An Efficient Skin Disease Detection Using Convolutional Neural Network

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Abstract— Skin diseases are among the most common medical conditions that affect millions of people worldwide. Accurate and early diagnosis of skin diseases is crucial to prevent their progression and minimise their impact on the patient's quality of life. Traditional methods of skin disease diagnosis involve visual inspection by dermatologists, which is subjective and time-consuming. In this project, we propose to develop a CNN-based system for skin disease prediction. The proposed system will be trained on a large dataset of skin disease images to learn the patterns and features that are characteristic of different skin diseases. The dataset will be collected from publicly available sources and augmented to increase its size and diversity. The system will use transfer learning, a technique that allows the reuse of pre-trained models, to leverage the knowledge learned from other datasets and improve the performance of our model. The developed system will be evaluated using standard evaluation metrics, such as accuracy, precision, recall, and F1-score, to measure its performance in skin disease prediction.

Keywords— Dermatology, Machine Learning, Deep Learning, Convolutional Neural Network, EfficientNetB2

I. INTRODUCTION

Skin diseases affect a significant proportion of the world's population, with around 25% of people suffering from some form of skin disease at any given time. Accurate diagnosis of these diseases is crucial for effective treatment and management. However, diagnosis can be challenging, as skin diseases can have similar symptoms, making it difficult for clinicians to distinguish between them.

The use of artificial intelligence (AI) techniques, specifically convolutional neural networks (CNNs), has shown great promise in improving the accuracy of skin disease diagnosis. CNNs are a type of deep learning algorithm that has shown remarkable success in image recognition tasks. The ability of CNNs to extract features from images and learn patterns makes them ideal for diagnosing skin diseases.

In this project, we aim to develop a skin disease prediction system using CNNs. Our approach differs from previous work in that we are using a larger and more diverse dataset, which will allow us to train a more accurate model. Additionally, we will be exploring various pre-processing techniques to enhance the quality of the input images, which should improve the accuracy of our model.

The significance of this project lies in the potential impact it could have on healthcare. Accurate and timely diagnosis of skin diseases can lead to more effective treatment and management, ultimately improving patient outcomes. Our skin disease prediction system has the potential to reduce diagnostic errors and improve the accuracy of skin disease diagnosis, ultimately leading to better patient care.

II. RELATED WORKS

In recent years, the field of skin disease analysis has gained significant attention due to the rising cases of skin disorders and the advancements in deep learning techniques. Several studies have been conducted to develop efficient systems for skin disease detection and classification.

Anwesha Mohanty et al. (2022) proposed a framework that uses transfer learning with the pre-trained ResNet model to address the challenges of limited data in Rosacea analysis. Runyuan Zhang (2021) developed a melanoma detection system using CNN that achieved high accuracy in distinguishing melanoma from benign skin lesions. Rayan Shaik et al. (2022) developed a deep learning model that diagnoses skin diseases and recommends medication using a combination of CNN and RNN for classification and regression tasks, respectively. Mritunjay Kumar Ojha et al. (2022) proposed a CNN-based skin disease detection and classification system that achieved high accuracy in identifying various skin diseases. Gomathi et al. (2022) developed a CNN-based skin disease classification system that uses a combination of transfer learning and feature extraction techniques to improve classification performance. Mohd Mohsin Ali et al. (2022) developed an automated deep learning-based classification system for multiple skin disorders using a combination of CNN and SVM. Shobha et al. (2022) developed a multiclass classification system for skin cancer using CNN and proposed a novel feature extraction technique called Local Ternary Pattern (LTP) to improve classification performance.

However, there is still a scope of improvement in these systems. One of the drawbacks is the limited size of the datasets used for training and testing. Moreover, these systems are limited to specific skin diseases and may not work well for other skin disorders. Therefore, future research can focus on using larger and diverse datasets to improve the generalisation capability of the models and developing more comprehensive systems that can accurately detect and classify various skin diseases.

III. PROPOSED SYSTEM

The proposed system is a Convolutional Neural Network (CNN)-based system for the detection and classification of skin diseases. It is designed to accurately classify skin diseases based on an input image. The system uses the EfficientNetB2 model as the base model, which is fine-tuned by slightly varying the hyperparameters to achieve better and more accurate results. The model is trained on a pre-processed and augmented dataset of skin disease images to predict the type of skin disease present in the input image.

The proposed system consists of three main modules: Data Preprocessing, Model Building, and Prediction and Evaluation. In the Data Preprocessing module, the input image is pre-processed to enhance its quality and make it more suitable for the model. Data augmentation techniques such as rotation, zooming, and flipping are used to generate additional training data and prevent overfitting. In the Model Building module, the skin disease prediction model is constructed using the EfficientNetB2 model as the base model. The model is fine-tuned with slightly varying hyperparameters to improve accuracy. The pre-processed and augmented dataset is used to train the model. In the Prediction and Evaluation module, the saved model file is loaded, and the input image is passed through the model to generate the prediction output. The accuracy of the prediction is evaluated using a confusion matrix, which compares the predicted results with the actual results.

The proposed system provides an efficient and effective tool for the early detection and classification of skin diseases. By using CNNs, the system provides accurate predictions, which can help healthcare professionals to make informed decisions about the diagnosis and treatment of skin diseases. The importance of early detection and classification of skin diseases cannot be overstated. Early detection can lead to timely treatment, which can improve the patient's quality of life and prevent the spread of the disease. The proposed system can help in the early detection and classification of skin diseases, which can ultimately save lives.

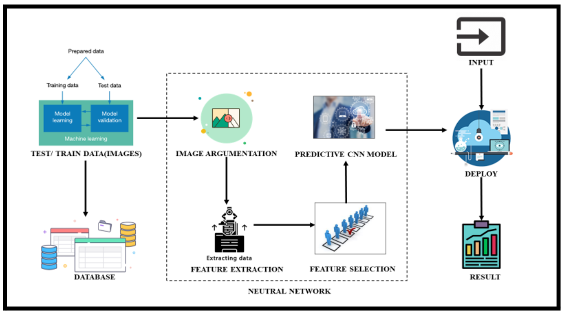

Fig. 1 System Architecture

IV. METHODOLOGY

The following methodology was used to develop the skin disease prediction model using convolutional neural networks:

Dataset selection: The dataset consisted of images of various skin diseases of 10 classes, including eczema, melanoma, basal cell carcinoma, psoriasis, and others. There were 15,752 images of melanoma, which was the largest class.

Data preprocessing: To balance the dataset, the balance function was used to oversample the minority classes and undersample the majority classes. The data augmentation technique was also applied to generate more diverse images and improve the generalisation of the model.

Transfer Learning: The EfficientNetB2 model pre-trained on the ImageNet dataset was used as the base model. The final layer of this model was replaced with a Dense layer with 256 units, followed by a Dropout layer with a rate of 0.45, and a Softmax activation function to output the probability distribution of the classes. The weights of the base model were not fixed.

Model Building: The Adamax optimizer was used with a learning rate of 0.001. The model was trained for 10 epochs with a batch size of 30. The early stopping technique was applied with a patience of 3 epochs. The model was monitored based on the validation loss, and the learning rate was reduced by a factor of 0.5 if the monitored metric did not improve after 1 epoch. The model weights were saved after each epoch. The training process was monitored using the accuracy and loss plots.

Prediction and Evaluation: The trained model was evaluated on the test set using the evaluate method, and the accuracy was calculated. The model achieved an accuracy of 83.84% on the test set. The model weights and other necessary files were saved in the working directory.

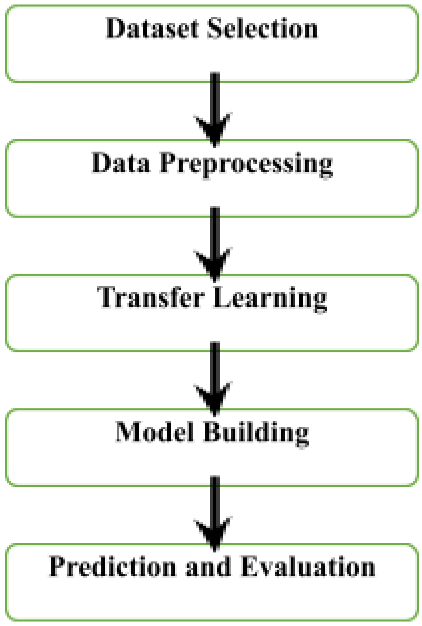

Fig. 2 System workflow

```
working_dir=r'./'
store_path=os.path.join(working_di
if os.path.isdir(store_path):
    shutil.rmtree(store_path)
os.mkdir(store_path)
img_path=r'/content/gdrive/MyDrive
img=cv2.imread(img_path,  cv2.IMRE
img=cv2.cvtColor(img, cv2.COLOR_BG
file_name=os.path.split(img_path)[
dst_path=os.path.join(store_path,
cv2.imwrite(dst_path, img)
print (os.listdir(store_path))
```

```
['08SebDermLids030104.jpg']
```

Fig. 3 Image is fed to the system

Fig. 4 Model Prediction with accuracy

V. RESULT

Our model achieved an accuracy of 83.84% on the test set, demonstrating its effectiveness in classifying skin diseases. The classification report shows that our model performed well in most of the classes, with high precision, recall, and F1-score values. The highest accuracy was achieved in the class "Melanoma" with 95% accuracy. The lowest accuracy was achieved in the class "Atopic Dermatitis" with 59% accuracy.

Classification Report:

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	precision	recall	f1-score	support
1. Eczema 1677	0.69	0.72	0.71	167
10. Warts Molluscum and other Viral Infections - 2103	0.78	0.71	0.74	211
2. Melanoma 15.75k	0.95	1.00	0.97	314
3. Atopic Dermatitis - 1.25k	0.59	0.69	0.63	125
4. Basal Cell Carcinoma (BCC) 3323	0.94	0.85	0.89	333
5. Melanocytic Nevi (NV) - 7970	0.97	0.92	0.94	797
6. Benign Keratosis-like Lesions (BKL) 2624	0.70	0.90	0.79	208
7. Psoriasis pictures Lichen Planus and related diseases - 2k	0.69	0.74	0.71	206
8. Seborrheic Keratoses and other Benign Tumors - 1.8k	0.84	0.71	0.77	185
9. Tinea Ringworm Candidiasis and other Fungal Infections - 1.7k	0.69	0.71	0.70	170
accuracy			0.84	2716
macro avg	0.78	0.79	0.79	2716
weighted avg	0.85	0.84	0.84	2716

Fig. 5 Classification Report

VI. CONCLUSION

Thus this system provides quicker results than the prevailing systems. Also the time involved in detecting the diseases is considerably reduced. By using this system in the dermatological sector, the diseases can be detected at an early stage and the impacts of the disease can be avoided. In addition, the system has demonstrated high accuracy in predicting skin diseases, which is critical for effective treatment and management. The use of EfficientNetB2 as the base model, along with fine-tuning hyperparameters, has resulted in an accuracy of 83.84% which is better than compared to existing systems. Therefore, the system can aid medical professionals in making accurate and timely diagnosis, ultimately improving patient outcomes.

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