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Skin Cancer Detection System Project

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ABSTRACT:

Skin is the body's largest organ and serves to protect internal organs, bones and muscles. When the skin breaks, the whole body is affected. Skin cancer is common because the skin is easily damaged by UV rays and other toxins. The most common types of skin cancer appear to be benign melanoma and malignant melanoma. Malignant moles are more destructive than benign moles and may bleed from the skin. They get their name because they affect the more lethal melanocytes. The United Cancer Society reports that more than 900,000 skin cancers are diagnosed each year in the United States. Skin cancer is one of the most common cancers in the world, and prompt treatment and good patient outcomes depend on early detection and diagnosis of pain. However, diagnosing skin cancer can be difficult because it requires a dermatologist with extensive training and experience. To help prevent the spread of the virus, The system combines various artificial intelligence algorithms, including neural networks and support vector algorithms.

The HAM10000 data set used in this study makes a significant contribution to the field as it contains excellent dermoscopic images of many different areas of the skin. The CNN model proposed in this study is a deep learning model that performs very well in imaging such as cancer screening. The system consists of three steps: collection and development, design and assimilation. While the app is a useful tool for dermatologists and researchers, it should not completely replace medical personnel-based diagnosis.

Keywords- Skin Cancer, Convolutional Neural Networks, HAM10000 set, HealthCare, Sequential CNN, KNN.

I. INTRODUCTION

Skin cancer has been the most common cancer worldwide since the 1970s. The number of diagnoses of both non-melanoma and melanoma skin cancer has increased in recent years. The World Health Organization (WHO) estimates that one in three people will develop skin cancer at some point in their lives, while the Skin Cancer Foundation estimates the number at one in five. To increase. This model is not exclusive to the United States, Canada or Australia; can be found in many countries. The rapid spread and high impact of skin diseases make them an important public health problem. The skin, which is the outer part of our body, is constantly exposed to environmental factors such as dust, pollution, bacteria and ultraviolet radiation, which can cause many diseases on the skin. Additionally, skin diseases are often caused by genetic imbalance, making them particularly difficult.

Of all skin diseases, skin cancer is the most dangerous and deadly; Melanoma and non-melanoma are the two main types. Although malignant melanoma affects only 4% of the population, it is responsible for 75% of skin cancer, especially in light-skinned people. Early diagnosis is very important in the treatment of skin cancer. According to a study published in 2017, skin cancer accounts for 1.79% of the global burden of disability-altering life years [1]. Skin cancer accounts for approximately 7% of new cancers diagnosed worldwide. Doctors often use biopsies to diagnose cancer. However, this method is difficult, slow and time consuming. By comparison, computer-based technology may be cheaper and better at diagnosing skin cancer. To achieve this, artificial neural networks (ANN), convolutional neural networks (CNN). and requires a variety of non-invasive technologies, including machine learning algorithms like Kohonen himself. -developed neural networks for image acquisition and prediction, segmentation, feature extraction and classification (KNN), and generative adversarial neural networks (GAN). This article provides an informative review of deep learning techniques for skin detection.

II. EXISTING APPROACHES

The problem of diagnosing skin diseases by image analysis has been addressed in previous studies [1]. Various techniques are used, such as noise removal and object extraction followed by classification. Although some publications focus on video extraction and disease prediction, others use neural networks or machine learning algorithms [2 , 3 , 4 , 5 , 6]. Computer vision techniques have also been used in the past, especially for preprocessing purposes. It focuses on improving knowledge using computer vision techniques. Krishna Monika (2020) [7] found that the number of skin cancer patients is increasing due to various reasons. Therefore, early diagnosis is important for diagnosis and treatment. Therefore, this work discusses a strategy based on MSVM classification, which achieves two effective extraction methods of ABCD and MSVM. Vijayalaxmi MM (2019) [8] proposed a project to study the accuracy of skin cancer prediction and classification of skin cancer as malignant or non-malignant melanoma. To achieve this goal, some preliminary steps such as epilation, shadow reduction, glare removal and segmentation are taken. For groups, support vector machines and deep neural networks will work. In an article by Mahmudul Hasan (2020) [9], a melanoma classification strategy based on neural networks was proposed. A tool has been developed to help patients and doctors detect or diagnose mild or moderate skin cancer. [10] described a deep learning method to identify skin lesions such as macules, nodules, papules, plaques, pustules, wheals, and bullae, focusing on initial classification and early diagnosis.

This framework uses deep learning technology to classify lesion images into seven different categories. In this paper, we will try several pre-trained deep convolutional neural networks to see which one is the most accurate. The results obtained from the training and testing process show that the ResNet-50 base model improves to achieve 85.95% accuracy. Chaturvedi et al. [11] developed a computerized diagnosis method for the classification of multiple skin (MCS) tumors. The proposed strategy outperformed both operators and deep learning methods in identifying MCS tumors. Using the HAM10000 dataset, five pre-trained convolutional neural networks (CNNs) and four cluster models were analyzed and improved, and the classification of people was evaluated in seven clusters.

III. EXISTING SOFTWARE

The project will be a way to diagnose melanoma using imaging as a functional tool. In this proposal, the system takes an image of a skin lesion and is then analyzed using imaging techniques to determine whether it is cancer. Lesions is an image analysis tool that analyzes various melanoma parameters, from color, surrounding area, diameter to texture, size to image focus, image segmentation and stage markers. The subtraction process was used to classify images into non-melanoma and melanoma cancer. return. Diagnostic imaging is difficult because it requires time and money as well as skilled and skilled professionals. CNNs are currently used to identify disease from dermoscopy images. These existing CNN architectures distribute prediction accuracy in different ways. Therefore, we are developing a convolutional architecture that can extract important features of biomedicine.

IV. PROPOSED METHODOLOGY

Dermoscopy is used as a tool in the diagnosis of skin diseases because it can be diagnosed early and has a high probability of recurrence. Diagnostic imaging is difficult because it requires time and money as well as skilled and skilled professionals. To solve this problem, CNNs are currently used to identify lesions from dermoscopy images. These existing CNN architectures distribute prediction accuracy in different ways. Therefore, we develop a convolutional architecture that can extract important features from biomedical images for high-precision image classification. The goal of skin cancer diagnosis is to develop a neural network (CNN) model that can classify skin cancer images.

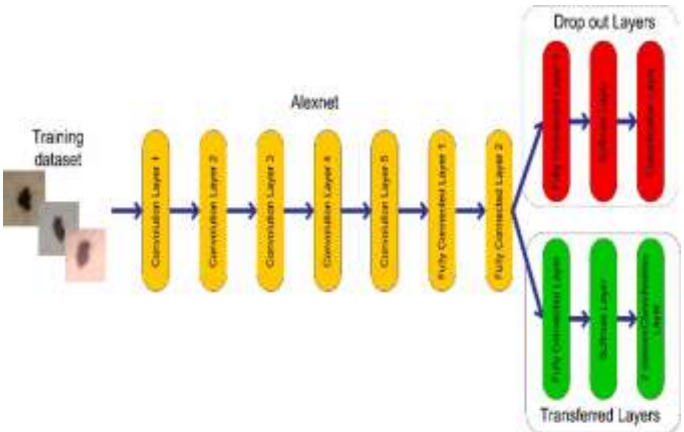

FIG 2: Workflow Diagram

3.1: Dataset Collection:

There are 10,015 pictures on the chip, their abbreviations are letters. The material used in the preparation process consists of high dermoscopic images. CSV file hmnist_28_28_RGB.csv File with multiple groups. Melanocytic nevus, basal cell carcinoma, benign keratosis-like lesions, dermatofibromas, actinic keratosis, intraepithelial carcinoma, pyogenic granulomas and hemorrhages, and melanoma.

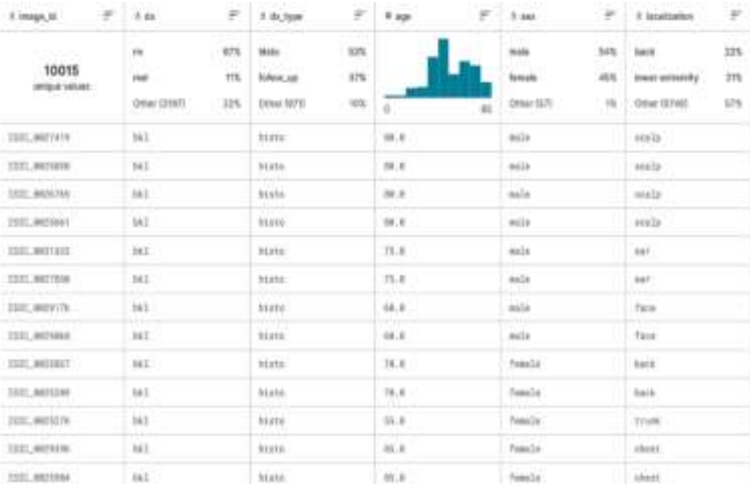

Fig. 2: Findings Data

3.2: Preprocessing:

Thus, the main purpose of the preprocessing step is to improve image parameters such as quality, clarity, etc. by removing or reducing unwanted parts of the image or background. The main stages of preprocessing are grayscale conversion, image enhancement and noise removal. In this proposed system, all images are first converted to grayscale.

Two filters called a Gaussian filter and a median filter are then used to enhance the image and remove noise. Along with filters, the Dull Razor method is used to remove unwanted hair from the skin lesion.Image enhancement aims to improve the quality of an image by increasing its visibility. In general, most of the skin lesions consist of body hair, which can prevent high accuracy during classification. So the blunt shave method is used to remove unwanted hair from the images.

The Dull Razor method mainly performs the following functions: a) Using a gray-scale morphological operation, it determines the location of the hair in the skin lesion. b) Once the location of the hair pixel is found, it checks the shape as either a thin or long structure and then replaces that hair pixel using bilinear interpolation.

c) Finally, it smooths the shifted hair pixel with an adaptive median filter. Gaussian filters are mainly used to blur images and remove extraneous features of skin lesions. These are low-pass filters with linear smoothing. This filter uses a 2D convolution operator whose weights are chosen in the form of a Gaussian function.

3.3: Segmentation:

Segmentation is the process of extracting a region of interest from an image. This separation can be done by considering each pixel in the image that has a similar attribute. The main advantage here is that instead of processing the whole image, you can process the image divided into segments. The most common technique is to mark the edges of a given region. Other approaches, such as thresholding, clustering, and region growing, use similarity detection in a given region. Color based k means grouping has been applied here.

3.4: Feature extraction:

Feature extraction is a module used to classify and identify the type of disease by extracting features from an image. We use the Keras TensorFlow module to detect diseases associated with skin damage. Many image processing and computer vision applications, including object recognition, image processing, and scene analysis, rely on feature extraction. The exact task and the characteristics of the images to be studied determine the feature extraction technique to be used.

3.5: Classification:

This is a module that helps to classify the diseases in the acquired image and helps to give an appropriate suggestion to the user using a recommendation model.This is a module that helps to classify diseases in the obtained image. The proposed system uses eight types of skin cancer for classification and high accuracy.

V. RESULT & DISCUSSION

This code provides a user-friendly GUI interface for loading, preprocessing, training, and skin cancer diagnosis and classification using CNNs. It displays instructions and is placed in a console-like text box, allowing users to interact with the system via buttons and dialog boxes.

Preprocessing stage: First use the blunt knife method for the input image, then convert to grayscale, and then use Gaussian filter and median filter. Initial results are shown in Figure 3. Segmentation: Color-based k-means clustering is used to classify the images, and the results are shown in Figure 3. Distribution: Use MSVM for distribution .Due to the complexity of the relationship involving approximately 25,000 images in the HAM10000 dataset, a total of 800 images were considered for tracking 200 images per category. The ratio of training to testing is 70:30. The confusion matrix is shown below. The confusion matrix is a table that is often used to represent the performance of a classification model on known test data.), malignant melanoma (7.9%), and other cancers [2]. Although malignant melanoma occurs less frequently than basal cell carcinoma and squamous cell carcinoma, it has a higher mortality rate; 75% of deaths are from the skin. It provides a GUI interface for loading, preprocessing, training, and skin cancer diagnosis and classification using CNNs. It displays instructions and is placed in a console-like text box, allowing users to interact with the system through buttons and dialog boxes. In this work, we aim to develop an effective deep learning neural network (DL-CNN) for various skin classification methods. Therefore, the results of this study can be used for the classification of all nine cancer types. Future studies will build on this research by using additional studies to accurately identify skin diseases.

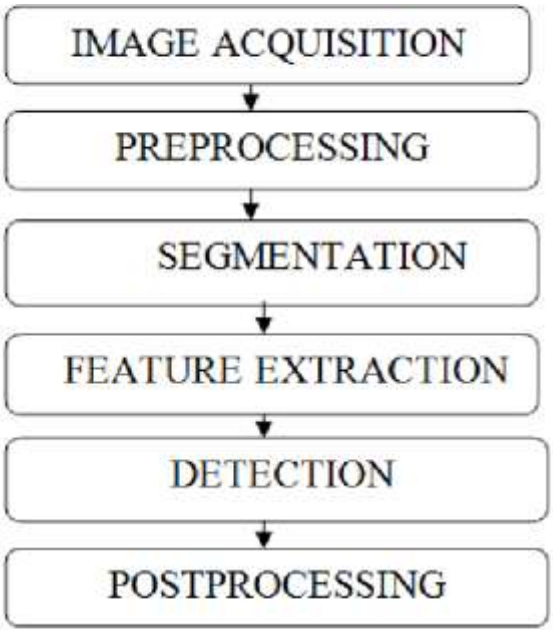

Fig. 4: Dataflow Diagram

Fig.5: Project Snapshots

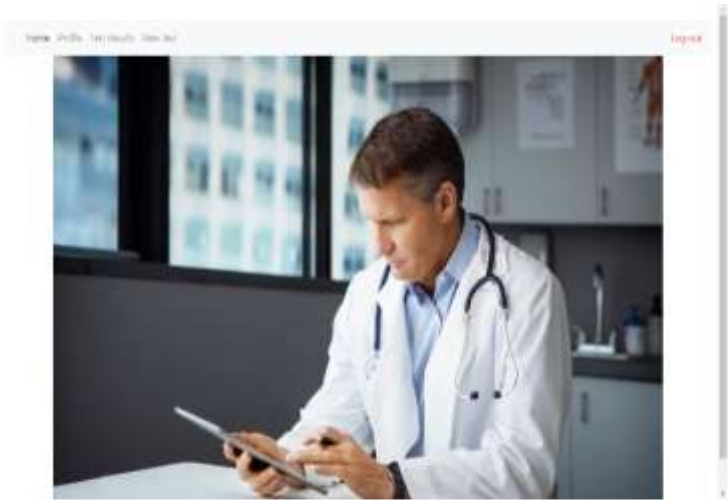

Fig. 5.1: Home Page

Fig. 5.2: Dashboard

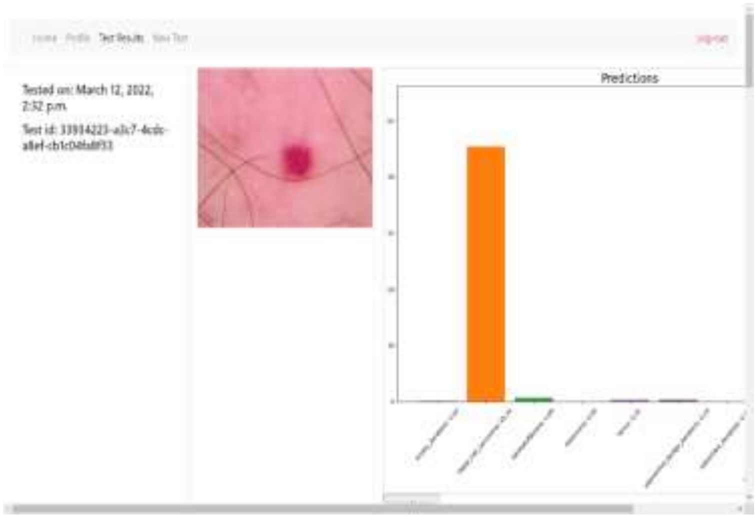

Fig. 5.3: Results

VI. CONCLUSION

In conclusion, the incidence of skin cancer is increasing worldwide for many reasons. Therefore, early diagnosis is important for diagnosis and treatment. Therefore, this article discusses how identifying cancer in its early stages can aid treatment. Applying different CNN models based on the data will help understand which model will be best in terms of speed and accuracy compared to other models. In addition, in cases where human resources are not available, suggested research studies can be carried out easily. Therefore, creating an application that is mature enough to be trusted in the clinic will be the next important step. Looking ahead, there are many opportunities for future research and development. Among many skin cancers, melanoma is the most dangerous and has a very low survival rate. Examine a variety of skin conditions to provide support to dermatologists during diagnosis. More research is still needed to address issues such as insufficient data and sample interpretation and to develop reliable and accurate models.

However, progress in this field marks a major step towards better detection and treatment of cancer. Our results show that our model has an accuracy of approximately 96.23% compared to existing methods, and the test model can help dermatologists diagnose skin problems more accurately and reduce the risk of misdiagnosis. Accuracy will be improved by creating a more effective removal process that can make a small difference between skin and no wound. For example, the model's ability to distinguish skin from benign diseases can be improved using advanced image processing techniques such as texture analysis, chemical evaluation, or deep learning.

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