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Artificial Intelligence Based Skin Cancer Detection

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ABSTRACT

In recent years, skin cancer has risen to prominence as a leading cause of cancer mortality in people. If caught early, skin cancer can be cured, and with the right treatment, the patient can live a long, healthy life. Skin cancer disorders are classified into numerous categories, each with its own set of characteristics. The classic method of detecting skin lesions includes the ABCDE approach, which is frequently utilized by doctors. However, with the present global increase in skin cancer occurrences, manual detection of skin lesions is no longer effective. In order to lessen the burden on doctors, speed up the detection process, and decrease diagnostic errors, automatic skin lesion detection is necessary. An intelligent system capable of accurately identifying skin lesions could be built with the use of various deep learning and machine learning techniques. When it comes to skin lesion feature extraction and classification, deep learning models like neural networks are invaluable. In this project we are using convolution neural networks, which is best for image processing. This analysis makes use of the skin cancer dataset, which documents seven distinct skin lesion types using a diverse array of images. Classification accuracy of 90% was achieved using CNN.

Keywords: Deep Learning, image pre- processing, Machine Learning, Convolutional Neural Network (CNN), Skin lesion.

INTRODUCTION

Humans are vulnerable to several types of skin infections in today's unsanitary environment. Skin cancer can develop when excessive exposure to ultraviolet (UV) light damages skin DNA and causes the production of abnormal cells. If the lesion grows and spreads quickly to other parts of the skin, it is considered malignant and becomes very dangerous. Surgically removing the affected area is one possible treatment option. Benign lesions, on the other hand, appear throughout the area but do not spread quickly, making them relatively safe. Getting medical help when a tumor is still in its early stages is crucial for reducing mortality. Benign skin cancers include benign keratoses (bkl), dermatofibroma (df), melanocytic nevi (nv), and vascular lesions (vasc), whereas malignant skin cancers include actinic keratoses and intraepithelial carcinoma (akiec), basal cell carcinoma (bcc), and melanoma (mel).The tumor could metastasize (spread to other parts of the body) and cause death if left untreated. Early detection of skin cancer can greatly reduce mortality.

LITERATURE SURVEY

H. Alquran et al. [4] developed a melanoma classification method that makes use of an SVM classifier with Otsu's thresholding, an ABCD feature extraction, and a GLCM. To select features, principal component analysis (PCA) is employed. The outcomes showed a 92.1% categorization accuracy.

An ABCD rule, GLCM, and HOG feature extraction–based skin lesion benign vs. melanoma classifier was created by M. Vidya and M. V. Karki [6]. To segment the images, the Geodesic Active Contour (GAC) method was employed. The SVM classifier outperformed the KNN and Naïve Bayes classifiers, with 97.8% accuracy.

A study comparing KNN, Decision Tree, and SVM classifiers for skin lesion classification was conducted in reference [8]. The preprocessing step involved the use of the Dull Razor method to remove hair. Dermoscopic images were segmented using the mean-shift

algorithm and feature extracted using the ABCD technique. The Relief algorithm selects characteristics, which are then classified using classifiers. The SVM classifier achieved the highest accuracy (78.2%).
The authors of [9] presented a system for automatically segmenting skin lesions that begins with noise and hair removal preprocessing and continues with image segmentation using the GrabCut and Flood fill algorithms. Using k-means clustering, skin lesions are categorized. The suggested method was 92% accurate on the ISIC 2017 dataset and 96% on the PH2 dataset. The Dice coefficient values are 0.82 for the ISIC 2017 dataset and 0.92 for PH2.
Vijayalaxmi M M (2019) proposed a study to investigate the accuracy of skin cancer prediction and classification as malignant or non-malignant melanoma. To accomplish this, several pre-processing stages were carried out, including hair removal, shadow reduction, glare removal, and segmentation. To categorize, SVM and Deep Neural Networks will be used.
M. Krishna Monika (2020) found that a number of factors are contributing to a notable rise in the number of skin cancer cases. Therefore, diagnosis and therapy rely on early detection. Consequently, this study introduces an MSVM- based classification strategy that combines the productive feature extraction methods ABCD with MSVM.

PROBLEM STATEMENT

Dermoscopy is being used as a method to detect disease-related skin lesions since it can be diagnosed early on and has a high recovery rate. Image diagnosis is difficult since it requires the expertise of highly trained specialists, as well as time and resources. To address this, CNN are already being used to automatically identify diseases from dermoscopy photos. These existing CNN architectures have classified their prediction accuracy in a number of different ways. So we're developing a neural architecture capable of extracting valuable characteristics from biomedical photos and classifying them with high accuracy.

EXISTING SYSTEM

Biopsy and dermoscopy are two of the more traditional ways to detect skin cancer. An invasive procedure known as a biopsy involves taking a tissue sample from the patient in order to diagnose skin cancer. Interpretation of skin cancer results will take longer after the relevant laboratory tests have been completed. Dermoscopy, on the other hand, uses a magnified lens to detect skin cancer and its outcome without invasive procedures. In order to interpret a skin lesion, doctors must carefully examine it under a microscope and then use the ABCDEapproach.
Because the doctors need to carefully study the skin lesion, this procedure takes a long time as well. Traditional methods, which take a long time, can't detect skin cancer in a growing number of patients. Therefore, auto-diagnostic methods must supersede manual skin cancer detection. Because it can lessen the burden on doctors to carefully observe and interpret the results, AI plays a much-appreciated role. In order to detect skin cancer through picture classification, deep learning models like Convolutional Neural Networks can be employed. Improvements in medical practice and a decrease in diagnostic error rates are both brought about by the use of deep learning and machine learning models.

PROPOSED METHODOLOGY

The proposed "Artificial Intelligence-Based Skin Cancer Detection" represents a significant advancement in medical field. Leveraging state- of-the-art Convolutional Neural Networks (CNNs), the system is designed to provide highly accurate and detection of skin cancer. By applying a robust CNN model, we are achieving an impressive accuracy rate of 90%. This system leverages deep learning for skin cancer classification. It utilizes transfer learning from a pre-trained InceptionV3 model, renowned for its image recognition capabilities. InceptionV3 extracts valuable features from dermoscopic images, which are then fed into trainable fully-connected layers for classifying various skin cancer types. To enhance the model's generalization ability and prevent overfitting, data augmentation techniques like random shearing, zooming, and flipping are applied to the training data. The trained model can analyze new images, predict their corresponding skin cancer class (e.g., benign, malignant), and even visualize the results. This system offers a promising approach for automated skin cancer screening, potentially aiding dermatologists in their diagnoses.

PRE-PROCESSING

Image preprocessing is a critical step in preparing data for a Convolutional Neural Network (CNN). This process involves several techniques to enhance the quality and uniformity of input images. Initially, data augmentation methods such as rotation, flipping, scaling, translation, and brightness adjustment are applied to artificially increase the diversity of the training dataset, thereby improving model robustness. Images are then resized to a standard dimension to meet the input requirements of the CNN architecture.

CONVOLUTIONAL NEURAL NETWORK

When dealing with structured grid data, such as images, a Convolutional Neural Network (CNN) is the deep learning algorithm of choice. Convolutional neural networks (CNNs) excel at picture recognition because they can learn feature hierarchies from input images automatically and adaptively.

CNN Layers:

Input Layer: This layer represents the raw input image data.

Convolution + Activation: Convolutional layers followed by ReLU activation functions to detect features.

Pooling: Reduces dimensionality and helps in extracting dominant features.

Flattening: Converts the 2D feature maps into a 1D feature vector.

Fully Connected Layers: Perform classification based on the extracted features.

Output Layer: The output layer produces the final prediction.

SYSTEM ARCHITECTURE

The conceptual model that specifies the structure, behavior, and additional perspectives of a system is known as its architecture. An architecture description is a formal depiction of a system that is structured to facilitate reasoning regarding the system's structure and behavior. System components and the sub-systems that will be developed are both part of the system architecture. These parts will collaborate to execute the system as a whole.

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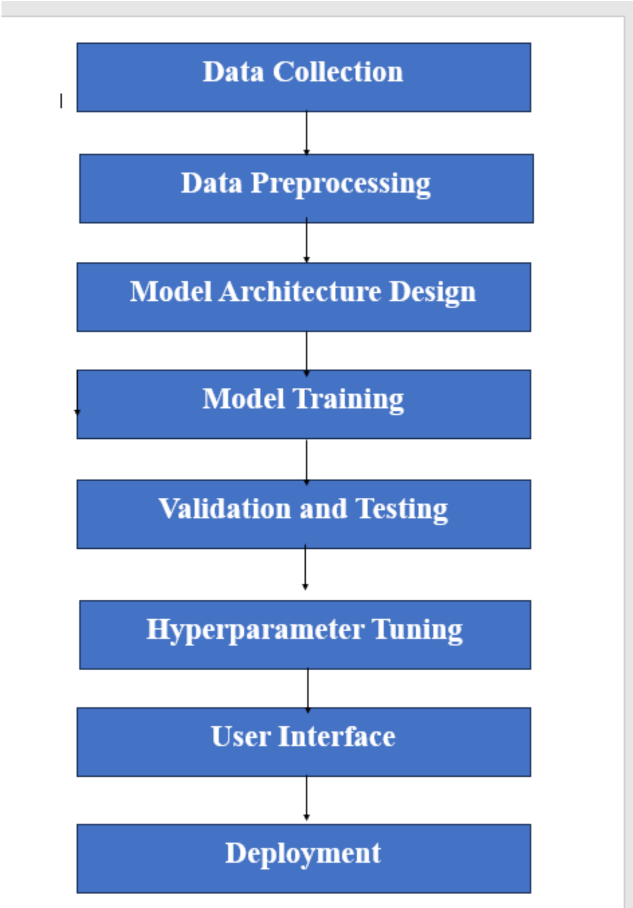

Figure 1: System Architecture

Data Collection: This module is responsible for gathering dermoscopic images of skin lesions from various sources, such as medical databases, research repositories, or hospitals.

Data Preprocessing: This module preprocesses the raw image data to prepare it for training, including tasks such as resizing, normalization, augmentation (e.g., flipping, rotating), and splitting into training, validation, and test sets.

Model Architecture Design: Choosing the architecture of the CNN model. Skin cancer detection custom-designed architectures, as well as popular options like VGG, ResNet, and Inception, are common choices. We are using InceptionV3 model.

Model Training: Training the CNN model using the labeled dataset. This involves optimizing the model's

parameters (weights and biases) using algorithms like gradient descent or its variants. Training is an iterative process that aims to minimize the difference between the predicted labels and the ground truth labels.

Validation and Testing: Trying out the trained model on new datasets that weren't part of the training process. In doing so, we can evaluate the model's overfitting detection capabilities and its capacity to generalize to new data.

Hyperparameter Tuning: Adjusting hyperparameters such as learning rate, batch size, and regularization techniques to optimize the model's performance.

User Interface: If applicable, this module designs and implements the user interface through which users interact with the skin cancer detection system, providing input images and viewing classification results.

Deployment: Integrating the trained model into a user-friendly interface or application where users can upload images for prediction. Deployment may involve considerations such as model size, inference speed, and platform compatibility.

RESULTS

Figures 2 and 3 show examples of browsing and detecting skin diseases, respectively.

Figure 2: Browse for input image

Figure 3: Skin cancer detection result

CONCLUSION

In conclusion, the implementation of AI-based skin cancer detection using Convolutional Neural Networks (CNNs) holds significant promise in revolutionizing healthcare. Through the utilization of deep learning algorithms, this technology offers a non-invasive and efficient method for early detection and diagnosis of skin cancer, potentially saving lives through timely intervention.

This study employs a convolutional neural network (CNN) classifier to categorize seven distinct skin lesion types derived from a skin cancer dataset. Results obtained with a CNN classifier achieving 90% accuracy. The classifier is run through an OpenCV simulation in real time. Compared to the other classifiers, the CNN model did a better job of detecting all seven kinds of skin cancer. The throughput is reduced because the CNN model has very high detection latency. Doctors can easily use this model in skin cancer diagnosis by deploying it onto a microcontroller interfaced with a high resolution camera.

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