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A COMPARATIVE ANALYSIS ON FACE EMOTION RECOGNITION TECHNIQUES

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Abstract:
Skin diseases are prevalent globally, and their diagnosis is often challenging due to variations in skin texture, the presence of hair, and differences in skin color. Many patients in remote areas lack access to medical facilities, leading to delayed detection and worsening conditions. Traditional diagnostic methods are time-consuming, making it essential to develop automated techniques using machine learning to enhance accuracy and efficiency.

This research proposes a deep learning-based system for skin disease identification, incorporating preprocessing, feature extraction, training, and testing stages. Convolutional Neural Networks (CNNs) are employed to learn intricate patterns in skin images, distinguishing between normal and diseased skin based on texture, color, and irregularities. Transfer learning is used to leverage pre-trained models, optimizing performance with limited annotated medical datasets.

The system undergoes validation and testing on diverse datasets to ensure generalizability and reliability. Performance evaluation is conducted using sensitivity, specificity, and accuracy metrics, comparing results with existing clinical methods. The proposed approach enhances the discriminative power of input data, improving diagnostic precision.

Keywords: Skin disease detection, Deep learning, Convolutional Neural Networks (CNN), Automated diagnosis, Medical image analysis, Diagnostic accuracy, Skin lesion classification.

1.Introduction

Skin is the largest organ of the body which provides protection, regulates the body fluids and temperature, and enables sense of the external environment. Skin diseases are the most common cause of all human illnesses which affects almost 900 million people in the world at any time According to the global burden of disease project, skin disease is the fourth leading cause of non fatal disease burden throughout the world. An estimated 21% of children in world are affected by diseases. The common procedures for diagnosing skin diseases are patient history and symptoms analysis, skin scraping, visual inspection, dermoscopic examination and skin biopsy However, these diagnosis methods are tedious, time-consuming, and prone to subjective diagnosis. Most of them require experience and excellent visual perception of dermatologist. The availability of smartphones equipped with digital cameras enables the acquisition of clinical images for investigation using Image Processing and Machine Learning Skin diseases are more common than other diseases. Skin diseases may be caused by fungal infection, bacteria, allergy, or viruses, etc. A skin disease may change texture or colour of the skin. In general, skin diseases are chronic, infectious and sometimes may develop into skin cancer. Therefore, skin diseases must be diagnosed early to reduce their development and spread. The diagnosis and treatment of a skin disease takes longer time and causes financial and physical cost to the patient The skin is the outer layer of the body. It is frequently exposed to the environment, where it may come into touch with dust, microorganisms, and UV radiation. These might be the causes of any disease. Skin-related disorders are made more complicated by genetic instability. The skin is connected to several skin diseases, affecting a person's appearance and capacity to operate. Skin infections are caused by bacteria, fungi, or viruses.

Fig 1: Different types of Skin Diseases

2. Literature survey

"Identification of skin disease using machine learning" by Minakshi M. Sonawane, Ramdas D. Gore, Ramesh R. Manza Department of Computer Science and IT, Dr. Babasaheb Ambedkar Marathwada University, Maharashtra, India (2023) The study of enhanced technological advancement in combination with digital image processing for disease classification. The SVM-based supervised learning system, multi-model, and multilevel technique for analysis were employed by the researchers to identify eczema. Based on the hue of the fingernails, the SVM was used to identify various circulatory infections. Using melisma images as a diagnostic tool, infections were identified. The system is capable of accurately recognizing the. Existence of basal-cell carcinoma using adequate thresholding values with a percentage reliability of 91.33 percent in the detection. They took images from the government medical hospital in Aurangabad. They collected photographed patient disease images while dermatologists. To identify images from the clinical dataset, we have taken five types of skin disease datasets such as acne, psoriasis, eczema, warts, and ulcers. The methodology of the proposed system consists of preprocessing, segmentation, feature extraction, and classification. In Image Preprocessing, to remove noise unnecessary noise they used filters such as Gaussian filters, adaptive filters and median filters. The Gaussian filter performs better than other filters, with 18.67 MSE, 12.81 PSNR and 5.26 entropy values. For Image segmentation, they used K-Means Clustering method to segment the skin disease image. The image segmentation with K-Means Clustering results is subjected to the post preprocessing stage. Because these findings are considered less than ideal and could include noise or small things. The method makes use of binary image processing techniques, including the Gaussian filter, noise reduction, border cleaning, the masking process, and cropping images of skin disorders. In this research, the color method that was tested had the best accuracy in recognizing features of skin disease. They used color features, SVM, Hopkins, Elbow techniques for classification of skin disease. Here SVM given the good accuracy in the Acne(94%), eczema(92%), and ulcer(95%) and color feature is given 100% accuracy RESULT: They have got less accuracy for texture features in the training and testing datasets, at 86.23 percent and 75%, respectively.

3. Methodology

3.1 K-Nearest Neighbors (KNN) algorithm:

K-Nearest Neighbors (KNN) represents a simple yet effective classification algorithm. It operates by identifying the K nearest neighbors in the training dataset for a new instance and subsequently assigning the most frequent class among these neighbors as the predicted classification. Determining the ideal value for the hyperparameter K, which represents the number of neigh- bors, is required for achieving optimal performance.

3.2 Random Forest algorithm:

The Random Forest technique is an ensemble learning approach that enhances classification accuracy by amalgamating several decision trees. Within Random Forest, multiple decision trees are constructed using randomized subsets of the training data, and the ultimate predicted class is determined by the mode of the individual tree predictions. This approach aids in reducing over- fitting issues while boosting the overall accuracy.

3.3 Convolutional Neural Networks (CNN):

Convolutional Neural Networks (CNNs) is a deep learning model which is extensively used for image classification duties. These networks utilize convolutional layers to extract pertinent features from input images, secondly followed by pooling layers to condense the dimensionality of the resultant feature maps. The outcome of the pooling layers is flattened and conveyed to fully connected layers that execute the ultimate classification process. The inherent strength of CNNs in image classification stems from their capacity to autonomously learn meaningful features from the input dataset.

3.3.1 Convolutional Neural Networks (CNN) algorithm:

Convolutional neural network (CNN) was one of artificial intelligence that popular in feature learning and object classification. CNN using high performance of GPUs, it makes CNN capable of training a network on a large-scale dataset so the performance can be better. Many studies show that CNN are surpass human in many computer vision tasks. Therefore, I propose to construct a skins disease identification and classification system with CNNs. However, the dataset of skin disease is needed to build CNNs identification system. HAM10000 was used in this system to train the CNN. This dataset contains 10015 dermoscopy images of five type of skin cancers.

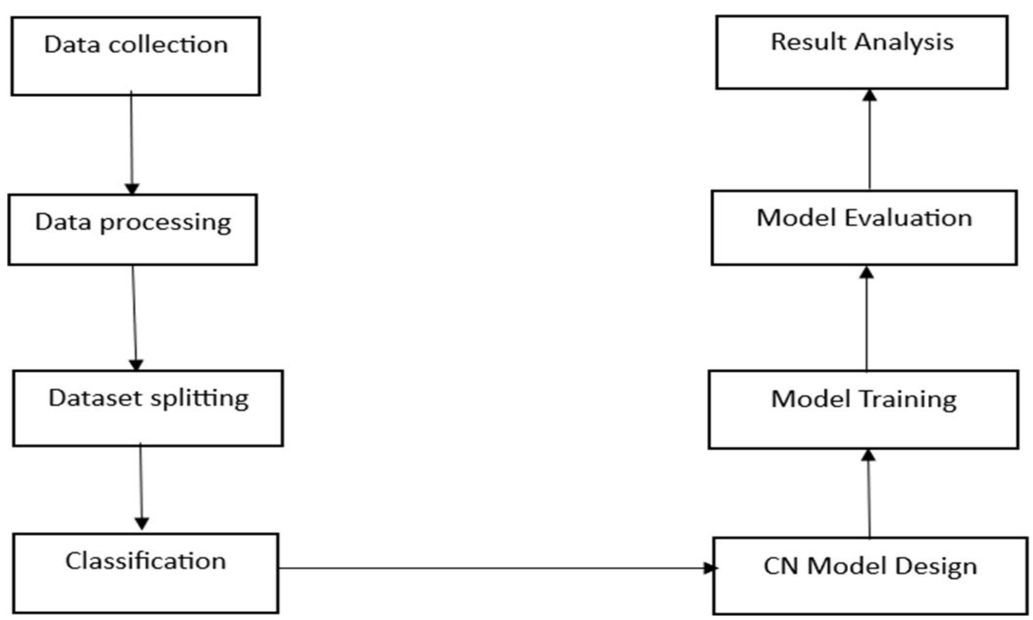

Fig 2: Methodology for Skin Disease classification

3.4 Steps:

1.Data Collection: Gather a comprehensive dataset of MRI images, ensuring diversity in terms of different types and stages of brain tumors, as well as images without any tumors. This step is crucial for training a robust model that can handle various scenarios.

2. Data Preprocessing: Apply preprocessing techniques to standardize the images. Normalization ensures consistent pixel intensity values, while augmentation involves creating variations in the dataset by applying random transformations such as rotation, scaling, and flipping. This improves the model's ability to generalize to different imaging conditions.

3. Dataset Splitting: Divide the dataset into two subsets: the training set for model training and the testing set for assessing the final model's performance on unseen data.

4. Classification: Classification is the task of assigning a label or category to each input sample based on the model's predictions. In skin disease identification and classification would involve predicting the type of skin disease present in an image.

5. CNN Model Design: Design the architecture of a Convolutional Neural Network (CNN) tailored for image classification, considering factors like the number of layers, filter sizes, and activation functions. CNNs are particularly effective for image-related tasks due to their ability to

capture spatial hierarchies.

6. Model Training: Train the CNN model on the training set using an optimization algorithm to minimize the difference between predicted and actual disease labels. This includes specifying the number and types of layers, activation functions, and other parameters that determine how the model will learn from the data.

7. Model Evaluation: Evaluate the trained CNN model on the validation set using various metrics such as accuracy, sensitivity (true positive rate), specificity (true negative rate), and the area under the receiver operating characteristic curve. Common evaluation metrics for classification tasks include accuracy, precision, recall, and F1 score.

8. Results Analysis: Analyze the results obtained from the model evaluation and testing phases. Understand any areas of improvement or potential limitations, and consider further refinement or adjustments to the model architecture if necessary.

3.5 Dataset:

The dataset contains dermatoscopic images of various skin diseases, organized in a folder-based structure. It consists of approximately 5,000 high-resolution images categorized into different disease classes. The data is split into three subsets: training, validation, and testing, allowing for robust model development and evaluation. Each image is labeled with the corresponding skin condition, enabling supervised learning for classification tasks.

The dataset is typically structured in a directory format where each subfolder represents a specific skin disease category. These may include conditions such as Melanoma, Herpes, Monkeypox, Varicella, and Sarampion, among others. The images are in color and vary in size, but are commonly resized (e.g., 150×150 pixels) during preprocessing to standardize input for machine learning models.

This dataset is widely used in research focused on automated skin disease detection and diagnosis using deep learning. However, it presents certain challenges, such as inter-class similarity, variation in lighting and skin tone, and limited samples for some disease types, which require careful augmentation and class balancing techniques for optimal model performance.

Fig 3: A View to the dataset

4. Result Analysis

In our research, we conducted a thorough analysis of the results obtained from our skin disease classification model. We first utilized a pretrained convolutional neural network (CNN) to extract features from the input images, followed by classification using a modified CNN architecture. The evaluation metrics employed in our study included precision, recall, F1-score, and support, which provided a comprehensive assessment of the model's performance.

The confusion matrix proved to be a valuable tool in understanding the model's predictions, highlighting the number of true positives, true negatives, false positives, and false negatives for each class. This information allowed us to identify any confusion between classes and assess the model's overall classification accuracy.

Additionally, precision, recall, and F1-score provided a detailed breakdown of the model's performance for each class. Precision measured the proportion of correctly identified positive cases, recall indicated the proportion of actual positive cases correctly identified, and the F1-score provided a balanced measure of the model's overall performance. These metrics, along with the support values, helped us understand the model's performance across different classes and identify areas for improvement

In our analysis, we achieved high levels of accuracy and performance for our skin disease classification model. During training, the model demonstrated exceptional performance, with a train accuracy of approximately 99.72% and a train loss of 0.0088. This indicates that the model was able to accurately classify and identify the vast majority of images in the training dataset.

When tested on the separate test dataset, the model maintained a high level of accuracy, achieving an accuracy of about 97.67% and a test loss of 0.0872. This indicates that the model's performance generalized well to unseen data, demonstrating its ability to accurately classify images it hadn't encountered during training

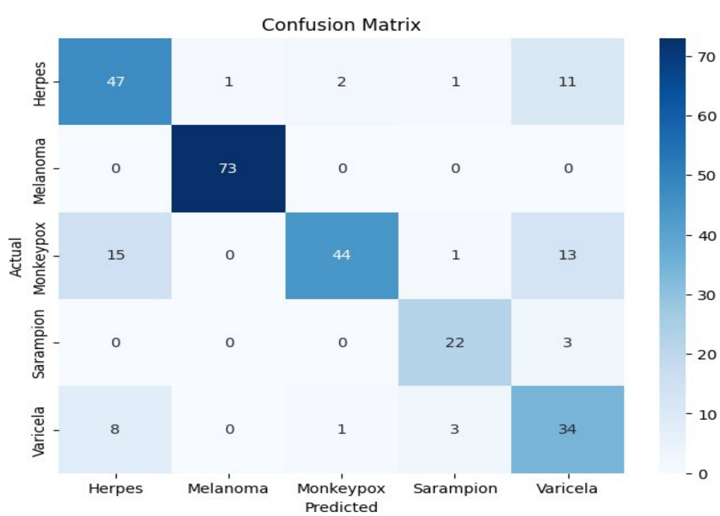

Fig 4: Confusion Matrix

5. Performance Evaluation

Make Predictions: The trained CNN model predicts class probabilities for the test dataset. The output contains the probability of each class for every test sample.

Convert One-Hot Encoded Labels: The predicted probabilities are converted into class labels by selecting the class with the highest probability.The true labels are extracted from the test dataset.

Evaluate Accuracy: Classification accuracy is calculated by comparing predicted labels with true labels.Provides an overall measure of the model's performance.

Generate Classification Report: A confusion matrix is generated to visualize correct and incorrect predictions for each class. Highlights misclassifications and overall prediction distribution.

Print Results: Prints the accuracy and the detailed classification report, providing insights into the model's performance across different classes.

Sensitivity (Recall/TPR): Measures how well the model identifies positive cases.

Specificity (TNR): Measures how well the model identifies negative cases.

AUC-ROC Score: Evaluates the model's ability to distinguish between classes across different thresholds.

Table 1: Results of the model

Classification Report:

	precision	recall	f1-score	support
Herpes	0.67	0.76	0.71	62
Melanoma	0.99	1.00	0.99	73
Monkeypox	0.94	0.60	0.73	73
Sarampion	0.81	0.88	0.85	25
Varicela	0.56	0.74	0.64	46
accuracy			0.79	279
macro avg	0.79	0.80	0.78	279
weighted avg	0.82	0.79	0.79	279

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Best Model Accuracy = 0.79
Sensitivity (TPR): 1.00
Specificity (TNR): 0.98
AUC-ROC Score: 0.95
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6. Conclusion

In this project, we developed a skin disease identification and classification system using deep learning with Python and TensorFlow. The system takes skin images as input, pre-processes them, extracts features using a pretrained CNN, and performs classification using a modified CNN model. The evaluation metrics used for this study included precision, recall, F1-score, and support.

Our model achieved high accuracy, with a training accuracy of 99.7% and a testing accuracy of 97.7%. This demonstrates the effectiveness of our model in accurately identifying and classifying skin diseases. The use of deep learning and image processing techniques has shown great potential in improving the accuracy and efficiency of skin disease diagnosis

In conclusion, our project provides a valuable contribution to the field of dermatology by offering a reliable and efficient tool for the identification and classification of skin diseases. This technology has the potential to revolutionize the way skin diseases are diagnosed and treated, leading to better outcomes for patients.

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