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# Melanoma Skin Cancer Detection Using ML and Image Processing

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*Abstract:* Melanoma is type of cancer that is caused on skin that develops in the melanocyte cells that produce the melanin pigment, the pigment which gives colour and tone to your skin. In this study, we came up with the thought of designing a model that uses medical imaging to reduce heavy dependencies on medical experts for diagnosis procedures. The model will work on different skin images which undergoes pre-processing, splitting and training so that the system would be able to label any fresh skin image as either malignant or benign. Through this we tend to maximize the large availability of devices and elicitation of diagnosis images set towards providing cost effective, easier and faster diagnosis.

***Index Terms* – Slice Strategy, Compression Algorithm.**

## INTRODUCTION

The most prevalent form of cancer among people is skin cancer. According to recent studies, the incidence of skin cancer has been progressively increasing in recent decades. According to predictions, there will be 62% more skin cancer cases in 2040 than there were in 2018. In the world each year, there are between 2 and 3 million non-melanoma skin cancers and 132,000 melanoma skin cancers, according to the World Health Organization (WHO). Melanomas cause 75% of skin cancer mortality although representing fewer than 5% of skin cancer incidence. Skin cancer is a significant public health issue as a result of its substantial annual medical and social expenses. Melanoma is one of the cancers that can be prevented, but in recent years, it has been expanding rapidly. Exposure to UV rays from the sun or indoor tanning is the primary cause. A frequent or uncommon nevus that changes in size, shape, uneven boundary, colour, or texture of pigmented patches can develop into melanoma. It is nearly always the kind of cancer that develops in the skin's pigment cells (melanocytes). An in-depth understanding of the mechanisms that contribute to the formation of melanoma is crucial because it is an aggressive malignant tumour with a high risk of spreading. The probability that a patient will survive is increased by early identification since more treatment options can be considered.

A thorough examination of a skin condition by a specialist can thereby save lives. However, mistakes can occur during a human visual inspection, leading to incorrect diagnoses for patients. These mistakes are subjective and can result from a lack of specialised experience. Dermatologists may correctly diagnose melanoma with a human eye examination utilizing 60% accuracy in the absence of technology. It has been established that using images to diagnose skin lesions improves accuracy compared to diagnosing without them. The non-invasive technique, which is based on images captured using dermoscopic equipment, is typically employed in an initial computational analysis to find melanoma. Therefore, automatic malignancy identification, particularly based on artificial intelligence, can become a crucial auxiliary tool for specialists in melanoma diagnosis. However, a surgically obtained sample's histological analysis allows for a precise diagnosis of skin cancer. Clinical pictures of skin lesions range greatly in terms of contrast, shape, size, border, weak resolution, and the presence of artefacts such as hair, veins, and texture, as well as other factors. Because of this, it might be challenging to tell melanoma lesions apart from non-melanoma lesions. Consequently, an image preparation stage is required. The most prevalent pre-processing procedures include: image decomposition on the use of colour channels, noise filtering, artefact removal, and contrast enhancement, lighting adjustment, and segmentation. These procedures can significantly increase the accuracy of detecting melanoma. Automated dermoscopy image analysis consists of three key steps: feature extraction, lesion categorization, and image pre-processing (noise rejection and segmentation). Different classifiers that focused on different characteristics, including texture, shape, colour, and size, were utilised to identify skin lesions in the images. The individual classifiers can be regarded as subjective components of artificial intelligence due to the particular nature of learning. We advise using several different classifiers as a novelty, with the final choice being dependent on the correlated interpretation of the classifier outputs.

By doing this, we provide a more impartial method for melanoma identification. The number of subjective actors that must be taken into account is still up for debate. This is an open issue from a theoretical standpoint. We did, although, apply classifiers based on the study of shape, colour, texture, and convolutional connections in order to balance cost and performance and take into account experimental findings. The innovative aspect of the work is the use of an artificial intelligence-based, highly efficient method that is more objective for detecting melanomas in images. To achieve this, the system has multiple separate, individualised classifiers that take advantage of various melanoma traits.

## LITERATURE SURVEY

### 1.Automated melanoma recognition, 2001.

Malignant melanoma is nowadays one of the leading cancers among many white-skinned populations around the world. The results of more than 96% correctly segmented lesion images (in a set of 4000 skin lesions) reflects a very reliable segmentation module for the special task of skin lesion segmentation. The fusion concept allows for the further extension of the segmentation module by integration of other segmentation methods (texture analysis, other colour segmentation algorithms). The overall performance of 61% achieved by classification into three classes and a performance of 73% for the class of melanomas in this experiment is comparable to rates observed in clinical routine and depicts a rather good performance for an automated system, since the data (overall 5393 skin lesions) was gathered in daily clinical routine and was not especially selected for this project.

### 2.A preliminary approach for the automated recognition of malignant melanoma, 2004.

The malignant melanoma is the most dangerous human skin disease. Even experienced dermatologists have difficulties for distinguishing melanoma from other pigmented lesions of the skin, such as typical and atypical lesions which are benign and it has stimulated interest in adjunctive diagnostic modalities that might facilitate clinical recognition of melanoma, including the automated interpretation of dermatoscopic colour images with computerized image analysis. In fact, after the acquisition and pre-processing of colour images of the skin, the next step of the whole image analysis process is the segmentation of the lesion from the surrounding skin.

### 3.Automatic detection of melanoma skin cancer using texture analysis, 2012.

Computer is not more intelligent than humans but it may be able to extract some information, such as texture features, that may not be readily perceived by human eyes. The term "texture analysis" describes the process of classifying areas of an image based on their texture composition. The texture features obtained from co-occurrence matrix contain 23 sufficient features. According to fisher score method 12 features were selected that represent the most significant features.

### 4.Skin cancer detection by deep learning and sound analysis algorithms: a prospective clinical study of an elementary dermoscope, 2019.

In 2018, 288,000 cases of malignant melanoma (MM) and 1 million cases of non-melanoma skin cancer were reported worldwide. Accurate diagnosis and practical detection are essential components of a comprehensive skin cancer prevention strategy due to an ageing population and constrained healthcare resources. It might be difficult for dermatologists and general practitioners to diagnose skin cancer, especially MM, early. The standard of care is dermoscopy, but due to the complexity of the visual inputs embedded in a dermoscopy image, dermatologists only obtain a limited diagnostic sensitivity of 40% MM identification in objective testing. As seen by a range of 28:1 to 9:1 number of biopsies that need to be removed in order to identify one melanoma and a 3:1 ratio for all skin cancer, the specificity of dermatologists' diagnoses also has to be improved. In order to increase the accuracy of detection, a first prospective clinical observational study reported on a two-step strategy, adding a second layer of sonification (visual data transformed into sounds) to a DL classifier. Technology can help doctors diagnose skin cancer more accurately and help them get over dermoscopy-related experience limitations, time restraints, and the physical discomfort of taking pictures.

### 5.An enhanced technique of skin cancer classification using deep convolutional neural network with transfer learning models, 2021.

One of the top three deadly cancers brought on by DNA damage is skin cancer, which can be fatal. For the precise categorization of benign from malignant skin lesions, we suggest a deep convolutional neural network (DCNN) model based on deep learning. The third step is data augmentation, which increases the number of images and increases classification accuracy rate. A powerful kind of cancer known as malignant melanoma originates from melanocytes found in the skin's epidermis. To get the highest prediction and classification accuracy, a big dataset with more annotated skin lesions must be used in conjunction with developing a successful DNN that includes pre-processing procedures. The CAD, which is user-friendly and reliable for any conditions of acquired images, can also be used to identify skin cancer.

## IMPLEMENTATION

### 1. System specifications.

It consists of an interface that is easy to use for the users where they can upload the image of the lesion and an output is obtained with a positive probability predictor in percentage. It then runs through three processes (CNN, DenseNet, and ResNet) at the same time, and the three outcomes from these are then combined to provide its sigmoid function. The user is then shown the results, including whether the lesion is cancerous or benign.

There are three processes, including lesion categorization, feature extraction, and picture pre-processing.

Image preparation gather examples of both benign and malignant skin cancers.

These layers take the input image`s edges, corners, and textures and extract them as features. Lesion classification is used to extract and merge the features of the input image, the CNN model performs a number of convolutions and pooling processes. A fully connected layer then receives the generated features and translates them to the likelihood that the input image is benign or malignant.

### 2. System requirements.

The proposed system comprises of mainly 3 algorithms such as:

- ResNet
- DenseNet
- CNN

### 2.1 ResNet Algorithm

ResNet, or Residual Network has become one of the most influential and widely used deep learning models in computer vision, achieving state-of-the-art performance in various visual recognition tasks. Residual connections help to mitigate the vanishing gradient problem by providing a way for the gradients to flow directly to the earlier layers of the network. The output of the first convolutional layer is passed through a non-linear activation function, before being processed by the subsequent layers. The residual connection allows the input to be added directly to the output of the block, which is then passed through another non-linear activation function before being sent to the next layer. The residual block can be stacked to create a deep neural network with hundreds of layers. ResNet is a ground breaking neural network architecture that has revolutionized deep learning in computer vision.

### 2.2 DenseNet Algorithm

DenseNet, short for Dense Convolutional Network, is a deep learning architecture. One of the main advantages of DenseNet is its ability to alleviate the vanishing gradient problem, which is a common issue in deep neural networks. DenseNet`s dense connectivity helps to address this issue by allowing gradient flow through multiple paths in the network. Since each layer receives feature maps from all preceding layers, DenseNet can learn more robust representations with fewer parameters than traditional CNNs. DenseNet is a powerful deep learning architecture that has gained popularity in recent years due to its superior performance and ability to address common issues in traditional CNNs. Its dense connectivity and feature reuse allow for better parameter updates, faster convergence, and more efficient use of parameters

### 2.3 CNN Algorithm

The basic building blocks of a CNN are convolutional layers, which apply a set of learnable filters to the input image to extract features such as edges, corners, and textures. It is a type of deep learning model that is commonly used for image and video recognition, classification, and analysis tasks. It is a type of deep learning model that is commonly used for image and video recognition, classification, and analysis tasks. This produces a 2-dimensional activation map or feature map that highlights the important spatial patterns in the input data. The size of the filter is usually much smaller than the input data, but it can be chosen to capture different types of patterns. These feature maps are then stacked together to form the output of the convolutional layer, which can be fed into the next layer of the network for further processing. Overall, the convolution step is a key operation in CNNs that allows them to learn and extract important features from the input data, which can then be used for tasks such as image classification, object detection, and image segmentation.

Technical Requirements of The System

Hardware Requirements

- System Processor: Core i3
- Hard Disk: 500 GB
- Ram: 4 GB

Software Requirements

- Operating system: Windows 8 / 10
- Programming Language: PHP
- Software Package: XAMP

**SYSTEM ARCHITECTURE**

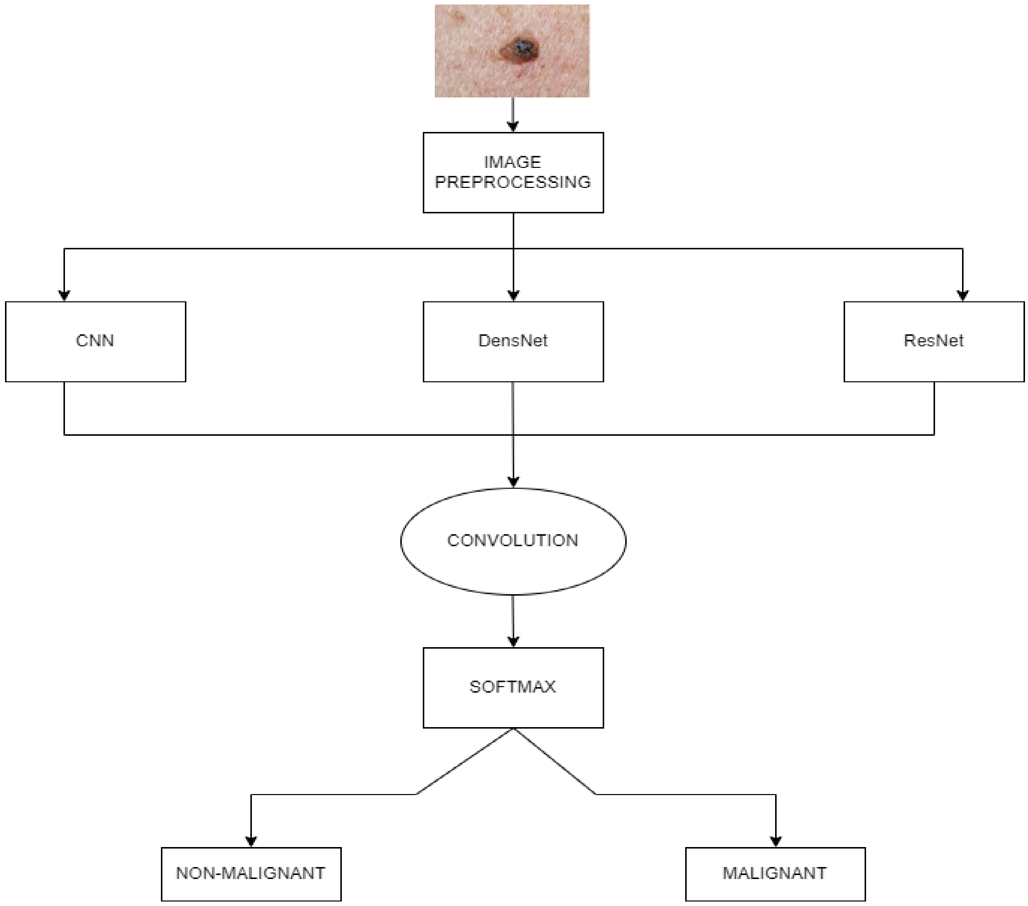



Figure 1. Architecture of the system.

Pre-processing is an essential step in CNNs (Convolutional Neural Networks) before feeding the data into the network. Pre-processing aims to simplify the data, reduce noise, enhance features, and ensure consistency across input samples. By performing pre-processing, the CNN can process the data more efficiently and improve its overall performance in tasks such as image classification, object detection, or segmentation. This conversion simplifies the input data, reduces computational complexity, and improves resource efficiency, making it easier for CNN models to process and analyse images effectively.

• Morphology: Morphology is specifically the combination of erosion and dilation operations in which it is used as a pre-processing step in CNNs (Convolutional Neural Networks) for image analysis tasks. Combining erosion and dilation can be beneficial in noise reduction, object enhancement, feature extraction and size normalisation.

• RGB TO GREYSCALE: RGB to greyscale is used to transform the input images from a three-channel RGB format to a single channel grayscale format. By doing so, the colour information is removed, and only the intensity or brightness values of the pixels are retained. This conversion simplifies the input data, reduces computational complexity, and improves resource efficiency, making it easier for CNN models to process and analyse images effectively.

• Thresholding: Thresholding is a common pre-processing technique used in CNNs for image analysis tasks. The thresholding process helps to simplify the image data, highlight specific regions or objects of interest, and improve the performance of the CNN in subsequent analysis tasks. By setting an appropriate threshold value, the image can be segmented into foreground and background, allowing the CNN to focus on particular areas or objects during analysis. Thresholding is a valuable tool for image segmentation and enhancing relevant features in CNN-based computer vision applications.

• Inpainting: Inpainting is a powerful pre-processing technique used in CNN for image analysis tasks. By incorporating inpainting as a pre-processing step in CNNs, the models can work with more complete and reliable image data. It uses convolutional layers to extract relevant features from the input data, capturing patterns and spatial relationships. Each layer processes the input data and extracts relevant features, which are then passed to the next layer until the final classification or regression layer.

## RESULT ANALYSIS

| LESION | RESULT | PROCESSING TIME |
|---|---|---|
| IMAGE 1 | MALIGNANT | 40 sec |
| IMAGE 2 | MALIGNANT | 38 sec |
| IMAGE 3 | BENIGN | 52 sec |
| IMAGE 4 | MALIGNANT | 41 sec |
| IMAGE 5 | BENIGN | 48 sec |
| IMAGE 6 | BENIGN | 55 sec |
| IMAGE 7 | BENIGN | 58 sec |
| IMAGE 8 | MALIGNANT | 45 sec |
| IMAGE 9 | MALIGNANT | 38 sec |
| IMAGE 10 | BENIGN | 36 sec |

Figure 2. Tabular Representation

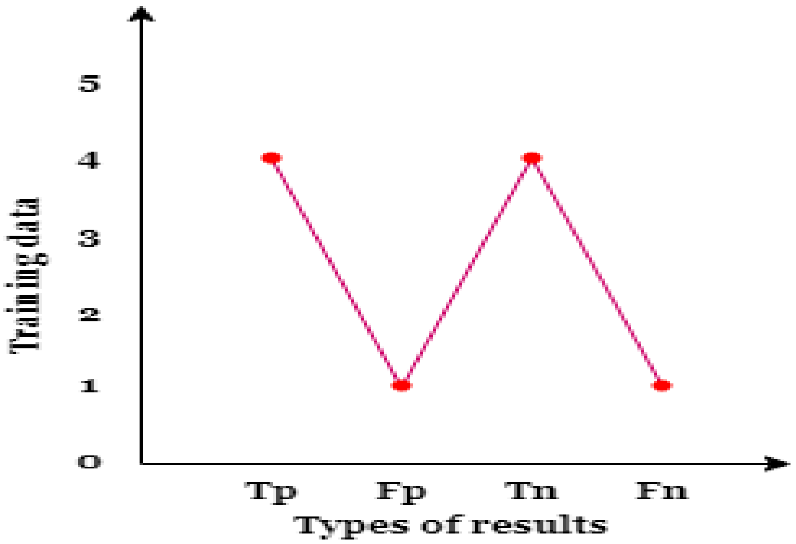



Figure 3. Graphical Representation

| | | ACTUAL | |
|---|---|---|---|
| | | POSITIVE | NEGATIVE |
| PREDICTED | POSITIVE | 4 | 1 |
| | NEGATIVE | 1 | 4 |

Figure 4. Prediction Table

Precision = TP / (TP + FP)
= 4 / (4 + 1) = 4 / 5
= 0.8

Recall = TP / (TP + FN)
= 4 / (4 + 10) = 4 / 5
= 0.8

Therefore, the recall of the system is 80% and precision is 0.8.

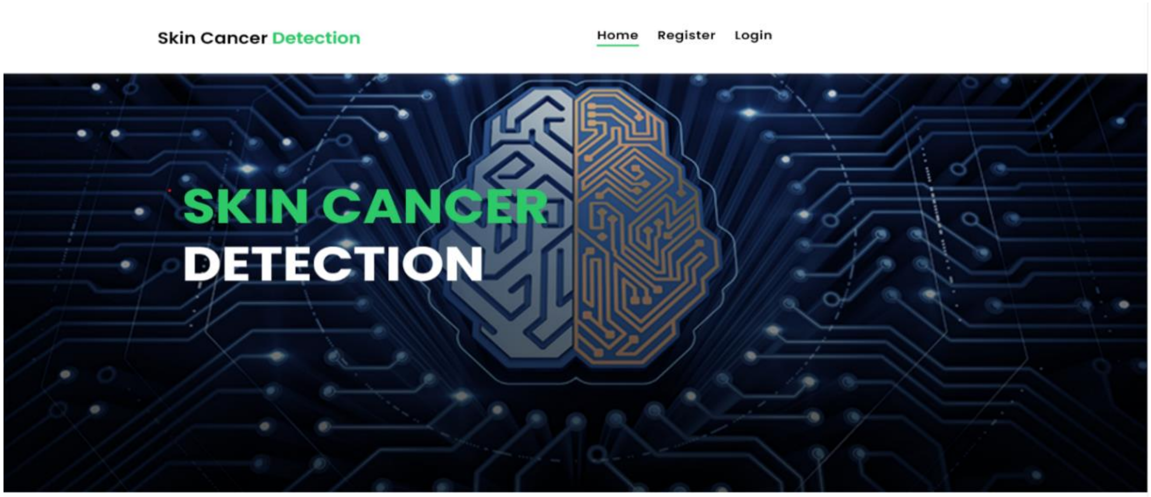
In order to evaluate the performance and guarantee the efficacy of the proposed system a series of tests were conducted with random dataset. The system accurately detected the result 84% of the time and classified the image lesion either as benign or malignant.

Advantages of the proposed system:

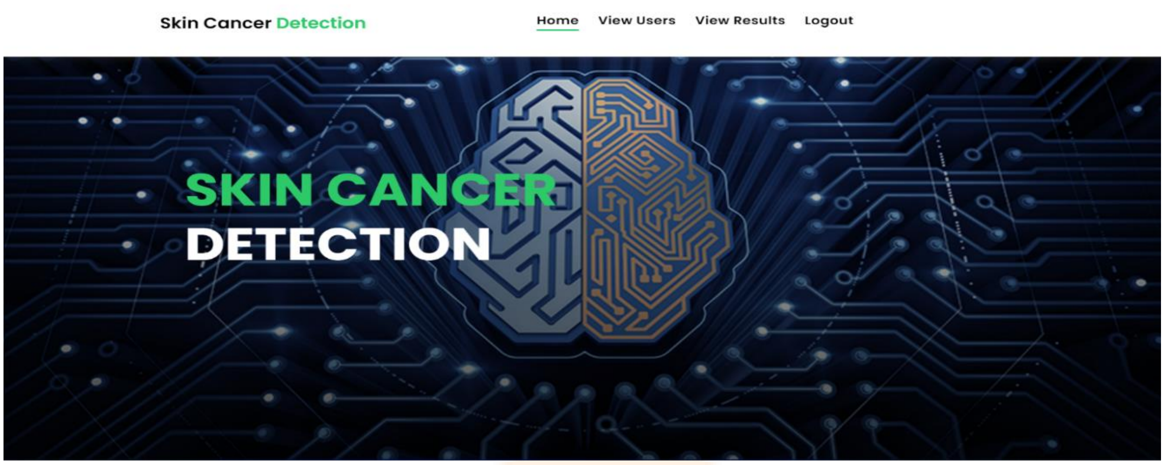
- Higher accuracy than previous systems.
- Lower run time.
- Doesn’t require dedicated computing systems.

## MODULES

### User Interface

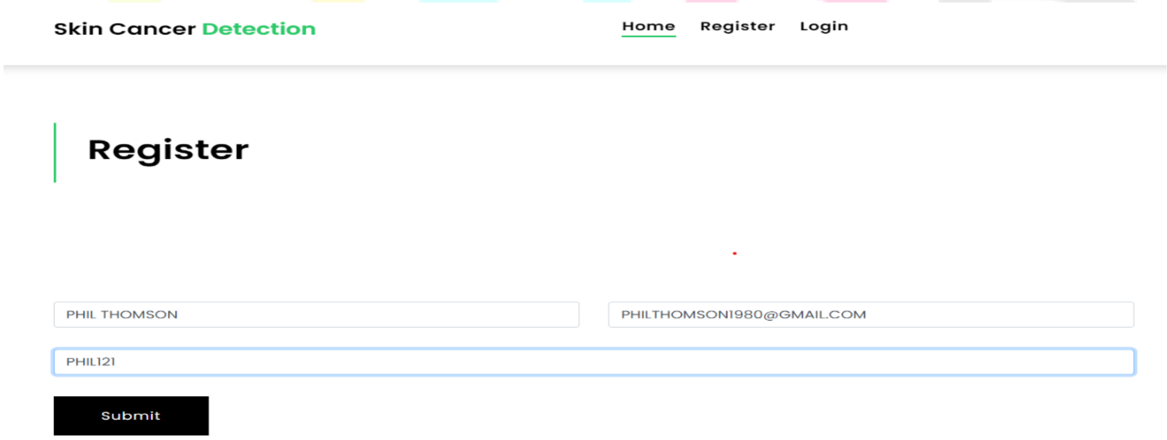



### Admin Page






### Registration Page



## RESULT

As a result, the above-described methodology and modules give a clear explanation of how to construct and design a web application that may be used to identify skin diseases. The two main causes that motivated the development of this concept were the absence of properly qualified practitioners and late diagnosis. Given that the goal of the project is to make it user-friendly, it may be said to be innovative in the current environment, especially given how busy people's lives are. Anyone with reliable internet connectivity can upload a skin image and have it assessed as benign or malignant by the system. The system works adequately in identifying melanoma skin cancer detection in a cheap and efficient manner.

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