more accurately identify diseases. Here we provide a hybrid approach to skin cancer diagnosis that may be used to any worrisome lesion, namely melanoma. The forecasts of two distinct approaches, namely SVM and CNN, form the basis of our suggested system. These two classifiers are utilized to identify melanoma in children and adults, respectively, according to the age disparity. The output is provided by the classifiers, and their relative efficiency is determined by comparison. Eight distinct pre-processing techniques were employed to enhance the precision of feature extraction. Image gray-scale conversion, sharpening, median, smooth, binary masks, RGB extraction, histogram, and sobel operator were some of the methods employed. It is necessary to extract the RGB values from the photos before they can be converted to gray-scale. To bring out more detail in the affected area, a sharpening filter is added to the gray-scale picture. From the binary picture, YCbCr was utilized to obtain the average color code of the affected region. Using the Euler value, we were able to extract the number of parts associated with the skin ailment from the picture. We employ GLCM and LBP, which stand for Grey Level Co-occurrence Matrix and Local Binary Pattern, respectively, for the categorization. According to a heuristic, the existence of a high number of injuries was indicated when the Euler value exceeded a certain threshold. Rosacea, psoriasis, moles, acne, and hives all share this key trait. The LBP feature is built from the histogram for LBP codes, which are computed for each pixel. The following figure Fig.2 shows the block diagram based on SVM algorithm.

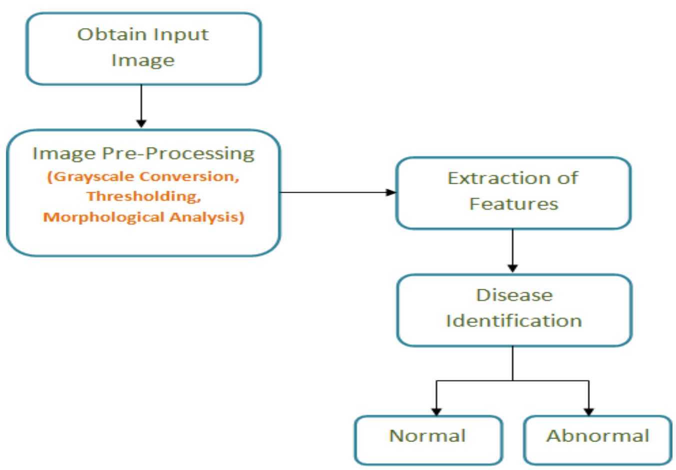


Fig.2 Block Diagram Based on SVM Algorithm

The following figure Fig.3 illustrates the block diagram based on CNN algorithm.

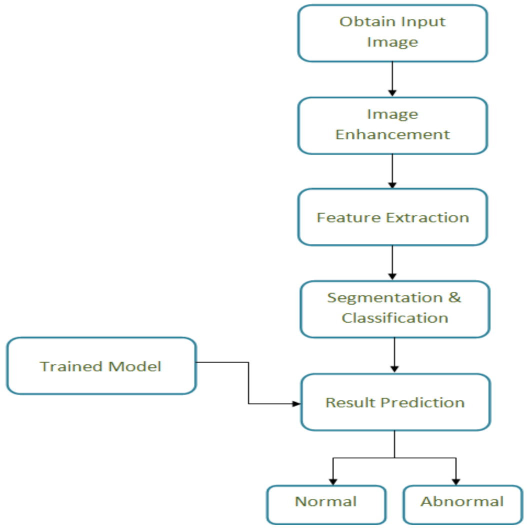


Fig.3 CNN based Block Diagram

(i) Acquiring Images: The initial stage of any system that processes images is picture acquisition. Transforming an optical picture (practical data) into a numerical array that can be modified on a computer is the overall goal of any image capture. Appropriate cameras are used to capture images. Choose an image from a dataset that contains photographs of skin diseases and use it as a basis for your classification.

(ii) Pre-Processing: Model training and inference rely on properly formatted pictures, which are prepared for use in these processes through image preprocessing. Resizing, rotating, and changing colors are all part of this. If the captured picture is expected to be a three-plane image with values varying up to 256, then two-plane conversions are performed in pre- processing by turning it into grey format.

(iii) RGB to Gray: The most basic method for transforming a three-dimensional array of color images into a two-dimensional array of gray-scale data is to average the values of the red, green, as well as blue pixels for each pixel. This produces a respectable gray-scale estimate by combining the brightness or lightness from each color band.

(iv) Threshold: Threshold is a method of picture segmentation that involves modifying individual pixels to facilitate analysis. To do thresholds, you must first transform your image from a color or gray-scale format into a binary format, meaning it is just black and white. It is a method for improving contrast by manipulating picture intensities. The improved visual quality makes it easier to analyze as a result of this upgrade.

(v) Morphological Operation: A wide variety of image processing processes known as "morphological operations" are used to manipulate digital pictures according to their forms. The morphology technique reduces noise for categorized pictures and obtains the intended one. Text is used to indicate the classified kind on images. In a morphological functioning, each image pixel is correlated with the value of other pixels in its neighborhood.

(vi) Local Binary Pattern: An efficient and straightforward texture operator, Local Binary Pattern assigns binary numbers to picture pixels by threshold their immediate surroundings.

(vii) Enhancement: If the source took the photos, you should make them seem better. The goal of picture filtering is to reduce the signal-to-noise ratio by converting the original image to a gray-scale version while extracting certain characteristics. By using various techniques, such as sharpening or smoothing, the goal of image enhancement is to render a digital picture more aesthetically pleasing. In the field of digital image processing, this is a crucial subject. It can aid in the correct extraction of information from the improved pictures by both individuals and computer vision systems. The enhancement technique increased the visual quality along with certain picture qualities, including brightness, contrast, ratio of signal to noise, resolution, edge sharpness, as well as color correctness. In particular, the segmentation stage will benefit from the improved image's information for post-processing. Every industry makes use of image enhancing software, whether it's for medical representation studies or analyzing satellite photos. In order to improve gray-scale pictures for use in later higher- level procedures like detection and identification, histogram transformation is a crucial step.

(viii) Threshold threshold, which can yield precise outcomes. As a form of picture segmentation, image threshold distinguishes between an image's foreground and background. Pixel values are assigned according to the given threshold values in the applied technique.

IV. RESULTS AND DISCUSSIONS

The following are the sample input images taken from Google for proposed implementation. A folder will be created to keep the many datasets that are collected in the same way. Each type of skin sample—normal skin and diseased skin—is collected and kept in its own folder. First, as seen in the figure above, Skin cancer illness images are inputted into the computer system as data. Unfortunately, my computer has to read the pixel values and convert them to a three-channel RGB (red, blue, and green) image because the original photos aren't in a machine-readable format. After that, they will be turned into grayscale pictures. The trained photos will be saved in a separate folder after training, following which the image will be trained using various datasets. In order to identify skin cancer and other skin illnesses, these photos will be processed using an image processing approach.

Fig.4 Input Image Samples

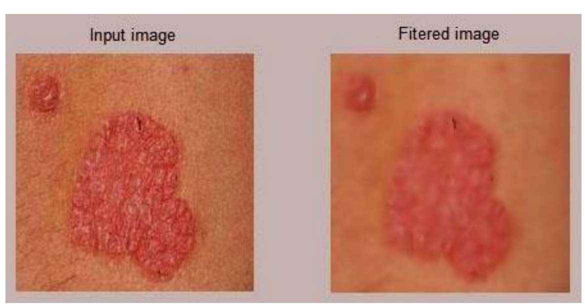


Fig.5 Filtered Image

A skin cancer lesion may be described by the segmented area in the corresponding photographs. It is necessary to separate this malignant tumour from the skin's background data. The input photos were segmented using clustering with centroid selection, using a value of K set to 2, to account for intensity variance. Fig. 6 and Fig. 7 show the segmented area and the corresponding boundary selection.

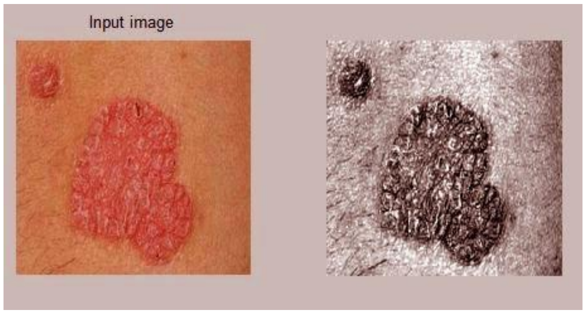


Fig.6 Image Segmentation

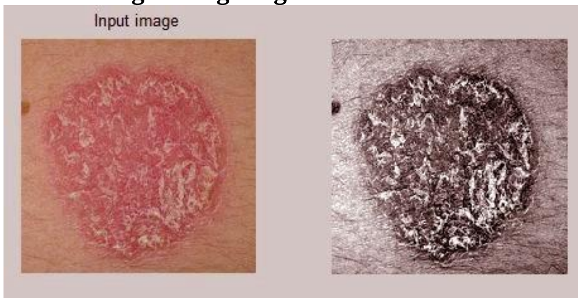


Fig.7 Boundary Selection

Melanoma is correctly diagnosed by employing the clusters that are produced over the photographs for further processing of the image. The enlarged, noisy, filtered, and segmentation results are displayed in Fig-8. We use it to identify the afflicted area and its limits, as well as to label the image's ground truth data inside our dataset with the aid of the doctor.

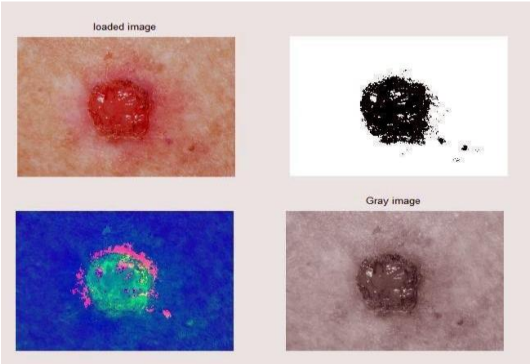


Fig.8 Melanoma Detection

By using the segmentation approach, the cancer-affected areas may be separated from the background pictures and the region of interest can be extracted. The degree to which the segmented region and the ground truth data overlap is a good indicator of a system's segmentation accuracy. The suggested result metrics, including Accuracy, Precision, Recall, and F1- Score, for both SVM and CNN are graphically shown in Fig. 9
(a) and (b).

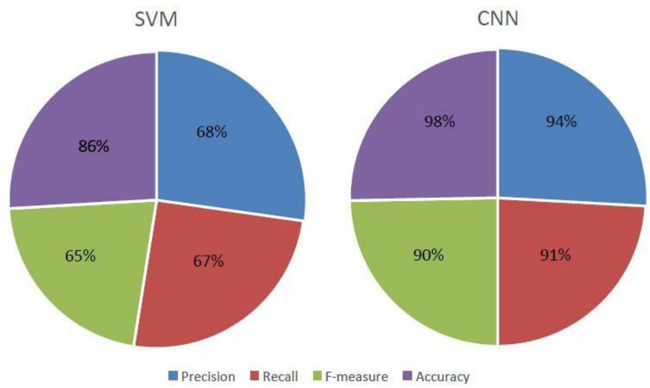
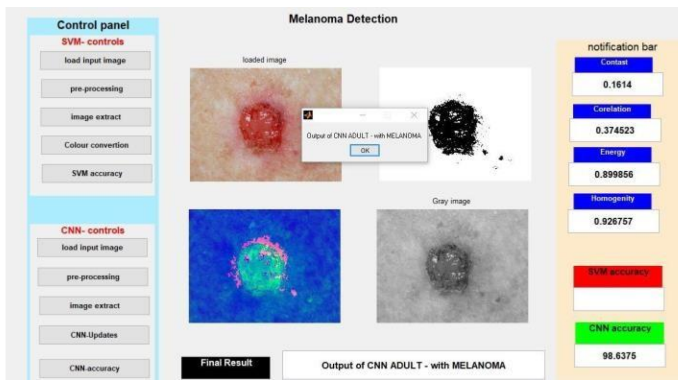


Fig.9 Result Metrics Evaluation (a) SVM and (b) CNN

The following figures, Fig-10 (a) and (b) represents the graphical user interface design for the identification of skin cancer using SVM and CNN.

(a)



(b)
Fig.10 GUI for Melanoma Identification (a) SVM and (b) CNN

V. CONCLUSION AND FUTURE SCOPE

The most common kind of skin cancer that causes mortality is the malignant lesion. There have been several suggestions for improvements to image processing and analysis that could aid dermatologists in their diagnosis and, perhaps, therapy if caught early enough. The procedure entails making use of a plethora of retrieved elements that might characterize the lesion, such as its structure, shape, texture, and colour. The features that were chosen using Info gain are what feed into the deep learning classifier. With the highest rating, the Ada boost classifier was chosen. We have created a technique to identify melanoma, a kind of skin cancer. An initial round of picture enhancement and region-of-interest extraction using a variety of pre- processing and segmentation algorithms yielded an accuracy of
98.6 percent after 96 seconds.

A number of characteristics were retrieved from the YCbCr and HSV colour spaces. We evaluate the performance of features on three different classifiers: Since the created system's specificity is higher than its sensitivity, it is able to more accurately identify benign instances. In comparison to earlier methods, the system's overall accuracy is higher. Enhancing sensitivity can be achieved by including additional characteristics that are compatible with the features retrieved from the HSV and YCbCr colour spaces. These features can include border, shape, and texture features. The improved precision of the system will be facilitated by this. Future iterations will use more sophisticated algorithms to provide more precise results than the base research.

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