AI-Enhanced Skin Disease Detection and Mental Health Prediction: An Integrated Android Application

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Abstract

This research presents the development and implementation of an Android application aimed at enhancing healthcare through the integration of machine learning models, image segmentation, and location-based services. The application leverages TensorFlow Lite (TFLite) models for two critical tasks: skin lesion analysis and mood and emotion recognition. For skin lesion analysis, a Convolutional Neural Network (CNN) is employed for image segmentation, allowing for precise detection and classification of skin conditions. When a skin image is provided, the model accurately predicts potential skin diseases, enabling early diagnosis. In the domain of mental health, facial images are processed to assess mood and emotion. The application employs a TFLite model to analyze facial expressions and provide valuable insights into the user's emotional state. This holistic approach recognizes the intrinsic connection between physical and emotional well-being. Furthermore, the system utilizes custom-created API to identify nearby healthcare providers, allowing users to locate doctors specializing in relevant medical fields.

Keywords: Convolutional Neural Network, Skin disease detection, Segmentation, Mood detection, Android App, API.

Introduction

Skin problems affect a huge number of people, about 1.8 billion. These conditions occur because of various factors, including prolonged exposure to Ultraviolet Radiation (UR) and other environmental elements. Many people, around 30% to 70%, are at higher risk [1]. Early detection and comprehensive healthcare are pivotal in effectively managing these skin diseases, as they significantly impact an individual's quality of life. Notably, mental health issues are growing worldwide, affecting a large number of people. These challenges result from various factors, including work-related stress, financial difficulties, family and relationship problems, violence, and environmental influences [2]. Approximately 450 million people are affected, making mental health a substantial part of the global disease burden [3]. In response to these challenges, machine learning (ML) steps forward as a vital partner. It extends its capabilities to not only diagnose skin diseases with precision but also to assess mental health by analyzing facial expressions, thereby promoting a holistic approach to well-being. In the case of skin disease, we utilize classification and segmentation techniques for precise diagnosis and analysis. In contrast, for mental health, we focus on classifying emotions and assessing overall mood status. Within this context, we introduce an Android application specifically crafted to leverage the capabilities of machine learning (ML). This application excels in predicting skin diseases with remarkable accuracy while simultaneously assessing mood and emotions. By integrating geolocation services, it ensures swift access to healthcare providers, emphasizing its dedication to facilitating prompt healthcare delivery.

Literature Review

Skin health has been a focal point of medical research for decades, leading to advancements in dermatology and the diagnosis of skin conditions. Traditional approaches have primarily relied on the expertise of medical professionals, often entailing visual inspection and manual assessment. However, recent developments in machine learning and image analysis have paved the way for more accurate and efficient methods of skin disease prediction [4][5]. In parallel, the field of mental health has witnessed significant advancements in understanding the intricate relationship between emotions, mood, and overall well-being [6]. Facial expression analysis, coupled with psychometric assessments, has enabled a more comprehensive understanding of an individual's mental state [7]. In the past, prior research into non-CNN segmentation models employed inventive preprocessing techniques. However, in recent developments related to CNN models, the emphasis has shifted towards enhancing the model's architecture rather than concentrating on data preprocessing [8].

In this study, we employ classification and segmentation techniques to closely examine each skin lesion image and predict the respective output. In the realm of mental health assessment, our focus centers on classifying emotions, followed by distinguishing between positive and negative emotions. We further analyze the ratio of happiness, sadness, and other emotions to predict an individual's mental status. The integration of skin disease prediction and mood assessment within a single health monitoring system represents a novel approach to holistic well-being. While prior research has explored these areas independently, "Skin n Sense" innovatively combines them to provide users with a comprehensive health profile.

Methodology

Data collection: The methodology commences with the compilation of a diverse dataset from Dermnet, encompassing images of skin lesions categorized into seventeen distinct categories. These categories include "Acne," "Actinic," "Atopic," "Bullous," "Cellulitis," "Eczema," "Exanthems," "Herpes," "Hives," "Light Disease," "Lupus," "Psoriasis," "Scabies," "Systemic," "Tinea," "Vasculitis," and "Warts." Each image is associated with a specific skin disease category label.

For mood detection, we utilized the FER 2013 dataset, comprising grayscale facial expression images of size 48x48. These images were annotated and categorized into distinct emotions, including happiness, neutrality, sadness, anger, surprise, disgust, and fear, forming the basis for training and evaluating our mood detection model.

Data preprocessing:

- **Data Augmentation:** To enhance the dataset's diversity and improve model generalization, data augmentation techniques are applied. These techniques include random rotations, scaling, and flipping of the images, effectively increasing the dataset size.
- **Image Preprocessing:** The collected images are loaded and resized to a consistent 180x180 pixel size. The pixel values are normalized to the [0, 1] range. Additionally, one-hot encoding is employed to represent the class labels, facilitating effective model learning.

Model creation: For skin disease prediction, we utilize the pre-trained VGG19 architecture from ImageNet as the foundation for feature extraction. Customization includes the addition of fully connected layers with 200 and 170 units, both employing ReLU activation functions. The final layer comprises seventeen units, each representing a skin disease category, with softmax activation for precise classification. Skin lesion segmentation employs the U-Net architecture, recognized for its exceptional capability in capturing fine details and localizing objects. This model is specifically designed to outline lesion boundaries in skin images. It undergoes training on the preprocessed dataset, optimizing with the Adam optimizer and employing categorical cross-entropy as the loss function. The training regimen extends for 25 epochs to secure model convergence.

Mood detection, on the other hand, relies on a CNN architecture. It features convolutional layers, maxpooling layers, batch normalization, and dropout layers, expertly designed to extract essential features from facial expression images. The CNN is followed by flattening and dense layers, each using ReLU activation functions, with batch normalization and dropout to prevent overfitting. Once the CNN processes the facial expression images, it calculates emotion scores, identifying both positive and negative emotions. Furthermore, we determine the ratio of happiness emotions, which helps in predicting an individual's mental status.

- **Performance Evaluation:** The performance of the trained model is assessed using evaluation metrics such as classification accuracy.

<u>For skin disease classifier model:</u>

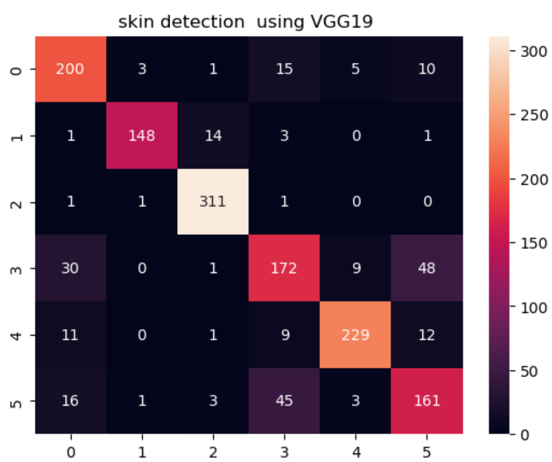

Figure-1 Heat Map

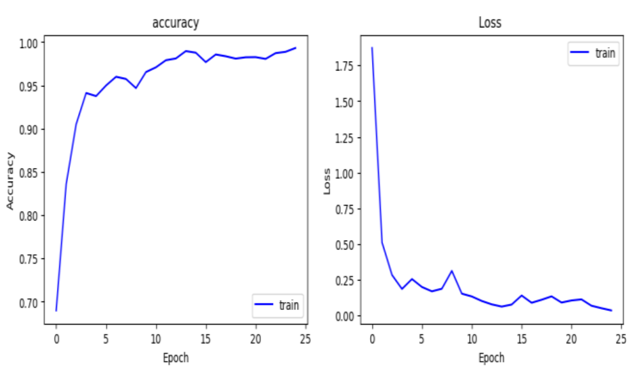

Figure-2 Accuracy of skin disease classification model

For mood detection model:

Figure-3 Accuracy of stress detection using emotion recognition model

- **TensorFlow Lite Conversion:** To facilitate real-time predictions on mobile devices, the trained model is saved and converted into a TensorFlow Lite model, ensuring its suitability for deployment in mobile applications.

<u>**Integration to android application:**</u> These TensorFlow Lite (TFLite) models were integrated into the Android application through the development of Java and Kotlin classes.

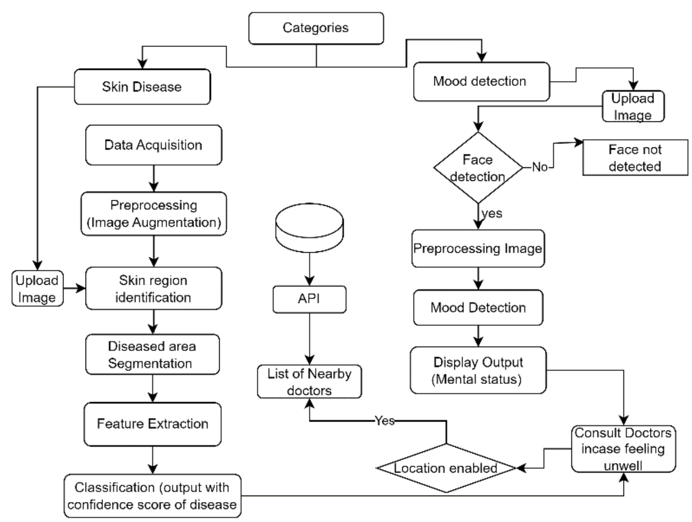

Figure-4 Flow Chart

<u>Applied Algorithms</u>

a) **Convolutional neural network (CNN) –** A Convolutional Neural Network (CNN) is a category of deep neural networks where the machine learns on its own and divides the provided data into levels of prediction, delivering accurate results in a very short time [9]. It is an integral component of deep learning that comprises a combination of following layers.

Convolutional Layer: The core building block of a CNN. It consists of a set of learnable filters (kernels) that slide over the input image to perform element-wise multiplication and aggregation. This process captures local patterns and features in the image.

Pooling Layer: Also known as subsampling, pooling layers reduce the spatial dimensions of the feature maps created by the convolutional layers. This helps in reducing computational complexity and controlling overfitting.

Activation Function: Activation functions, like ReLU (Rectified Linear Unit), introduce non-linearity into the model. They are applied to the output of convolutional and fully connected layers, allowing the network to learn complex relationships in the data.

Fully Connected Layer: These layers connect every neuron in one layer to every neuron in the subsequent layer, similar to a traditional neural network. In CNNs, fully connected layers are often used in the later stages for classification tasks.

Feature Maps: Intermediate representations of the input data obtained after convolutional and pooling layers. Each feature map corresponds to a specific learned feature or pattern in the image.

Stride: A hyperparameter that defines the step size at which the filters move across the input image during convolution. It influences the size of the feature maps and the network's receptive field.

Padding: Padding is the process of adding extra rows and columns of zeros around the input data. It helps in preserving spatial dimensions and can be "valid" (no padding) or "same" (padding added to maintain output size).

In the context of the project, CNN algorithms are pivotal in processing and extracting relevant features from skin lesion and facial expression images. These algorithms are instrumental in identifying patterns and characteristics that aid in skin disease prediction and mood assessment. CNNs can capture intricate details in skin images and facial expressions, which are crucial for accurate diagnosis and emotional state analysis. By leveraging CNNs, the project enhances its ability to provide precise and reliable insights to users, contributing to the overall effectiveness of the healthcare application.

b) **U-Net for Segmentation –** U-Net is a deep learning model introduced in the paper "U-Net: Convolutional Networks for Biomedical Image Segmentation." Its unique design includes two main parts: the contracting and expansive paths, making it great for image segmentation.

The contracting path's job is to pick out vital features from the input image. It uses encoder layers with convolutional operations to shrink the feature maps' size while deepening their content. This helps it gather abstract information, a crucial step in segmentation, similar to other neural networks.

Conversely, the expansive path rebuilds the encoded data while keeping the image's details intact. Decoder layers in this path enlarge the feature maps and also apply convolutional operations. What sets U-Net apart is the use of skip connections. They connect the contracting and expansive parts, letting the decoder layers use the detailed information retained from the contracting path. These skip connections boost the accuracy of locating features in the expansive path.

In the context of the project, it helps pinpoint and define objects of interest within images, like skin lesions, which are essential for further analysis and predictions

Result

For skin disease

Method	Accuracy	Loss
classification with segmentation	98%	3.09%

Figure-5 Skin Disease Classification Results

For emotion recognition

Method	Accuracy	Loss
classification with CNN	80.3%	7.02%

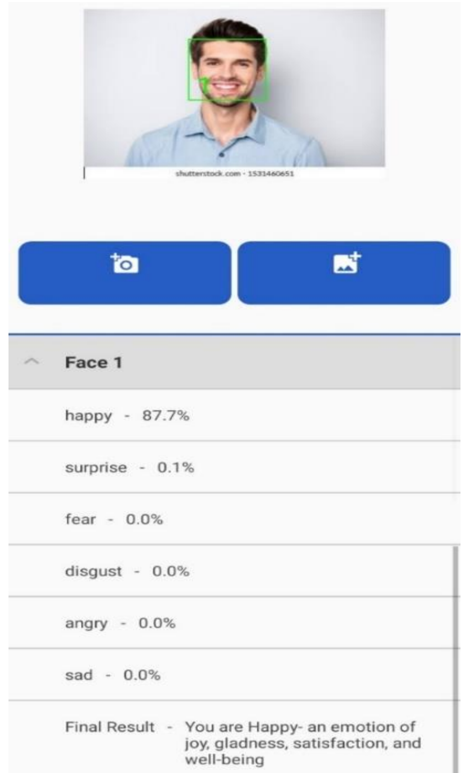

Figure-5 Mood Detection Diagnosis Results

Conclusion

This research signifies a substantial contribution in the realm of healthcare and digital well-being, emphasizing the pivotal role of Machine Learning (ML). Through the integration of ML models, the study has successfully developed an Android application that enables users to predict skin diseases with remarkable accuracy and assess their emotional well-being based on facial expressions. Rigorous model training and evaluation have demonstrated the efficacy of these predictive tools. The seamless integration of these models, coupled with the utilization of a custom API and geolocation services, underscores their practicality and accessibility for end users. This application holds the potential to significantly mitigate health risks associated with skin diseases and stress-related concerns. By offering early detection and emotional well-being assessments, it empowers individuals to proactively manage their health, thereby reducing the likelihood of severe skin conditions and addressing mental health challenges at an early stage.

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