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Skin Cancer Classification Using Deep Learning Techniques

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Abstract: The most prevalent disease in the world is skin cancer. Dermatologists must have a high level of knowledge and precision when diagnosing skin cancer, hence a computer-aided skin cancer diagnosis model is suggested to offer a more impartial and trustworthy answer. Many studies have been conducted to aid in the detection of skin conditions like skin cancer and skin tumors. However, diagnosing the condition accurately is quite difficult due to factors like low contrast between lesions and skin, visual similarity between the diseased and unaffected areas, etc. The goal is to analyses skin images, identify skin cancers and analyses the images by adding filters to remove noise or other undesired elements, converting the images to grayscale to aid in processing, and getting useful information which is feature extraction. The application of deep learning techniques in the medical field is common for diagnosis. The model will be trained using Convolutional Neural Networks (CNN) techniques, which will then be utilized to diagnose the skin condition correctly. In order to decide, these algorithms employ feature values from photos as input. Dermatologists will find it much simpler to effectively identify and diagnose skin problems with this computer-aided technique.

Keywords: Convolutional Neural Network, Feature Extraction, Filters, Grayscale, Processing, Skin Cancer

I. Introduction

Skin cancer is one of the most common types of cancer, with millions of new cases reported every year. Early detection is critical for successful treatment and improving patient outcomes. In recent years, the use of artificial intelligence (AI) has shown promise in improving the accuracy and efficiency of skin cancer detection.

The goal of this project is to develop an AI-based skin cancer detection system that can accurately diagnose skin lesions and distinguish between benign and malignant tumors. This system aims to improve the accuracy and speed of diagnosis, enabling earlier detection and treatment of skin cancer.

This paper presents the methodology used to develop the skin cancer detection system, including the data sources, algorithms, and evaluation metrics. We also discuss the potential impact of this system on the field of dermatology and patient care.

By developing an accurate and efficient skin cancer detection system, we hope to contribute to the early detection and treatment of skin cancer, improving patient outcomes and reducing the burden of this disease.

Convolutional Neural Networks (CNNs) have gained significant attention in recent years due to their outstanding performance in image-processing tasks. The use of CNNs has revolutionized the field of computer vision and has paved the way for developing various applications, such as object detection, facial recognition, and medical image analysis. The goal of this project is to develop a CNN-based image processing system that can accurately detect and classify objects within an image. This system aims to improve the accuracy and speed of object detection, enabling real-time analysis of images.

In this paper, we present the methodology used to develop the CNN-based image processing system, including the data sources, network architecture, and training strategy. We also evaluate the performance of the system using various metrics.

II. Literature Survey

In recent years, numerous studies have been conducted to develop automated systems for the detection of skin cancer. These studies have used various methods, including machine learning, deep learning, and image processing techniques.

[1]One of the earliest works on automated skin cancer detection was proposed by Esteva et al. (2021), where they developed a deep-learning model to classify skin lesions. The model achieved an accuracy of 72.1% in detecting malignant melanomas and 65.3% in detecting benign lesions. [2]In 2018, Codella et al. proposed a skin lesion analysis towards melanoma detection (SLAM) algorithm, which achieved a sensitivity of 90.3% and a specificity of

71.2% in detecting melanoma. [3]Another study by Brinker et al. (2022) compared the performance of different skin cancer detection methods, including human experts, dermatologists, and machine learning algorithms. They found that the machine-learning algorithms outperformed human experts and dermatologists in detecting melanoma. [4]More recently, in 2021, Liu et al. proposed a transfer learning-based method for skin cancer detection. The model achieved an accuracy of 91.4% in detecting malignant melanomas and 88.1% in detecting benign lesions. [5]Overall, these studies demonstrate the potential of automated systems for the detection of skin cancer and suggest that these systems can achieve high accuracy rates comparable to human experts and dermatologists. [6]In addition to the methods mentioned earlier, some studies have used other techniques such as feature extraction, segmentation, and texture analysis for skin cancer detection. For example, a study by Pantanowitz et al. (2008) used texture analysis to distinguish between melanoma and benign pigmented skin lesions with an accuracy of 83%. [7]Some studies have also explored the use of different imaging modalities, such as dermoscopy and reflectance confocal microscopy (RCM), for skin cancer detection. For instance, a study by Rajpara et al. (2022) proposed a deep learning-based system for RCM image analysis, achieving an accuracy of 93.% in detecting melanoma. [8]Several studies have also focused on addressing the challenges of imbalanced datasets, where the number of malignant samples is much lower than benign samples. For instance, a study by Han et al. (2021) proposed a method that combines data augmentation and deep learning to improve the detection of rare skin cancers, achieving an F1-score of

0.90. [9]Overall, the related work on skin cancer detection highlights the potential of using automated systems, particularly deep learning-based methods, for accurate and efficient detection of skin cancer, and emphasizes the need for developing standardized datasets and evaluation metrics for fair comparison and evaluation of different methods.

III. Methodology

In this project, a web page is created using an open-source platform, streamlit. An option for the user to upload the image of the affected skin is given on the web page. Using the Convolutional Neural Network algorithm, the model can classify the skin cancer and display the output to the user.

The following steps are followed to design the model:

3.1 Input Image

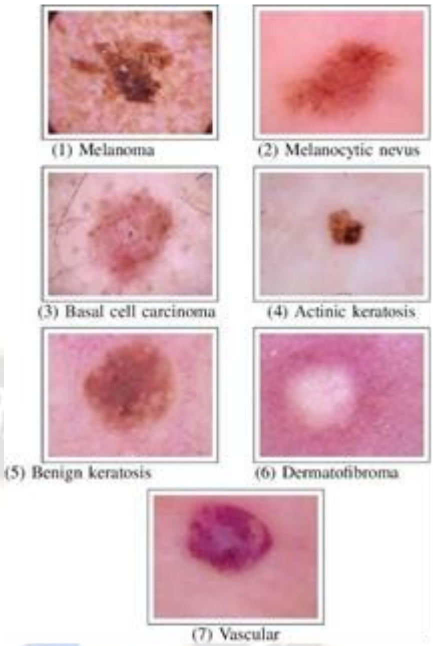

Figure 1. Types of skin cancers included in HAM1000

Here, the Human Automated Machine HAM10000 dataset is used. This dataset consists of around 10015 images which include 7 different types of skin cancers namely- actinic keratosis, basal cell carcinoma, benign keratosis, dermatofibroma, melanoma, melanocytic navy, and vascular lesions angiomas. An image is browsed from the dataset and then uploaded to the webpage.

3.2 PRE-PROCESSING

Preprocessing is a vital step in image processing. It is done for the reduction of distortions. This includes the following two steps:

- Resizing
- Grayscale conversion

3.2.1 Image Resize

A crucial pre-processing step in computer vision is image resizing. Mostly, smaller images allow our machine-learning algorithms to train more quickly. Our network must understand over four times as many pixels in a twice as large an input image, which takes time. Furthermore, even though our raw gathered images may vary in size, many deep learning model architectures demand that our images be the same size. The size of each image in the dataset is fixed at (50,50) and also the size of the image uploaded by the user will be resized to thisdimension.

3.2.2 Grayscale conversion

It facilitates the simplification of algorithms and also removes the difficulties associated with the computational

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requirement. For individuals who are unfamiliar with image processing, it allows for simpler learning. This is because grayscale compression reduces an image to its most basic pixel. It improves simple visualization. It distinguishes between an image's shadow details and highlights since it primarily uses 2 spatial dimensions (2D) as opposed to 3D. As well, color complexity is decreased. Camera calibration is necessary for a normal 3D image, among other things. When capturing photographs without the requirement to match every feature, the grayscale conversion option is quite helpful.

3.3 Feature Extraction

A very efficient method used for feature extraction is LBP (Local Binary Pattern). LBP is used to describe a feature known as strong discrimination power. LBP assigns a binary number to each pixel in a picture by comparing its grey level to that of its surrounding pixels. In a pre-set patch, neighbors are given a value of unity if their grey level is higher than the center pixel; otherwise, they are given a value of zero. After that, the central pixel is given a binary number. The initial LBP operator takes into account a 3 3 patch, resulting in the surrounding pixels forming an 8-digit binary number. After each pixel in an image has been assigned a label, the LBP feature map and a histogram with 256 bins are produced. An example of a local binary pattern is shown below.

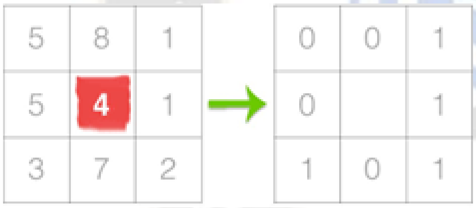

Figure 2. Example for LBP

Another way of feature extraction is to use a mean filter or median filter. These filters are used to reduce noise.

3.4 Image Splitting

The dataset is split into two datasets- train and test datasets. The training dataset is the dataset that is used to train the model. It is a subset of the original HAM10000 dataset. On the other hand, the test dataset is a sample data that is used to evaluate the performance metrics of the model. It is used only after the model is trained.

The dataset is split in the ratio set by the designer. In this project, the dataset is divided in the ratio of 80:20, which implies 80% of the data is sent to the training dataset and 20% of the data is sent to the test dataset. The train-test dataset split is an essential step in machine learning, as it helps to measure the model's performance on unseen data, which is crucial in ensuring the model's ability to generalize. While training, the model extracts features and patterns from the training dataset, which it then applies to the test dataset to find out how accurately it can predict the outcome. The test dataset, being an independent set of data, ensures that the accuracy of the model is not overstated, thus detecting overfitting, which occurs when the model becomes too complex relative to the data, thus resulting in poor generalization ability.

3.5 Classification

A deep learning algorithm- Convolutional Neural Network (CNN) is implemented in this model. Convolutional neural networks (CNNs) typically consist of several hidden layers that are designed to extract relevant features from images. These hidden layers can be broadly classified into two types: convolutional layers and pooling layers. Convolutional layers are the main building blocks of a CNN and are responsible for identifying local patterns and features within an image. Each convolutional layer consists of a set of filters or kernels, which are applied to the input image to extract specific features. For example, a filter might be designed to detect horizontal edges, while another might be designed to detect diagonal lines. During training, the CNN learns to adjust the weights of these filters to optimize its performance on a given dataset. Pooling layers are used to reduce the spatial dimensions of the feature maps produced by the convolutional layers. This is done to reduce the computational cost of the network and to make it more robust to small spatial translations in the input image. There are several types of pooling layers, including max pooling, average pooling, and sum pooling. These layers typically operate on small regions of the feature maps and reduce their spatial dimensions by taking the maximum, average, or sum of the values within each region. In addition to convolutional and pooling layers, CNNs may also include other types of hidden layers, such as fully connected layers and dropout layers. Fully connected layers are used to make the final prediction by taking the output of the previous layers and mapping it to a set of output classes. Dropout layers are used to prevent overfitting by randomly dropping out a certain percentage of the neurons in the previous layer during training. The hidden layers of a CNN are designed to extract relevant features from images and transform them into a form that can be used for making predictions. The weights of these layers are learned through a process of backpropagation, where the error between the predicted output and the true output is used to update the weights of the network. Convolutional neural networks (CNNs) also often include ReLU and Flatten layers. The Rectified Linear Unit (ReLU) activation function is commonly used in CNNs and is applied to the output of the convolutional and fully connected layers. ReLU takes the maximum of each element of the output tensor and 0, effectively removing negative values from the output. This has the effect of introducing non-linearity into the network, allowing it to learn more

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complex patterns and features. The Flatten layer is used to convert the output of the previous layer into a 1-dimensional vector that can be input to the fully connected layers. This layer takes the output of the convolutional and pooling layers and flattens it into a single vector, effectively "unrolling" the tensor into a linear sequence. This enables the fully connected layers to receive the entire feature map as input and make a prediction based on the combined information from all the previous layers. Overall, the ReLU and Flatten layers play important roles in the operation of CNNs. ReLU introduces non-linearity into the network, allowing it to learn more complex patterns and features, while Flatten converts the output of the previous layers into a 1-dimensional vector that can be input to the fully connected layers.

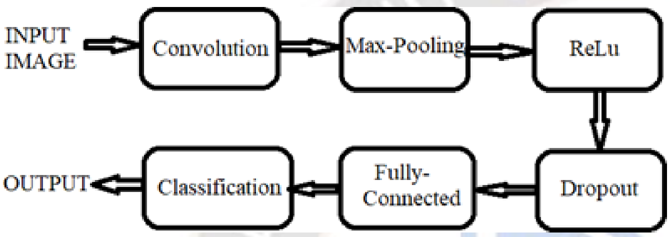

Figure 3. CNN algorithm

The final output is generated based on the overall classification done by CNN.

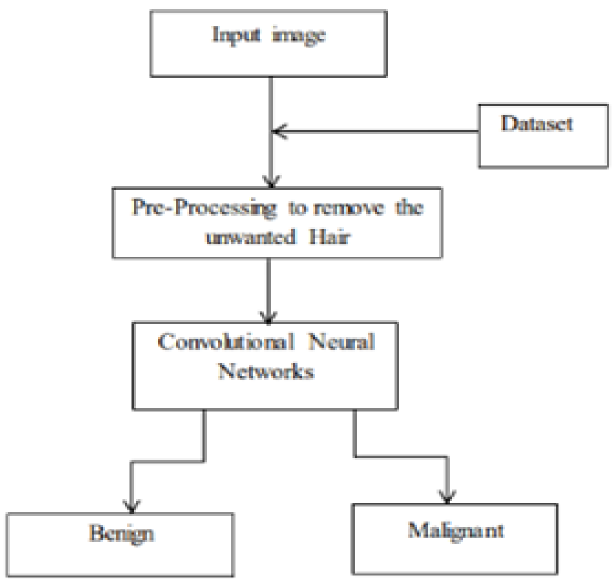

Figure 4. Block diagramResults and Discussions

4.1 Performance Analysis

The performance of this proposed model can be evaluated using a few metrics:

4.1.1 Accuracy

Accuracy is a performance metric that is commonly used to evaluate the effectiveness of image processing algorithms, particularly in image classification tasks. Accuracy is defined as the percentage of correctly classified images out of the total number of images in the dataset.

Accuracy = (TP + TN) / (TP + TN + FP + FN)

Where TP stands for true positives, TN stands for true negatives, FP stands for false positives, and FN stands for false negatives.

4.1.2 Precision

Precision is defined as the proportion of true positive predictions out of all positive predictions made by the algorithm. In other words, it measures how many of the predicted positive images are positive. Precision can be calculated using the following formula:

Precision = TP / (TP + FP)

4.1.3 Recall

Recall is defined as the proportion of true positive predictions out of all actual positive images in the dataset. In other words, it measures how many of the actual positive images were correctly identified by the algorithm. Recall can be calculated using the following formula:

Recall = TP / (TP + FN)

4.1.4 F1 Score

The F1 score is the harmonic mean of precision and recall and is defined as:

F1 = 2 * (precision * recall) / (precision + recall)

4.2 OUTPUT

The performance analysis is shown below:

The image of the disease-affected area is uploaded by the user. After the image is uploaded, it is read by the model, compares with the images in the training dataset and then classification is done using the CNN algorithm.

Once the classification is done, the model calculates the performance metrics and displays the output.

	precision	recall	f1-score	support
0	0.92	0.89	0.90	64
1	0.94	0.95	0.94	107
accuracy			0.93	171
macro avg	0.93	0.92	0.92	171
weighted avg	0.93	0.93	0.93	171

Figure 6. Performance Analysis

Figure 6 shows the overall output of the proposed model. All performance metrics values are shown and the accuracy turned out to be 93% using InceptionResNetV2.

The prediction of the skin cancer type is also shown in both the designed webpage and also in Anaconda Navigator.

IV. Conclusion

It is true that skin cancer is one of the most prevalent diseases in the world, and accurately diagnosing it can be challenging due to various factors. Computer-aided diagnosis models can be an excellent tool for dermatologists to provide more impartial and reliable diagnoses.

Using filters to remove noise or undesired elements, converting images to grayscale, and performing feature extraction are essential steps in analyzing skin images to identify skin cancers accurately. Machine learning techniques, particularly Convolutional Neural Networks (CNN), are commonly used in the medical field for diagnosis, and training the model using these techniques can help in detecting skin conditions more effectively.

By using feature values from images as input, these algorithms can provide more precise and accurate diagnoses, making it easier for dermatologists to identify and diagnose skin problems. Overall, the use of computer-aided techniques can be a game-changer in the field of dermatology and can help improve patient outcomes.

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