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# AUTOMATIC SCREENING OF SKIN CANCER USING DEEP LEARNING

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ABSTRACT:

Skin lesion segmentation plays a crucial role in the prompt and precise diagnosis of skin cancer through computerized systems. Nevertheless, the automated segmentation of skin lesions in dermoscopic images poses a formidable challenge due to issues such as artifacts (e.g., hairs, gel bubbles, ruler markers), unclear boundaries, low contrast, and variations in the sizes and shapes of the lesions. This study introduces an innovative and efficient approach for skin lesion segmentation in dermoscopic images, integrating a deep convolutional neural network with the active contour segmentation algorithm. The proposed method executes lesion segmentation in dermoscopic images through five sequential steps: 1. Preprocessing, 2. Lesion location detection, 3. Segmentation of the lesion area from the background, 4. CNN classification, and 5. automatic notification via the Arduino controller and GSM technology. The methodology underwent evaluation using datasets, yielding results that closely align with those obtained by other methods in the literature. The assessment focused on metrics such as accuracy, specificity, Dice coefficient, and Jaccard index, affirming the method's efficacy in skin lesion segmentation.

## INTRODUCTION :

Cancer is characterized by the uncontrolled growth and alteration of cells within the body. To comprehend the implications of cancer, it is essential to understand the normal functioning of the body. The body is composed of cells, the fundamental building blocks, which grow when needed and undergo programmed cell death when no longer necessary. In contrast, cancer comprises abnormal cells that proliferate despite the absence of a bodily need for them. Typically, these aberrant cells coalesce to form a lump or mass known as a tumor, with the potential to invade adjacent areas and, in more advanced stages, metastasize to other parts of the body.

Skin cancer is a malady originating in the skin cells, and the affected skin area is often referred to as a lesion. Various types of skin cancer, such as melanoma and nonmelanoma skin cancer (carcinoma), exist. The skin, being the body's largest organ, serves as a protective barrier against heat, sunlight, injury, and infection, while also playing roles in water and fat storage and vitamin D synthesis.

The skin's outer layer, the epidermis, consists of flat squamous cells, under which lie round basal cells. Melanocytes, responsible for pigment production, are found in the lower part of the epidermis and darken the skin upon sun exposure. Melanoma, a severe form of skin cancer, arises in melanocytes. These cells produce melanin, contributing to skin color and shielding the skin's deeper layers from sun-induced damage. Malignant transformation of melanocytes results in the aggressive growth and invasion seen in melanoma, potentially spreading through the blood or lymph system to other organs and bones.

Although early detection and surgical intervention can cure melanoma, it poses a serious threat if left untreated and allowed to progress. Timely identification and removal through surgery are highly successful in treating most cases, but the likelihood of a cure diminishes in advanced stages of the disease.

## LITERATURE REVIEW :

Amir Mirbeik et al. introduced a set of new, stable, and broadband skin-equivalent semisolid phantoms designed to simulate interactions between millimeter waves and human skin, including skin tumors. These realistic skin phantoms offer a valuable tool for assessing the feasibility of emerging technologies and refining design concepts associated with millimeter-wave skin cancer detection methods.

Pegah Kharazmi et al. proposed an innovative framework for detecting and segmenting cutaneous vasculature from dermoscopy images. The extracted vascular features are then explored for skin cancer classification. Their approach involves decomposing dermoscopy images using independent component analysis into melanin and hemoglobin components to segment vascular structures within lesions.

Afsaneh Keshavarz et al. presented a highly sensitive method for detecting skin cancer using a water-based terahertz (THz) metamaterial (MM) and a semiconductor film. The study applied terahertz pulsed imaging in reflection geometry to investigate skin tissue and related cancers.

Omar Abuzaghleh et al. introduced two key components of a noninvasive real-time automated skin lesion analysis system for early melanoma detection. The first component involves real-time alerts to prevent sunlight-induced skin burns, incorporating a novel equation for computing the time required for skin to burn.

Amir Mirbeik et al. introduced a millimeter-wave imaging system with a "synthetic" ultrawide imaging bandwidth of 98 GHz, designed for ultra-high resolutions crucial for early-stage skin cancer detection. The proposed approach divides the required ultra-wide imaging bandwidth into four sub-bands, assigning each sub-band to a separate imaging element or antenna radiator.

Konstantin Korotkov et al. proposed a photogrammetry-based total body scanning system with 21 high-resolution cameras and a turntable for skin surface image acquisition using cross-polarized light. The system automates the mapping of potentially significant lesions (PSLs) and estimates changes between explorations.

Thanh-Toan Do et al. investigated the design of a mobile imaging system for early melanoma detection, focusing on smartphone-captured visible light images. Their design addresses challenges associated with distortions in smartphone-captured images under loosely-controlled environmental conditions.

Cemanur Aydinalp et al. developed optimized measurement techniques and tools for skin cancer detection, presenting dielectric property measurements with open-ended coaxial probes customized for this purpose.

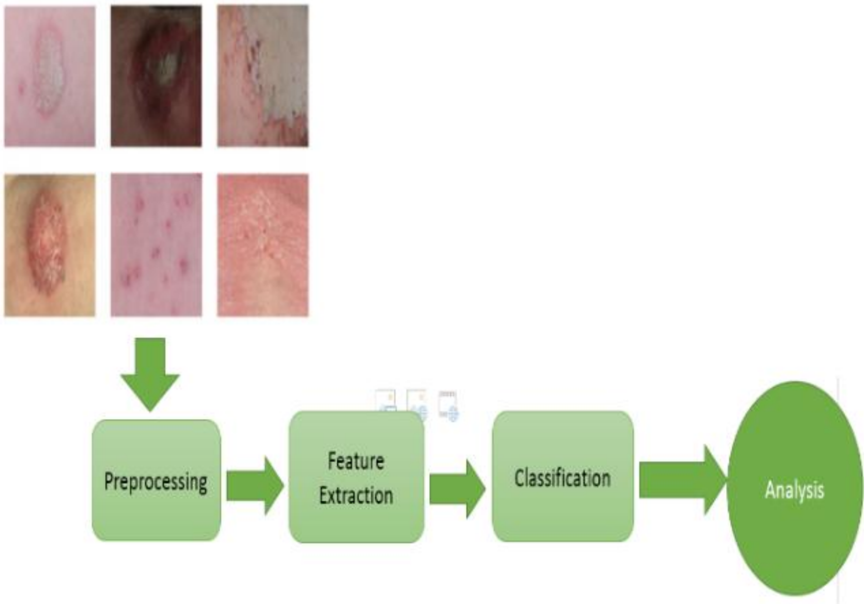
Prachya Bumrungkun et al. proposed an image segmentation scheme based on Support Vector Machine (SVM) and Snake active contour for automatic skin cancer detection. This approach utilizes SVM to assist in finding appropriate parameters for the snake algorithm.

## PROPOSED SCHEME :

In this study, we undertake the segmentation of skin lesions, followed by the extraction of the lesion's peripheral region. Subsequently, we employ a two-step approach involving feature extraction and classification using a Convolutional Neural Network (CNN) to detect melanoma. The segmentation process utilizes an active contours method, beginning with an initial contour of the lesion. This method involves the application of a curve to refine the lesion boundaries, enhancing the precision of the segmentation.

Following the successful segmentation of the lesion, our focus shifts to the extraction of its periphery. This peripheral region is then subjected to feature extraction, where relevant image features are identified. These features serve as input for a CNN-based classification model, contributing to the accurate identification of melanoma.

By combining the active contours segmentation method and CNN-based classification, our approach aims to enhance the overall efficiency and accuracy of melanoma detection, providing a robust framework for automated analysis of skin lesions.




**Modules**

- Preprocessing
- Segmentation
- CNN
- Performance analysis

- Converting Color to Grayscale

**Conversion of Color Image to Grayscale:**

Converting a color image to grayscale involves different weighting of color channels, simulating the effect of using colored photographic filters when shooting black-and-white film. A common strategy is to match the luminance of the grayscale image to that of the color image. The process includes obtaining RGB values in linear intensity encoding through gamma expansion. The resulting linear luminance is computed by combining 30% of the red value, 59% of the green value, and 11% of the blue value. This linear luminance is often gamma compressed to achieve a conventional grayscale representation. This method contrasts with systems like Y'UV, PAL, NTSC, and Lab, which directly compute gamma-compressed luma as a combination of gamma-compressed primary intensities.

**Filtering an Image:**

Image filtering is a versatile tool used for smoothing, sharpening, noise removal, and edge detection. Filters are defined by kernels, small arrays applied to each pixel and its neighbors. Convolution is the process used to apply filters, occurring in either the spatial or frequency domain. In the spatial domain, convolution involves multiplying kernel elements by matching pixel values, averaging the resulting array, and replacing the original pixel value with this result. The convolution process can also be applied in the frequency domain by multiplying the FFT of the image by the FFT of the kernel. Filters serve as the building blocks for various image processing methods, and examples show their application for tasks like computing the first derivatives of an image.

**Convolutional Neural Networks (CNNs) in Image Classification:**

In neural networks, CNNs play a pivotal role in image recognition and classification. They are widely used for object detection, face recognition, and other image-related tasks. CNN image classification involves taking an input image, processing it through convolution layers with filters (kernels), pooling, fully connected layers (FC), and applying the Softmax function to classify the object under specific categories. The input image, viewed as an array of pixels, undergoes processing based on its resolution (h x w x d, where h = Height, w = Width, d = Dimension). The deep learning CNN models train and test on each input image, providing probabilistic values between 0 and 1 for object classification.

The figure below illustrates the complete flow of a CNN, showcasing how it processes an input image and classifies objects based on assigned values.

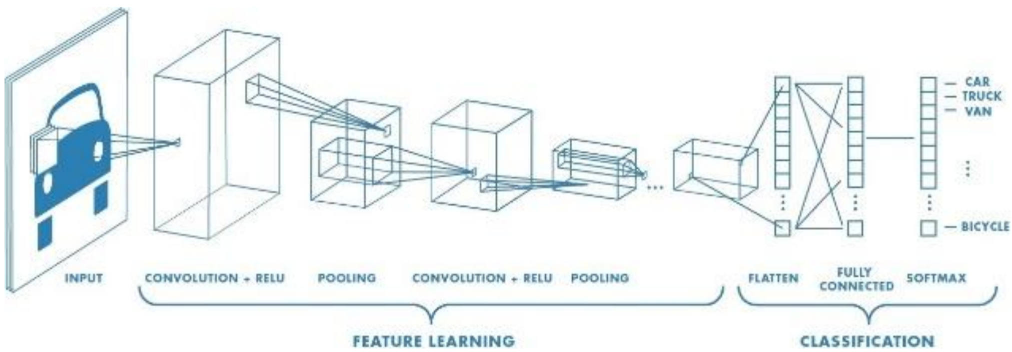



**Figure 2 : Neural network with many convolutional layers**

***Convolution Layer***

Convolution is a fundamental operation in the first layer of a neural network, serving to extract features from an input image. This process is crucial for preserving the spatial relationships between pixels and learning relevant image features using small squares of input data. The essential components involved in convolution are the image matrix and a filter, also known as a kernel.

In this mathematical operation, the filter is systematically applied to the input image by sliding it across the image matrix. At each position, the element-wise multiplication between the filter and the underlying portion of the image is computed. The results are then summed to generate a single value, representing a feature of the input data. This operation is repeated across the entire image, capturing different features and patterns.

Convolution plays a pivotal role in feature extraction because it enables the network to identify spatial hierarchies, edges, textures, and other relevant patterns within the input data. As the convolutional layers progress through the network, they learn to recognize increasingly complex and abstract features, contributing to the overall ability of the network to understand and classify images.

- An image matrix (volume) of dimension **(h x w x d)**
- A filter **($f_h$ x $f_w$ x d)**
- Outputs a volume dimension **(h - $f_h$ + 1) x (w - $f_w$ + 1) x 1**

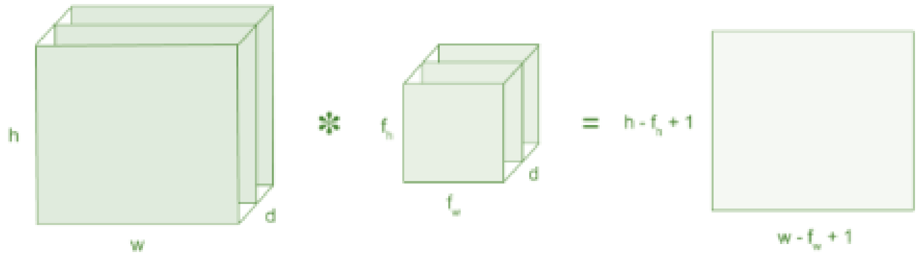



**Figure 3: Image matrix multiplies kernel or filter matrix**

Consider a 5 x 5 whose image pixel values are 0, 1 and filter matrix 3 x 3 as shown in below

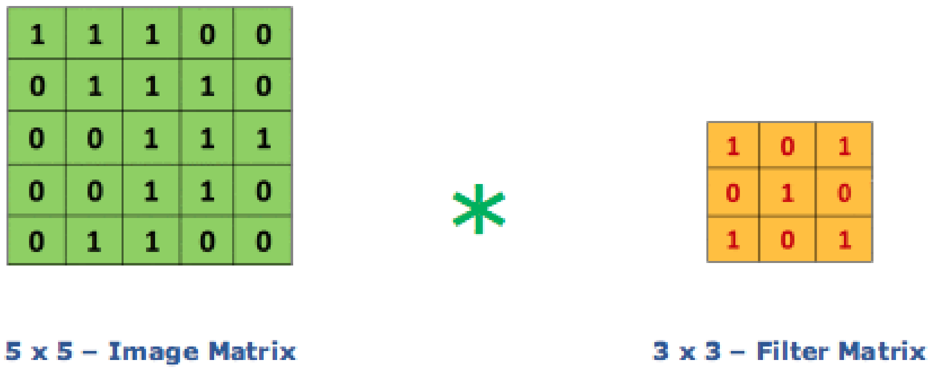



**Figure 4: Image matrix multiplies kernel or filter matrix**

Then the convolution of 5 x 5 image matrix multiplies with 3 x 3 filter matrix which is called **"Feature Map"** as output shown in below

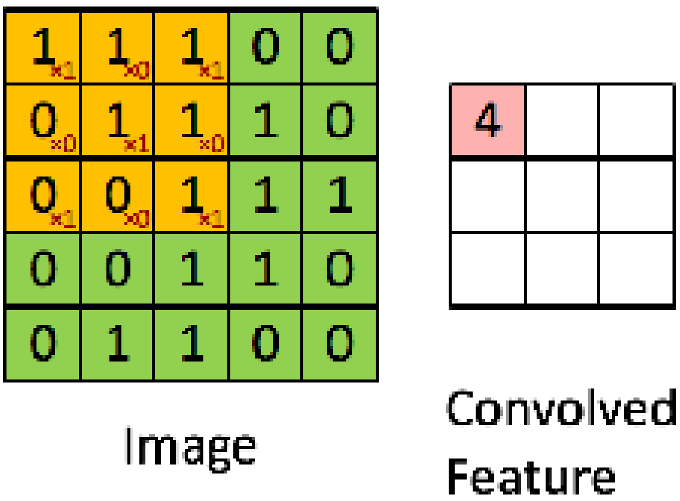



**Figure 5: 3 x 3 Output matrix**

Convolution operations with diverse filters play a crucial role in image processing, enabling operations like edge detection, blur, and sharpening. Different filters, such as Sobel or Gaussian filters, are employed to accentuate specific image features, resulting in distinct visual effects. For instance, edge-detection filters emphasize abrupt intensity changes, blurring filters smooth out pixel intensity variations, and sharpening filters enhance fine details and edges. The convolution process involves systematically applying these filters to the image, producing modified images that highlight or alter particular characteristics based on the filter's purpose.

***Strides***

The stride refers to the number of pixel shifts the filters make over the input matrix during the convolution process. A stride of 1 means the filters move one pixel at a time, while a stride of 2 means they move two pixels at a time, and so forth. In the convolution operation, the filters slide over the input matrix based on the specified stride value.

For example, when using a stride of 2, the filters advance two pixels in each step of the convolution process. This can result in a downsampled output compared to using a stride of 1, as fewer computations are performed.

The figure below illustrates how convolution operates with a stride of 2:

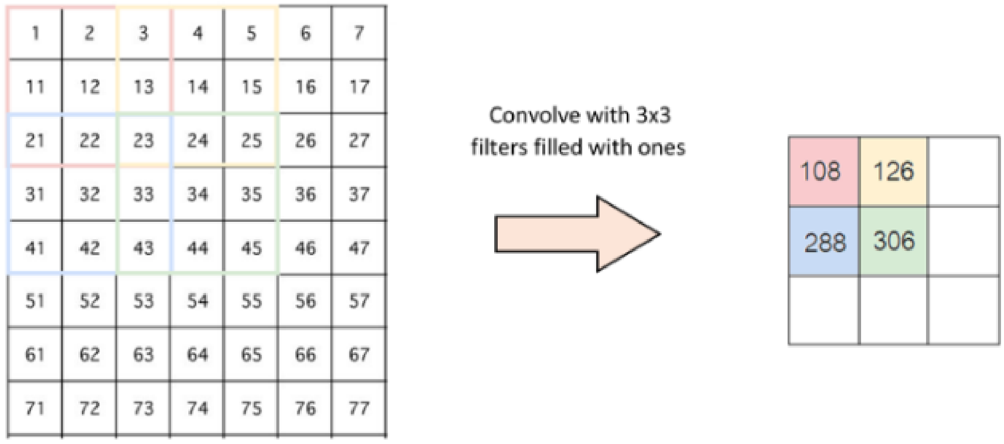



**Figure 6 : Stride of 2 pixels**

***Padding***

In situations where the filter does not perfectly fit the input image, two common options are available:
Zero-padding (Zero-padding):
This involves adding zeros around the borders of the input image so that the filter can fit properly. The additional pixels, often referred to as padding, create a border of zeros, allowing the filter to process the entire image without losing information at the edges. Zero-padding helps maintain the spatial dimensions of the input image and is particularly useful when preserving information at the image boundaries is important.
Valid Padding (No padding):
Valid padding, also known as "no padding," involves excluding the parts of the image where the filter does not fit. In this case, the filter is applied only to the parts of the image where it fits entirely, and any portions of the image beyond the filter's reach are not considered. Valid padding results in a smaller output size compared to the input image.
The choice between zero-padding and valid padding depends on the specific requirements of the task at hand. Zero-padding is often preferred when preserving spatial information at the edges of the image is crucial, as it helps mitigate issues related to information loss. On the other hand, valid padding might be chosen when downsampling or reducing the spatial dimensions of the data is intentional or acceptable for the given application.

***Non Linearity (ReLU)***

ReLU, short for Rectified Linear Unit, serves as a non-linear activation function in neural networks, particularly in Convolutional Neural Networks (ConvNets). Expressed as \( f(x) = \max(0, x) \), ReLU introduces non-linearity by returning the input value if positive and zero otherwise. Its significance lies in enabling the network to capture and model complex, non-linear relationships within real-world datasets. This non-linearity is crucial for learning intricate patterns that may exist in the data. Additionally, ReLU offers computational efficiency, sparsity in activations, and helps address issues such as the vanishing gradient problem, making it a widely utilized activation function in neural network architectures.

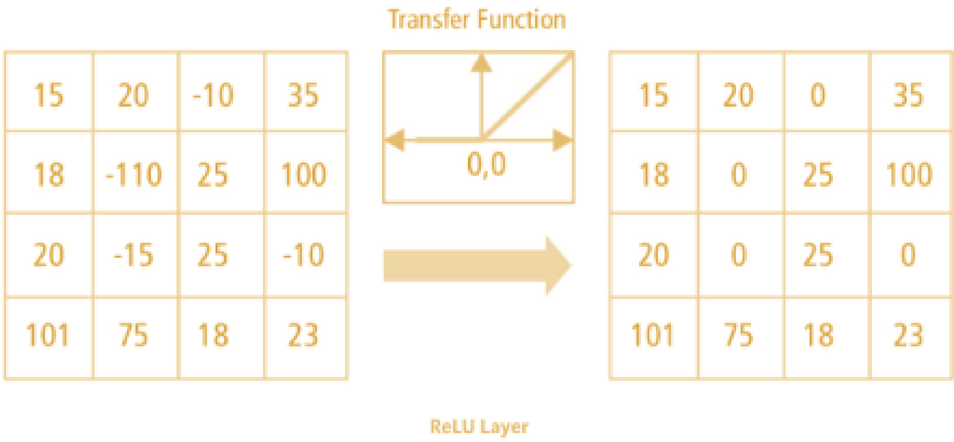



**Figure 7 : ReLU operation**

Data scientists often favor ReLU over alternative non-linear activation functions like tanh or sigmoid due to its superior performance, especially in the training of deep neural networks.

***Pooling Layer***

The pooling layers play a crucial role in reducing the number of parameters, particularly when dealing with large images. Spatial pooling, also known as subsampling or downsampling, is employed to decrease the dimensionality of each map while retaining essential information. Various types of spatial pooling include:

***Max Pooling:***

This method involves selecting the largest element from the rectified feature map. Alternatively, average pooling could be employed, where the average of all elements in the feature map is taken.

***Average Pooling:***

In this type of spatial pooling, the average value of all elements in the feature map is computed.

***Sum Pooling:***

Sum pooling involves calculating the sum of all elements in the feature map.
Each of these spatial pooling techniques contributes to dimensionality reduction while preserving crucial information from the input data.

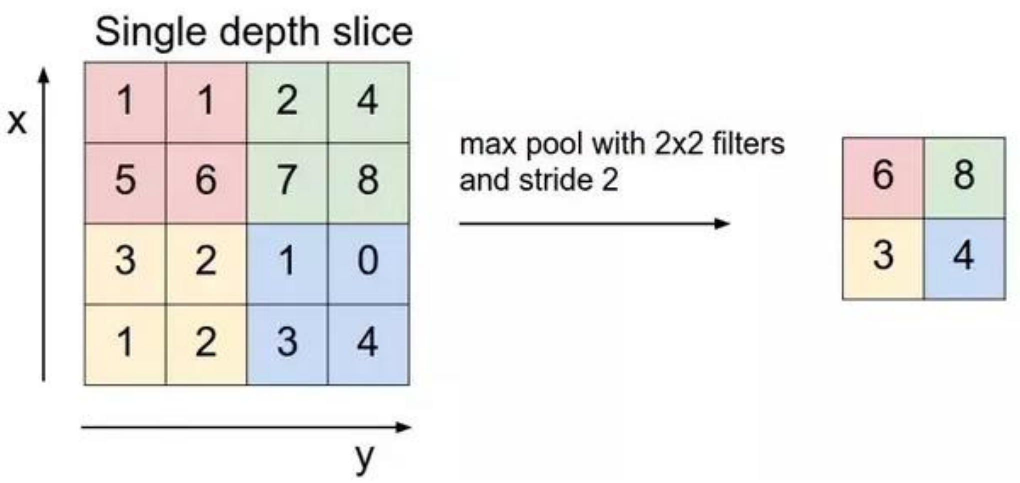



**Figure 8 : Max Pooling**

***Fully Connected Layer***

The layer referred to as the Fully Connected (FC) layer involves the flattening of a matrix into a vector, which is then fed into a fully connected layer similar to a neural network.

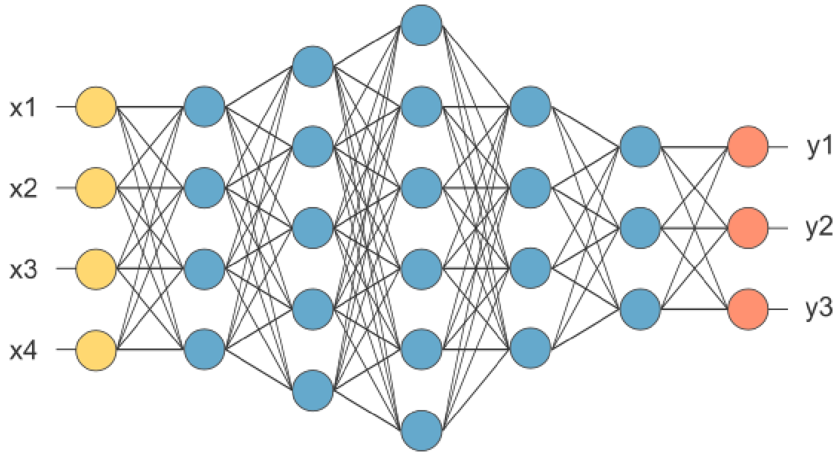



**Figure 9 : After pooling layer, flattened as FC layer**

In the above diagram, feature map matrix will be converted as vector (x1, x2, x3, …). With the fully connected layers, we combined these features together to create a model. Finally, we have an activation function such as softmax or sigmoid to classify the outputs as cat, dog, car, truck etc.,

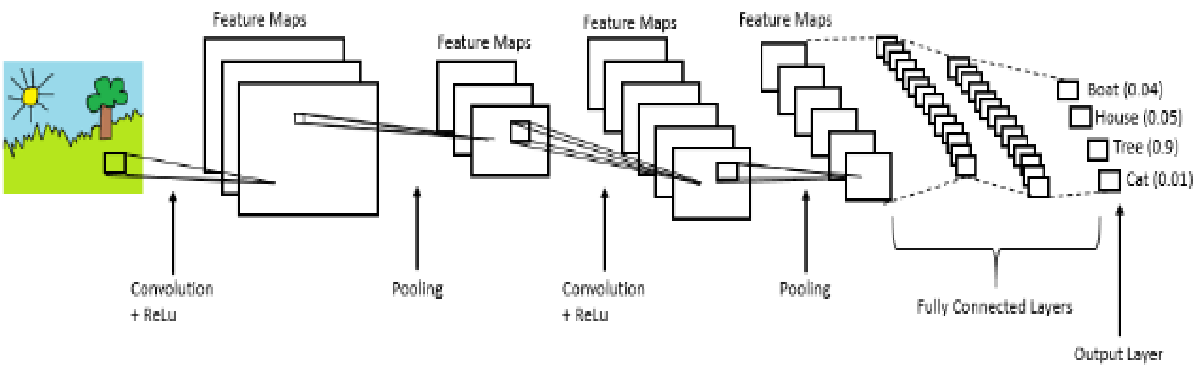
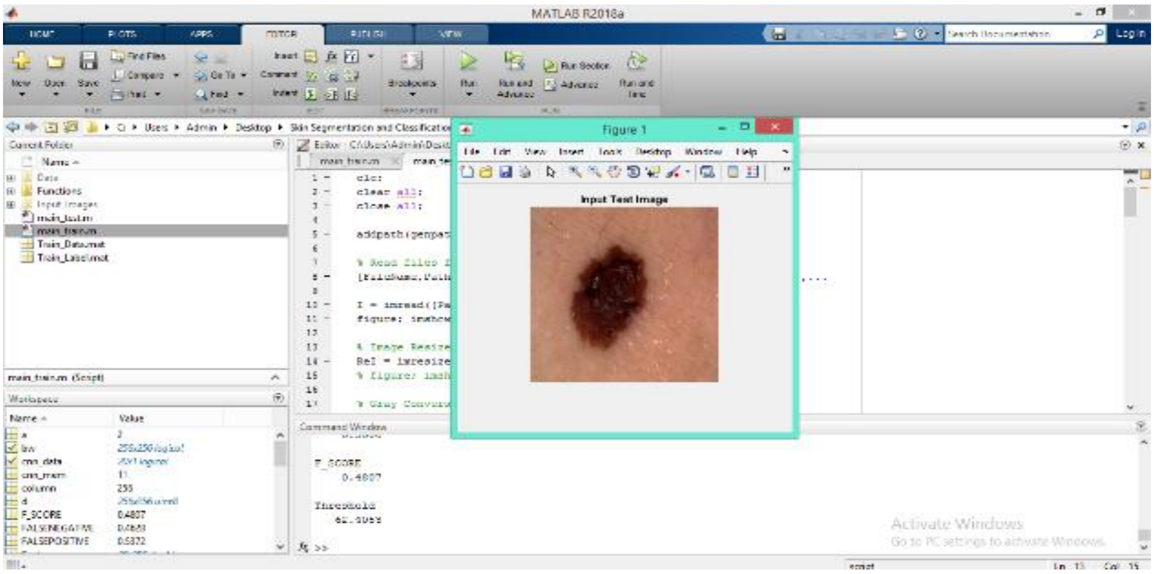
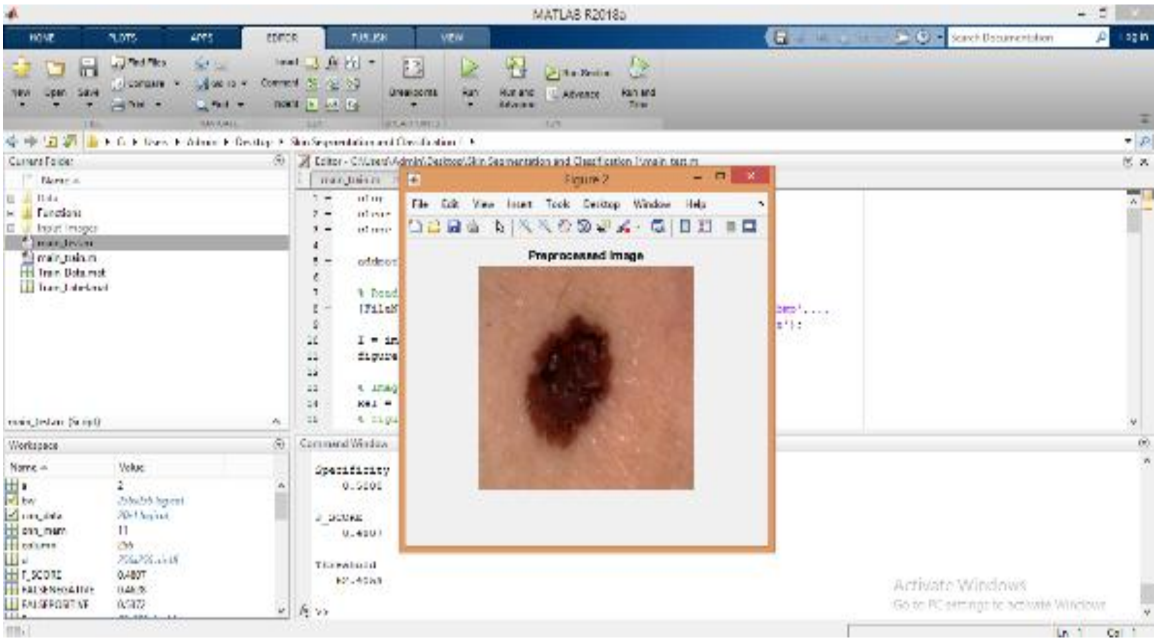



**Figure 10: Complete CNN architecture**

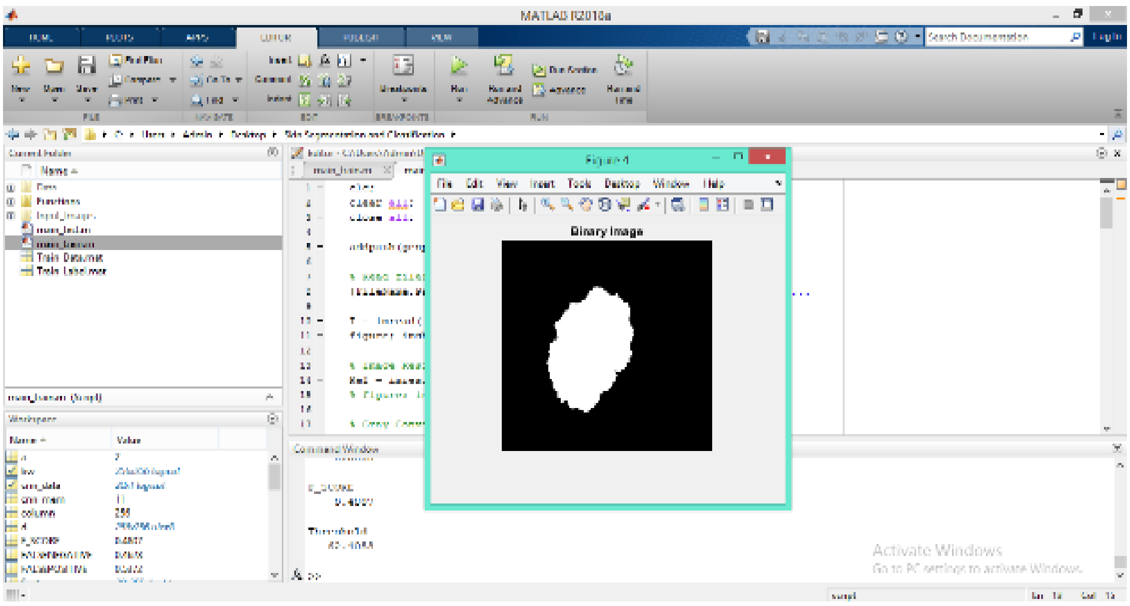
## RESULTS ND DISCUSSION :



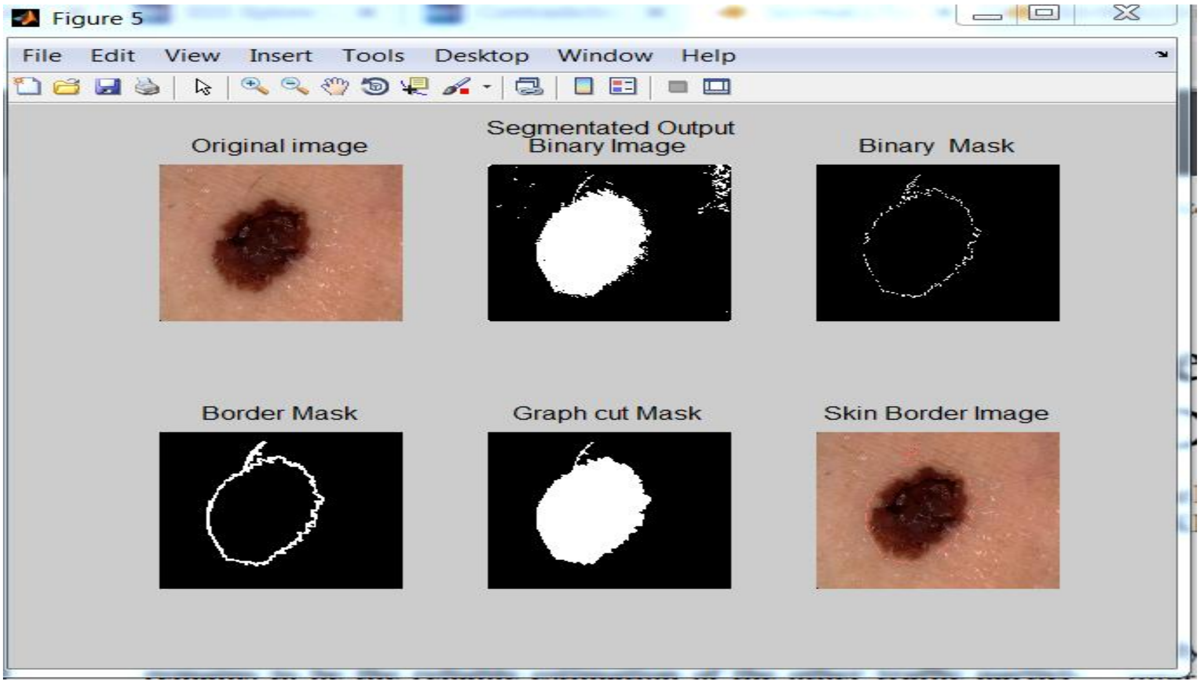

**Input Test Image**



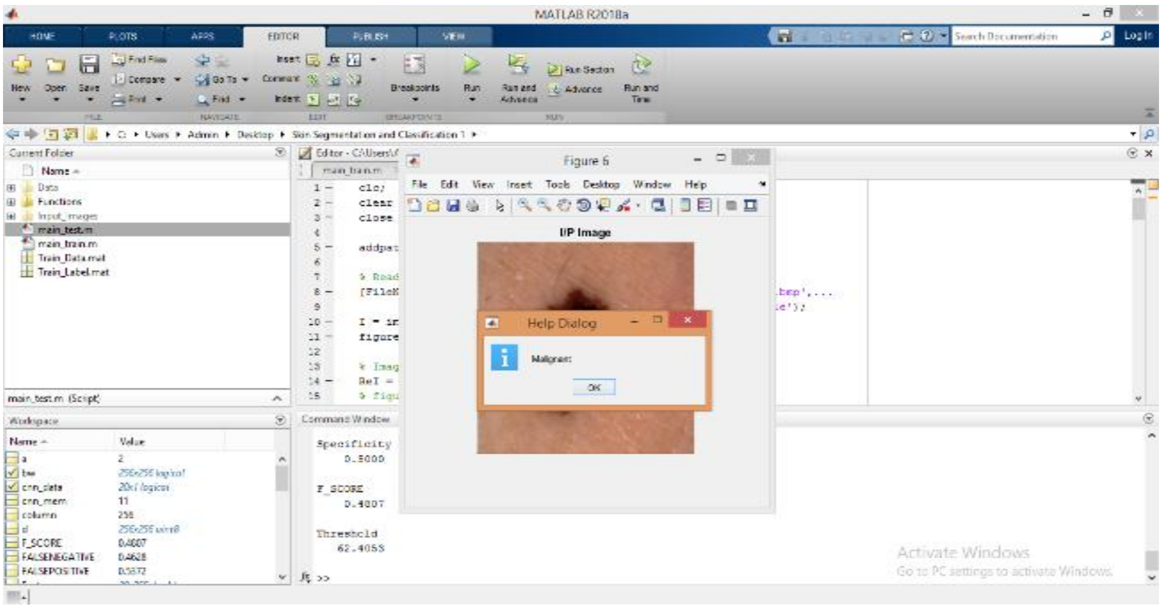

**Preprocessed Image**



**Binary Image**




**Segmented Image by Graph cut**




**Comparing Input Image with trained data set**

## SOFTWARE AND HARDWARE SPECIFICATION:

Arduino is a collaborative open-source initiative encompassing both computer hardware and software. It serves as a community-driven project and company, specializing in the design and production of microcontroller-based kits. These kits are utilized for constructing digital devices and interactive objects capable of sensing and controlling elements in the physical world.

The project operates on diverse microcontroller board designs, manufactured by various vendors and employing different microcontrollers. These boards are equipped with sets of digital and analog Input/Output (I/O) pins that facilitate connections to an array of expansion boards known as "shields" and other electronic circuits. Featuring serial communication interfaces, including USB in certain models, these boards enable the loading of programs from personal computers. For programming the microcontrollers, the Arduino project offers an integrated development environment (IDE) rooted in the Processing project. This IDE provides support for programming languages such as C and C++, fostering a user-friendly platform for developing and implementing code for the microcontroller-based systems.

## LCD – Liquid Crystal Display


**Fig 5.4 LCD**

Liquid Crystal Displays (LCDs) utilize materials that exhibit properties characteristic of both liquids and crystals. Unlike substances with a distinct melting point, LCD materials operate within a temperature range where molecules possess fluid-like mobility yet maintain an ordered structure reminiscent of crystals. The LCD structure comprises two glass panels, with the liquid crystal material positioned between them, creating a "sandwiched" configuration.

## SIM800A Quad Band GSM/GPRS Module with RS232 Interface :

The SIM800A Quad-Band GSM/GPRS Module with RS232 Interface presents a comprehensive Quad-band GSM/GPRS solution in an LGA (Land grid array) form factor, suitable for integration into customer applications. Supporting Quad-band frequencies (850/900/1800/1900 MHz), the module facilitates the transmission of Voice, SMS, and data information with minimal power consumption. Measuring a compact 100 x 53 x 15 mm, the module is designed to meet the space constraints of slim and compact custom designs. Its Embedded AT feature contributes to overall cost savings and expedites time-to-market for customer applications. The SIM800A modem incorporates a SIM800A GSM chip and an RS232 interface, providing easy connectivity with computers or laptops via a USB to Serial connector, or with microcontrollers using an RS232 to TTL converter. When connected through the USB to RS232 connector, identifying the correct COM port in the Device Manager of the USB to Serial Adapter is essential for seamless operation.

## RESULT & DISCUSSION :

### *CONCLUSION*

Automated segmentation of skin melanoma poses a significant challenge due to the considerable variations in lesion size, shape, intensity, and position. To address this, we employ a sophisticated approach integrating an active contour segmentation and a Convolutional Neural Network (CNN) structure. This hierarchical framework utilizes the original pixel values of the image as input, learning a series of nonlinear transformations that effectively capture the image contents. The model comprises essential components, including local filters, a convolution layer, linear unit activation function, maximization layer, dropout layer, batch normalization layer, merge layer, flatten layer, and sigmoid layer. This intricate architecture is designed to facilitate robust image feature learning, leading to satisfactory results in test segmentation. Evaluation of our program involves comparing the segmentation results with ground truth using melanoma test images and calculating index parameters. The results demonstrate that our method consistently achieves higher accuracy than existing architectures in the majority of cases, affirming its efficacy in melanoma segmentation.

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