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Simulation Study of Skin Tumors Detection Tool Using Artificial Intelligence (AI)

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Abstract

The objective of this research was to develop a system for early skin tumor diagnosis using artificial intelligence. With advancements in technology, early detection of skin tumors has become possible, and this study successfully achieved its objective. The chosen technology involves employing the Support Vector Machine (SVM) algorithm, along with image processing tools and artificial intelligence, resulting in a significantly improved accuracy rate of 85%. The software was developed using MATLAB. The methodology implemented in this research focuses on vertically segmenting skin tumor images obtained from the Kaggle platform, which provides diverse datasets. The proposed system aims to detect six distinct types of skin tumor diseases. To enhance detection accuracy, the research integrates the Gray Level Cooccurrence Matrix (GLCM) and Gabor Filter. These techniques contribute to developing a robust system structure. The classification of the six different diseases is based on analyzing input images. The research encompasses various stages, including preprocessing, segmentation, feature extraction, and the detection process. These steps collectively yield satisfactory results in addressing the challenges associated with skin tumor detection.

Keywords: Skin, Tumors, Cancer, Detection, SVM, GLCM, Gabor Filter, MATLAB, AI.

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دراسة محاكاة لأداة كشف أورام الجلد باستخدام الذكاء الاصطناعي

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الملخص

كان هدف هذه البحث هو تطوير نظام لتشخيص أورام الجلد في مرحلة مبكرة باستخدام الذكاء الاصطناعي. مع التقدم في التكنولوجيا، أصبح الكشف المبكر عن أورام الجلد ممكنًا، وقد حققت هذه الدراسة هدفها بنجاح. تتضمن التكنولوجيا المختارة استخدام خوارزمية دعم المتجهات(SVM) ، إلى جانب أدوات معالجة الصور والذكاء الاصطناعي، مما أدى إلى تحسين كبير في معدل الدقة بنسبة 85%. تم تطوير البرنامج باستخدام MATLAB .تركز المنهجية المطبقة في هذا البحث على تقسيم صور أورام الجلد عموديًا التي تم الحصول عليها من منصة Kaggle ، التي توفر مجموعات بيانات متنوعة. يهدف النظام المقترح إلى الكشف عن ستة أنواع متميزة من أمراض أورام الجلد. لتعزيز دقة الكشف، تدمج الدراسة مصفوفة التوافق الرمادي (GLCM) ومرشح جابور. تساهم هذه التقنيات في تطوير هيكل نظام قوي. يعتمد تصنيف الأمراض الستة المختلفة على تحليل الصور المدخلة. تشمل الأبحاث مراحل متعددة، بما في ذلك المعالجة المسبقة، والتقسيم، واستخراج الميزات، وعملية الكشف. تؤدي هذه الخطوات بشكل جماعي إلى نتائج مرضية في مواجهة التحديات المرتبطة بكشف أورام الجلد.

الكلمات المفتاحية: الجلد، الأورام، السرطان، الكشف، SVM، GLCM، مرشح غابور، MATLAB، الذكاء الاصطناعي.

Introduction

The skin is the outermost layer of tissue that covers the human body. Therefore, individuals are highly conscious of and sensitive to the appearance of their skin. Consequently, the appearance of the skin has garnered significant interest in various scientific and

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technological fields. Human skin is the largest and fastest-growing organ in the body. It serves as a protective barrier, separating the internal body from the external environment and safeguarding against bacteria, viruses, microbes, and other elements. Furthermore, it regulates body temperature and facilitates the senses of touch, heat, and cold [1]. Skin tumors is a malignant tumor that develops in the skin cells and is one of the most prevalent types of tumors in humans, accounting for more than 50% of all tumor cases worldwide. Moreover, the incidence of skin tumors has increased by 44% from 2008 to 2018, accompanied by a notable rise in fatalities. Skin tumors is an unwanted growth on the skin, with various causes and varying degrees of malignancy. It has the potential to rapidly spread throughout the human body via the lymphatic or blood system [2-3]. Early detection of skin tumors is crucial for successful treatment and improved outcomes. However, accurate diagnosis can be challenging and necessitates a comprehensive examination of skin lesions by dermatologists. In recent years, there has been a growing interest in the utilization of computer-aided diagnosis (CAD) systems to aid in the detection and diagnosis of skin tumors. Dermatologists conventionally assess the following characteristics of skin lesions: asymmetry, borders, colors, diameter, and evolution. If a patient's lesion exhibits asymmetry, indistinct borders, more than four colors, a large diameter, and an evolving shape, it is likely to be a case of skin tumors. Dermatologists typically consider these features to gain an initial understanding and proceed with a skin biopsy if a clear result cannot be obtained [4].

This method of diagnosing skin tumors is time-consuming and may pose a financial burden for some individuals. Additionally, skin biopsies frequently result in visible scars on the skin, as a substantial portion of the lesion is excised for examination. By integrating artificial intelligence and digital image processing for skin tumors detection, diagnosis can be performed without any physical contact with the skin [5-6]. This can be accomplished on a computer using specialized software. The computer-aided skin tumors detection system involves acquiring an image of the skin lesion, delineating the lesion from the surrounding skin area, extracting relevant features of the lesion, and classifying these features. Segmentation, or boundary detection, is the process of separating the lesion from the surrounding skin to isolate the region of interest.

Dermatologists employ image processing-based systems in

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conjunction with artificial intelligence to diagnose skin tumors. Computer systems can provide accurate predictions comparable to those made by dermatologists. In 2018, an artificial intelligence system outperformed dermatologists by more than 8% in classifying skin lesions as benign or malignant [7].

The primary objective of this research is to automate the identification of skin tumors based on raw images of skin lesions, creating a more efficient and cost-effective method for disease detection without leaving visible scars. The research findings aim to assist dermatologists and other professionals in making more informed judgments, but they are not intended to replace their professional expertise. Furthermore, this research will enable dermatologists to see a greater number of patients each day, work more efficiently, and focus on the most critical cases [8].

Literature review

Over the years, a considerable number of computer scientists and researchers have devoted their efforts to leveraging image processing methods and machine learning for the detection of skin tumor. The examination of their works and the derivation of inspiration from them has played a vital role in the development of this research. We were particularly influenced by the publications cited as [9] and [10]. These works extensively discuss and elaborate on the use of image-processing techniques for the early detection of skin tumors. Moreover, these papers reference other publications and evaluate their methodologies, significantly contributing to our understanding of the challenges and procedures associated with this research. In our investigation, we were able to implement certain methods employed in those papers, while also introducing novel ideas.

The research proposed in [11] presents a comprehensive technique that encompasses the following stages to enable faster, more accurate, and less invasive early detection of skin tumors compared to skin biopsy, without leaving a scar on the skin. The authors suggest that the images should undergo preprocessing, involving the removal of hair and noise, as well as the enhancement of contrast. Subsequently, lesion segmentation using various methods, including edge-based, morphological, and region-based segmentation, becomes necessary [12]. Furthermore, after lesion segmentation, features need to be extracted. According to the authors, features such as contrast, diameter, borders, and merging should be extracted from the images. Additionally, these extracted

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features are stored in a dataset or framework for training the machine learning model. The final step involves predicting whether a new image indicates the presence of skin tumor or not.
In this study [16], a group classified 135 images into cancerous and non-cancerous lesions with the assistance of an original neural network system. They employed the Fuzzy C-means algorithm to divide the images, based on repetitive gradient analysis, to initiate level setting. Features were extracted using graph features and statistical features obtained through the Gray Level Cooccurrence Matrix (GLCM). Subsequently, a feedforward neural network with two layers was trained using three training algorithms. The achieved accuracy using the gradient descent with the momentum training algorithm was 91.9% [17].
A comparative study was conducted on numerous relevant previous works that contributed to image processing, feature extraction, and classification based on SVM. Prior papers discuss the impact of utilizing color features and identifying the human skin surface by differentiating changes in color ratios in each skin region, employing the (RGB-HSV) technique. We observed a clear distinction compared to the research we are currently undertaking for skin tumors detection. The focus here solely centers on determining the location or surface of the skin, whereas in tumors detection research, this method can be pursued for disease detection purposes. Furthermore, there exist various other methods to accomplish the objective of extracting energy values from the image, which we will explore in this research. While it is possible to enhance the performance of the research by extracting more than one feature, the detection system presently extracts color and energy features to validate the successful classification of images each time a new user image is utilized.

Proposed Methodology

The categorization of tumors images holds paramount importance in the creation of classification maps. Hence, tumor image classification represents a significant area of ongoing research with the potential to yield practical applications in real-time settings. This system proposes an innovative approach to classify six distinct types of skin tumor ailments, namely actinic keratosis, basal cell carcinoma, cherry necrosis, dermatofibroma, melanocytic necrosis, and melanoma, by utilizing tumor images. To establish an efficient framework for tumors image classification, this system breaks down

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its processes into several steps, each of which plays a crucial role in ensuring a more precise classification.

Proposed System Flow Structure

The methodology of the system has been described using a series of steps that outline a general procedure for diagnosing skin tumors. The workflow structure of this system is depicted in Figure 1.

Before starting the research, it was important to establish a process that outlines several stages that need to be completed to conclude the study. The system takes a color image as input, which then undergoes preprocessing to reduce noise and enhance contrast. Various segmentation algorithms and techniques are used to separate the lesion from the surrounding normal skin. Additionally, image processing is performed to remove isolated pixel units and focus on focal lesions.

Once the images have been processed and divided into slices, the feature extraction stage begins. This involves extracting all relevant image features, such as color count, diameter, and border fuzziness, and saving them in a data framework. After applying these procedures to multiple images, a data framework containing the extracted features is provided for the machine learning model. This model is trained to predict whether a new image represents a benign or malignant tumor as it illustrates in figure 1.

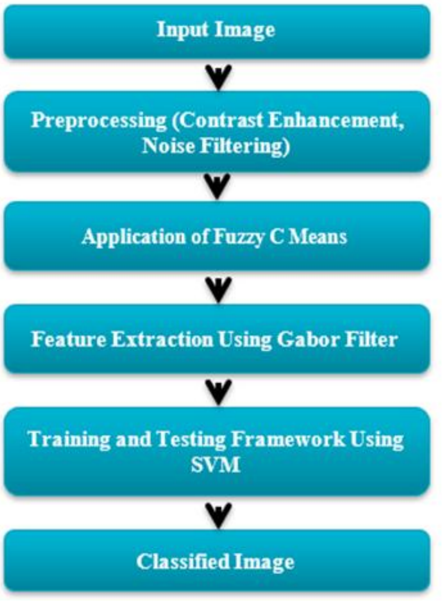

Figure 1. Proposed System Flow Structure

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Proposed Technique

The entire system is integrated through a Graphical User Interface (GUI) to provide a user-friendly interface. By referring to the flowchart in Figure 2, a thorough explanation of the innovative operating system can be presented, wherein the detection of skin diseases involves several sequential stages, each serving a specific purpose. Uploading the image, accessing the database, and predicting the corresponding disease are crucial steps in this process.

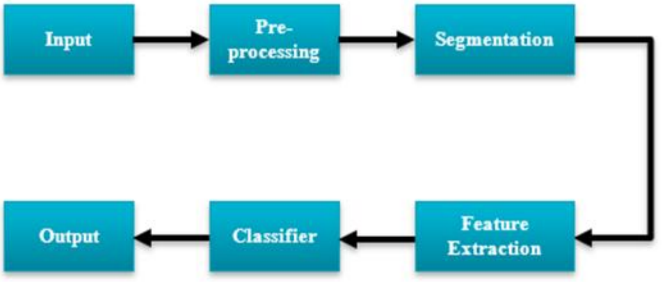

Figure 2. Flowchart of the Proposed System

Steps of the Proposed System:

Step 1: Input Image

•A tumor image for classification is chosen from a database sourced from skin tumor image repositories, such as Kaggle. Our database comprises around 30 benign and malignant skin tumor images, stored in the training folder as it illustrates in figure 3. These images are captured in JPEG format and have been resized to dimensions of 256 × 512 pixels.

Figure 3. Training Folder (Train)

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Step2: Preprocessing (Contrast Enhancement, Noise Filtering)

•The utilization of the gray gradient transformation enables the conversion of a color image into a grayscale image, thereby facilitating expedited and simplified processing. To eliminate redundant information and various forms of noise, noise filtering techniques are implemented through the utilization of image processing and grayscale images as it shows in figure 4 bellow.

170	238	85	255	221	0
68	136	17	170	119	68
221	0	238	136	0	255
119	255	85	170	136	238
238	17	221	68	119	255
85	170	119	221	17	136

Figure 4. Representation of a Grayscale Image

Step 3: Application of Fuzzy C Means

•Fuzzy C-means are commonly used for image segmentation and clustering in academic literature. This technique has found considerable application in the field of data analysis, as it effectively partitions datasets into multiple distinct subgroups, referred to as fuzzy clusters. The assignment of elements to these clusters is determined by evaluating the fuzzy similarity between individual data points.

Step 4: Feature Extraction Using Gabor Filter

•GLCM and Gabor filters are utilized to extract feature vectors from tumor images, with a focus on capturing texture. Texture features are derived from the RGB color image through the computation of color contrast using the HSV channel as it demonstrates in figure 5.

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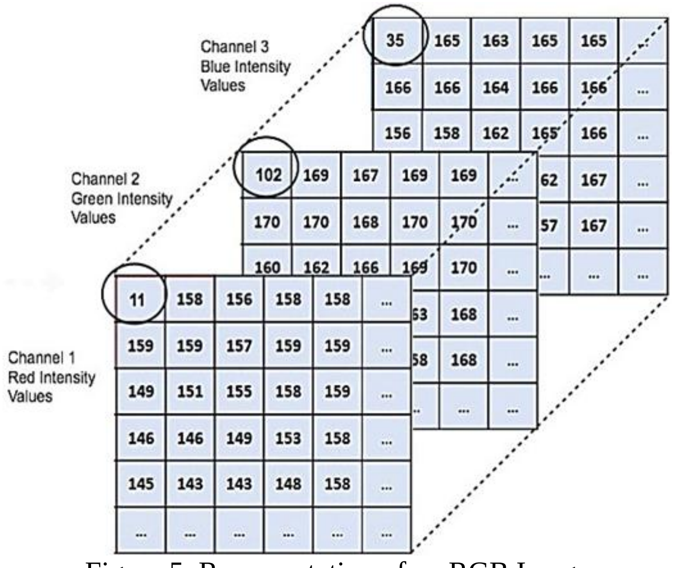

Figure 5. Representation of an RGB Image

•The Gray Level Co-occurrence Matrix (GLCM) is a robust image processing technique used to analyze the frequency of gray level occurrences among neighboring pixels within an image. This method effectively enhances the identification of shapes, patterns, and various features present in images.

•The Gabor Filter is used to enhance and analyze the quality of an image. This filter, composed of small kernels or templates, applies mathematical transformations to the original image, effectively filtering out significant and valuable information while disregarding extraneous details.

Step 5: Training and Testing Framework Using SVM

•The Support Vector Machine (SVM) algorithm makes use of feature vectors, specifically color and texture, to construct and train the proposed model. The database stores the color and texture information of each tumor image, which will be employed in the subsequent classification phase, drawing upon these fundamental elements.

Step 6: Classified Image

•The SVM classifier computes the feature value of the input image as well as the feature value of the database images. Utilizing this value, the SVM classifier categorizes the input image into one of the five predefined categories or other specific categories.

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This proposed methodology, which integrates preprocessing, segmentation, feature extraction, and classification, aims to improve the accuracy and efficiency of skin tumor diagnosis through a comprehensive system.

Experimental Results

- Dataset

The success of this research depends on the availability of a suitable dataset. Kaggle is an online platform that provides access to many datasets and allows data scientists to share their datasets with the public. Several skin tumor datasets were discovered after a comprehensive search on Kaggle. However, not all datasets were classified, so we couldn't determine whether a specific image depicted a case of skin tumors or not. Only a few datasets contained images with a high-quality classification.

The images in the dataset used for this research, as seen in figure 6 and figure 7, were categorized into six different classes. Additionally, this dataset includes raw, unenhanced images that have not been modified since they were captured. The dataset consists of 30 images depicting both benign and malignant skin tumors.

Figure 6. Presents a model for an image of a benign skin tumor lesion from the selected dataset

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Figure 7. Shows a sample image of a malignant skin tumor (Cancer) lesion from the chosen dataset

- Graphical User Interface (GUI)

We employed graphical user interface (GUI) technology as a critical element in source identification and image evaluation. A GUI was designed to include five buttons, each with a unique name and function when pressed, as depicted in Figure 8. The system consists of five buttons and a display page for the classified image. The first button, labeled "Load Test Image," serves the purpose of receiving an image from an external source and loading it into the program for presentation in the designated area. The second button, named "Pre-Processing," enables the reading of each image stored in the training folder, which contains images of both cancerous and non-cancerous diseases. During this process, features are extracted and saved in the database.The third button, labeled "Segmentation," facilitates the segmentation and assembly of images. The fourth button, "Feature Extraction," extracts GLCM & Gabor Filter feature vectors from the input tumors images. Finally, the fifth button, "Classification," applies SVM training to predict the disease by comparing the test image with the database. Pressing this button provides disease predictions for a specific image.

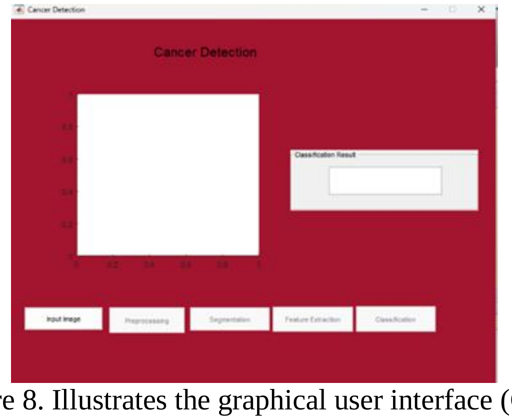

Figure 8. Illustrates the graphical user interface (GUI)

-Image Input

All digital images are composed of a combination of three primary colors: red, blue, and green. These specific color channels are commonly referred to as RGB channels. Within such images, each pixel is attributed with three distinct values, indicating the intensity of red, blue, and green present at that specific pixel. To illustrate this

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process, Figure 9 offers a visual representation of the input of an image into the proposed system.

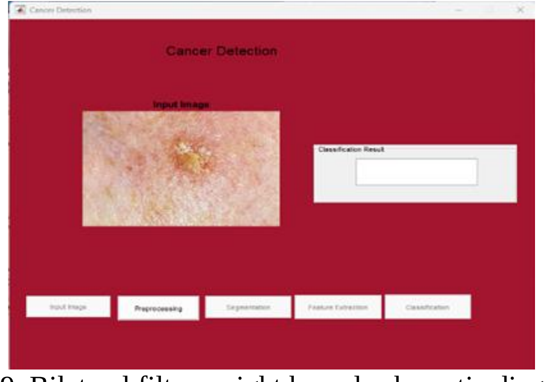

Fig. 9. Bilateral filter weight kernel schematic diagram.

-Pre-Processing

The objective of pre-processing is to improve the image data by reducing undesired distortions and emphasizing crucial image features for subsequent image processing, as depicted in Figure 8.

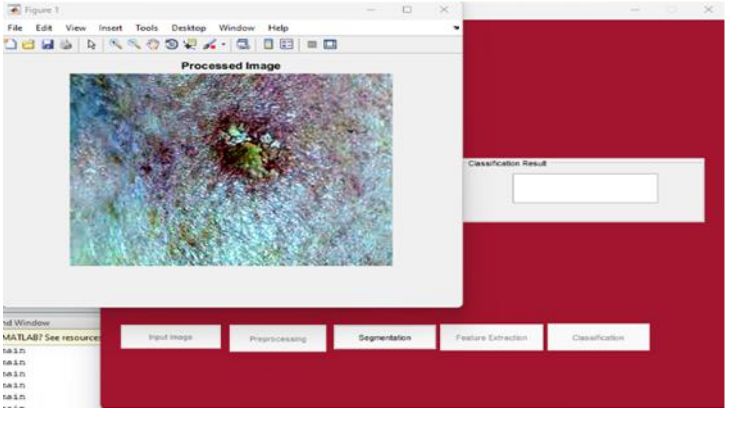

Figure 8. Pre-Processing (Contrast Stretching, Noise Filtering)

Image pre-processing consists of three primary components:

1) Grayscale Conversion
2) Noise Removal
3) Image Enhancement

1) Grayscale Conversion

A grayscale image encompasses exclusively information about brightness, where the value of each pixel corresponds to the quantity of light. Grayscale images solely measure light intensity.

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In our proposed system, the transformation of a colored or RGB image into a grayscale image is accomplished by employing the weighted sum method with the following equations:
Grayscale Intensity = 0.299 R + 0.587 G + 0.114 B

2) Noise Removal

The objective of noise removal is to identify and eliminate undesirable noise from the digital image [15]. The task is to effectively differentiate genuine image features from those induced by noise. Noise manifests as random fluctuations in pixel values. In our suggested approach, we employ the Gabor Filter to eliminate unwanted noise.

3) Image Enhancement

Image enhancement is a process that seeks to enhance the clarity of features of interest within an image [17]. To achieve improved results, contrast stretching is employed.

-Segmentation

This section of the research endeavors to isolate the lesion from the encompassing skin, as illustrated in Figure 9. This stage assumes paramount significance as it necessitates the preservation of all lesion characteristics, ensuring their effective extraction in subsequent stages. If the segmentation method impairs the images by distorting the lesion's shape, for instance, the feature extraction process will be rendered ineffective, thereby impeding the extraction of accurate information. Consequently, the machine learning model will be trained on erroneous data, resulting in inaccurate predictions. Various segmentation methods, including K-means clustering, have been implemented.
K-means clustering is a widely used clustering algorithm in the field. This algorithm involves categorizing data points into K clusters. The value of K is specified as an input to the algorithm, along with the dataset. Subsequently, the algorithm assigns each data point to a particular cluster while simultaneously computing the coordinates of the centroid. In the context of the K-means algorithm, the centroid represents the geometric center of a given cluster. As new elements are added to the cluster, the position of the centroid is reevaluated, often resulting in modifications. The algorithm stops once the centroids of the clusters no longer undergo any further changes [17].
It is of utmost importance to highlight that the selection of K should be done judiciously, taking into consideration the distribution of the

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data. In this study, the K-means clustering technique was employed to effectively segment the lesion from the surrounding skin, employing a value of K equal to 2. To elaborate further, the K-means algorithm was applied specifically to RGB pixels. Simply put, the algorithm successfully grouped the pixel units within the image into two distinct clusters: one representing skin and the other depicting the lesion, due to their marked dissimilarity.

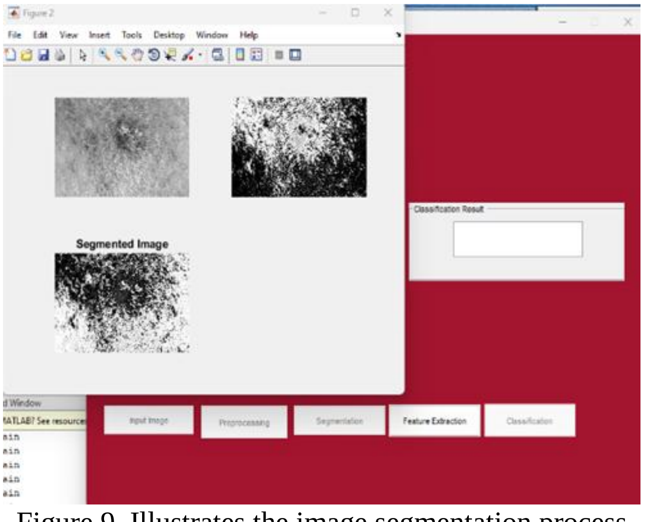

Figure 9. Illustrates the image segmentation process

-Feature Extraction

For a computer to comprehend an image, it is crucial to extract features from the image through analysis. Feature extraction plays a significant role in reducing the size of the data, thereby facilitating data processing.

During the early stages of skin tumor development, an immediate change in skin color is observed. The color of the skin continuously varies from brown to black. Extracting color features involves statistical calculations of various parameters related to colors, such as color space channels, contrast, and standard deviation for red, green, and blue (RGB) readings, or color gradient, saturation, and value (HSV). Dermatologists examine specific characteristics of skin lesions to gain initial insights, including inconsistency, area, perimeter, circular boundaries, the number of colors within the lesion, diameter, and the lesion's evolution over time [16].

In this research, we employ the Gray Level Co-occurrence Matrix (GLCM) and Gabor Filter for analyzing the texture of the image. The GLCM captures spatial dependencies between pixels in the

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image. It operates on a gray-level image matrix and captures frequently occurring features like contrast, mean, energy, and homogeneity. The objective of this stage is to simulate the initial diagnosis of skin tumors performed by dermatologists.

GLCM is a powerful technique in image processing that enhances the recognition of shapes, patterns, and various features in images. It generates a matrix of gray-level occurrences, which can be utilized to determine spatial relationships between pixels in the image. This enables the classification and automatic recognition of shapes. The process involves identifying the central pixel and its adjacent pixel in the image, determining the gray value for each pixel, and recording it in the matrix. This process is repeated for each pixel in the image to obtain a comprehensive matrix that reflects the gray-level occurrences between adjacent pixels. Subsequently, the matrix can be used to extract a variety of useful information.

The Gabor Filter relies on enhancing key features of the image, such as edges, corners, and other distinctive points. This filter can be employed to analyze the image and identify significant patterns, thereby aiding in image classification and better understanding. Additionally, it has various applications in the fields of artificial intelligence and machine learning. In Figure 10, the Gabor filter is applied to the image by calculating the standard deviation for each kernel and applying it to the entire image. The results are then utilized to create a map of prominent features in the image, distinguishing them from other details.

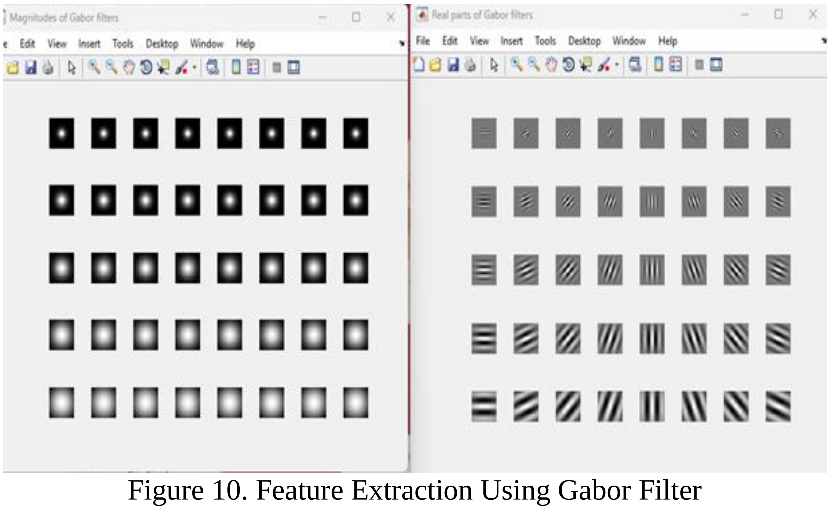

Figure 10. Feature Extraction Using Gabor Filter

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Result

A classifier is used to categorize skin tumors images into six distinct categories of dermatological diseases. To simplify things, a support vector machine (SVM) classifier is used in this study. The SVM algorithm is widely recognized and frequently used in the field of machine learning, effectively addressing classification and prediction challenges across various domains.

In this research, the sample number and training number are determined based on the extracted features, such as color and texture characteristics. In our proposed system, the SVM classifier is fed with GLCM outputs, which serve as inputs. The classifier uses a set of images from the training data to test, gather information, and predict the category to which each input image belongs. These categories include both cancerous and non-cancerous conditions. To provide an overview of our findings, we present the results and predictions for the six distinct tumor diseases found within the dataset used in this study.

Our prediction in Figure 11 for actinic keratosis, a skin condition that typically occurs on sun-exposed skin, is attributed to prolonged sun damage. It presents as hardened, scaly patches that, in some cases, can progress to skin cancer.

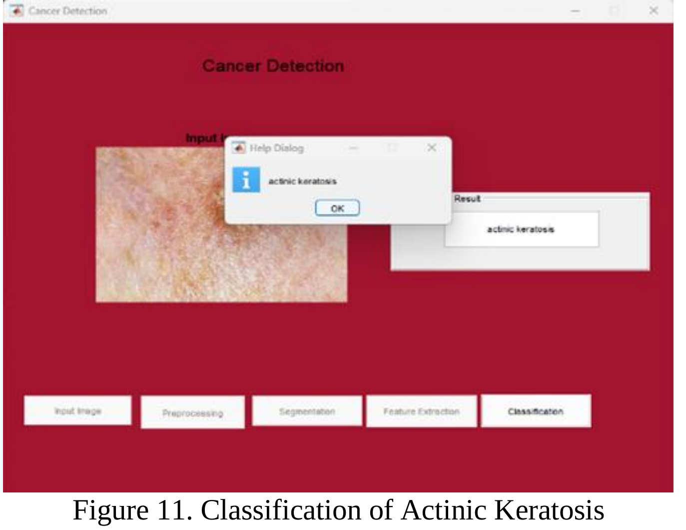

Figure 11. Classification of Actinic Keratosis

In Figure 12, our prediction pertains to basal cell carcinoma, which is recognized as the most prevalent and comparatively less hazardous type of skin tumor. Typically originating from the basal

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cells of the skin, this condition manifests as minuscule growths or sores that exhibit minimal protrusion and are prone to bleeding.

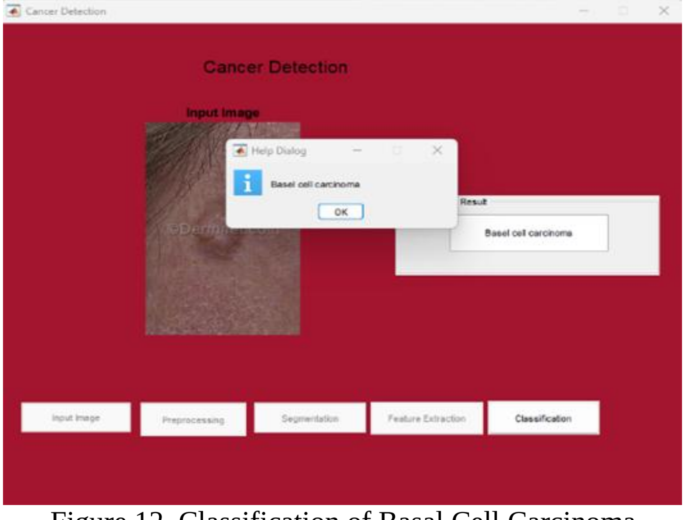

Figure 12. Classification of Basal Cell Carcinoma

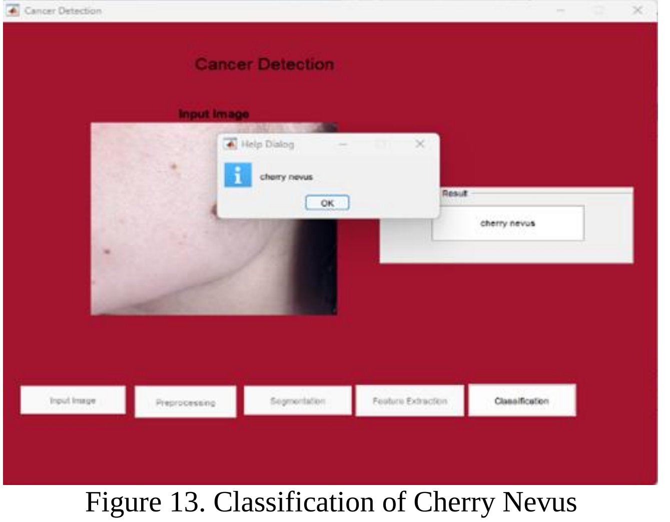

Figure 13. Classification of Cherry Nevus

The prediction depicted in Figure 13 regarding Cherry Nevus, a benign tumor that manifests on the skin as a velvety spot or a small red ball, is commonly regarded as innocuous and generally does not necessitate treatment unless it poses aesthetic concerns.
The image depicted in Figure 14 is classified as a dermatofibroma, which is a benign tumor that originates in the skin and typically presents as a small, solid mass beneath the skin. This condition is

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generally non-threatening and does not necessitate medical intervention.

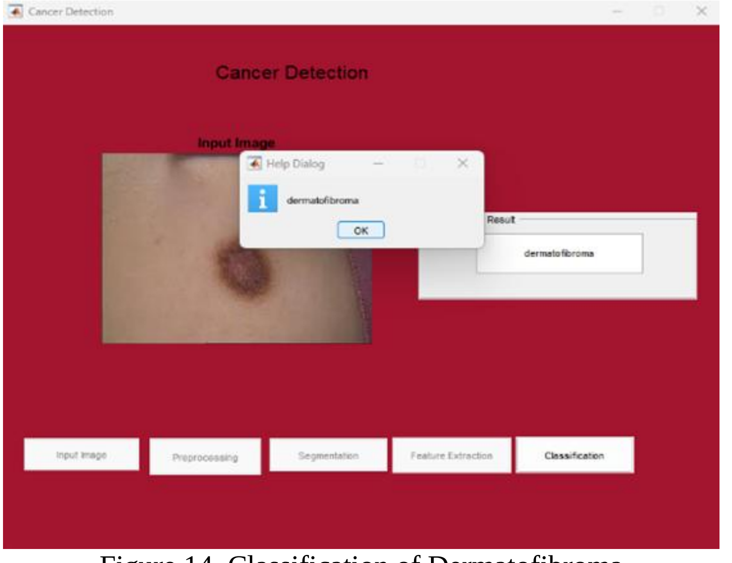

Figure 14. Classification of Dermatofibroma

In Figure 15, the depicted image has been classified as a melanocytic nevus. These nevi are characterized by benign pigmented accumulations in the skin, manifesting as brown or black spots. Melanocytic nevi are considered harmless and do not necessitate treatment unless there exists an indirect suspicion of malignancy.

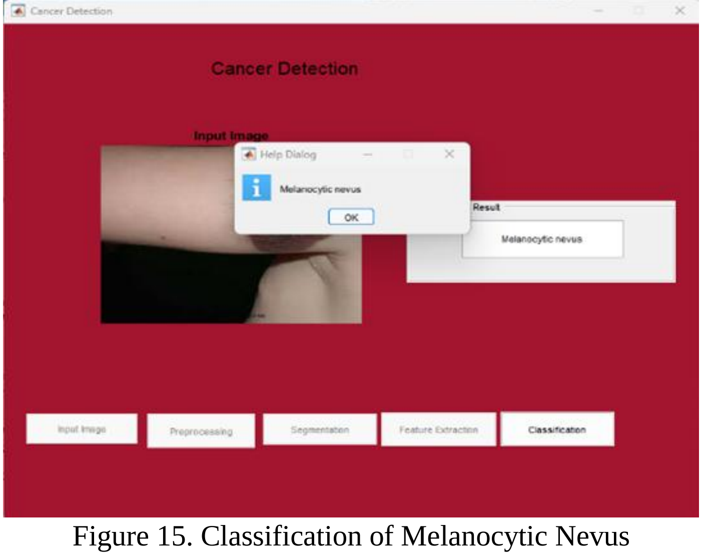

Figure 15. Classification of Melanocytic Nevus

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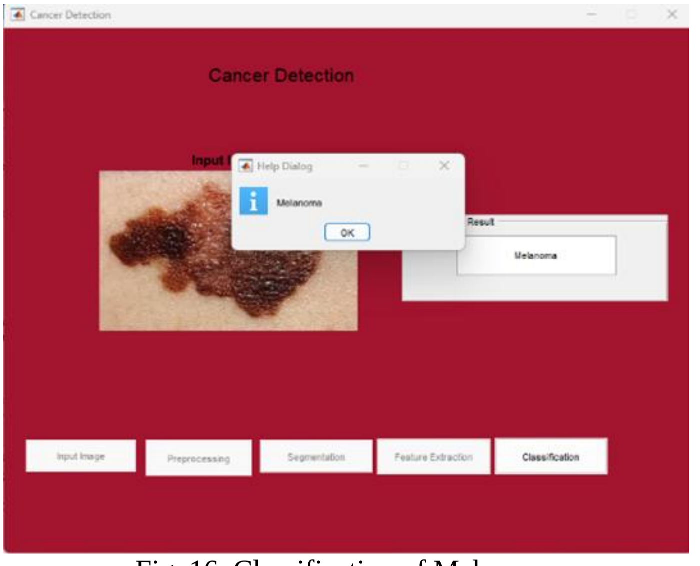

Fig. 16. Classification of Melanoma

The image depicted in Figure 16 is classified as melanoma, which is the most malignant form of skin cancer. This cancer arises from the abnormal growth and rapid spread of melanocyte cells in the skin. Clinically, it can manifest as an atypical skin patch or dark skin protrusions.
These images depict instances of skin tumors that were chosen from the Kaggle skin tumors database. Our proposed system employed several preprocessing techniques, including grayscale conversion, Gabor filter maximum suppression, and the GLCM method. Subsequently, all extracted features were provided to the Support Vector Machine (SVM) for the classification of images into cancerous and non-cancerous categories.

Conclusion

The main goal of this paper was to develop a system for early skin tumor diagnosis using AI. With improvements in technology, early detection of skin tumors has become possible, and this study successfully achieved its objective. The chosen technology involves employing the Support Vector Machine (SVM) algorithm Skin tumor diseases have a profound impact on individuals' lives and health. The present research proposes an effective method for identifying six types of skin tumors diseases. It is imperative to modify traditional methods and develop automated approaches to enhance the diagnostic accuracy of multiple skin tumors diseases. In this study, a system for detecting

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skin tumors using artificial intelligence through MATLAB software is designed to detect and identify skin tumors diseases.

The development of skin tumors detection has undergone several stages of testing to achieve more precise image processing. A simulation test was conducted using MATLAB software on six skin tumors diseases. This research has greatly enriched our understanding of MATLAB. The results of the developed system were utilized in conjunction with the graphical user interface technique to ensure user-friendliness for all users, including doctors, nurses, professionals, programmers, and laypeople.

The results suggest that the proposed system can be effectively utilized by both patients and doctors for a more accurate skin tumors diagnosis. This tool is precious in rural areas where medical experts may not be readily available. As the tool has become more user-friendly and powerful for images obtained under any conditions, it can automate skin tumors diagnosis.

Recommendations

We strongly urge governmental and private healthcare entities to embrace the progress of this system by:

1. Expanding the scope of included dermatological diseases.
2. Employing multiple features to extract image data and enhance accuracy.
3. Simultaneously detecting multiple images from diverse patients.
4. Integrating a feature to identify the quantity and type of prescribed medication for each patient.
5. Augmenting the training dataset to improve classification accuracy.

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