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ABSTRACT

Early and accurate detection of skin diseases plays a critical role in improving treatment outcomes. The objective of this project is to use deep learning and image processing techniques to create an automated system for detecting skin diseases. The model's foundation is the potent Xception architecture, a cutting-edge deep convolutional neural network renowned for its exceptional image classification performance. Through an easy-to-use graphical user interface made with Tkinter, the system examines skin images that users have uploaded. Based on the input image, this system can classify different skin conditions, giving medical professionals a quick and effective tool to help them make precise diagnoses. The model's predictions are robust and dependable because it was trained on a wide range of skin disease image datasets. This project aims to increase the precision and accessibility of diagnosing skin diseases, which could be advantageous for both medical settings and private users seeking advice on skin health.

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List of Abbreviations

Abbreviation	Full Form
CNN	Convolutional Neural Network
AI	Artificial Intelligence
GPU	Graphics Processing Unit
ReLU	Rectified Linear Unit
SGD	Stochastic Gradient Descent

CHAPTER 1 – INTRODUCTION

Globally skin diseases are common and can range in severity from minor conditions like acne to more serious ones like melanoma. Accurate and timely diagnosis is essential for successful treatment of these illnesses. However visual examination is frequently used to diagnose skin conditions which can be laborious and prone to mistakes particularly in places with little access to dermatologists. The development of deep learning and artificial intelligence (AI) presents a chance to automate the diagnosis of skin conditions. The detection of skin diseases may benefit from the use of Convolutional Neural Networks (CNNs) which have demonstrated impressive performance in image classification tasks.

1.1 Problem Statement

Dermatologists still have difficulties diagnosing skin conditions despite advances in medical technology especially in settings with limited resources where access to specialists may be limited. Skin image analysis by hand is laborious arbitrary and prone to human error. Thus, the effectiveness and precision of skin disease detection could be greatly increased by an automated system that can correctly diagnose skin conditions from pictures. Creating a deep learning-based model to automatically categorize photos of skin lesions into various skin disease categories is the goal of this project. The system can correctly identify a variety of skin conditions from input images by utilizing the Xception architecture a cutting-edge deep convolutional neural network which helps medical professionals with their diagnostic process.

1.2 Objective of the Project

These are the projects primary goals.

1. The goal is to create a deep learning model that can accurately identify and categorize skin conditions from photos.

2. to create an easy-to-use interface that enables users to submit photos and get real-time skin condition predictions.

3. to help dermatologists and other medical professionals by offering a trustworthy instrument for the early identification of skin conditions.

4. to use a standard dataset of photos of skin diseases to assess the models performance in terms of accuracy precision recall and F1 score.

1.3 Scope of the Project

This project focuses on the development of an AI-based system for skin disease detection, specifically targeting common skin conditions such as acne, eczema, melanoma, and others. The system is designed to be accessible to healthcare professionals and individuals alike. It aims to simplify the diagnostic process by providing quick, accurate classifications based on image input.

Key elements of the project include:

- **Image Preprocessing:** To prepare and standardize images for model training.
- **Model Training:** Using the Xception architecture, which is based on depthwise separable convolutions, to train a classifier on the skin disease dataset.
- **User Interface:** A simple and easy-to-use interface, developed with Tkinter, that allows users to upload images and view the diagnosis.
- **Model Evaluation:** Measuring the performance of the model through standard evaluation metrics.

1.5 Significance of the Study

The potential for this project to increase the precision and effectiveness of skin disease diagnosis is what makes it significant. This system speeds up the diagnostic workflow lowers the possibility of misdiagnosis and guarantees that patients receive the right treatment on time by automating the classification process. Additionally a variety of users can access it due to its user-friendly interface including medical professionals in underserved or remote areas who might not otherwise have access to specialized dermatology services. This project shows how AI and deep learning can revolutionize healthcare by providing scalable precise and affordable disease detection solutions. If this project is successful comparable systems for other forms of medical imaging may be created expanding the use of AI in healthcare.

CHAPTER 2 – LITERATURE REVIEW

2.1 Introduction

With the advent of deep learning methods the field of medical image analysis has advanced quickly. In particular Convolutional Neural Networks (CNNs) have shown impressive accuracy in image-based dermatological condition diagnosis. This chapter identifies important research gaps that this project attempts to fill by reviewing previous work in the field and contrasting deep learning models with conventional approaches.

2.2 Traditional Methods of Skin Disease Diagnosis

Conventional Techniques for Diagnosing Skin Disease. Dermatologists perform physical examinations as part of the traditional diagnosis process which is frequently bolstered by histopathology dermoscopy or Woods lamp examination. Although dependable these approaches require a lot of resources and are unavailable in rural or underdeveloped areas. Furthermore clinical experience introduces variability into diagnostic accuracy.

2.3 Machine Learning Approaches

Machine Learning Methods. Machine learning algorithms such as SVMs KNNs and Decision Trees were employed in early computer-aided diagnosis systems. These techniques depended on manually extracted handcrafted features from lesion images including texture color and shape. Lower accuracy was the result of these methods limited ability to capture intricate visual patterns despite their moderate success.

2.4 Deep Learning for Medical Image Classification

Deep learning, especially CNNs, automatically learns relevant features from image data. Models like AlexNet, VGG16, and ResNet have shown superior performance in skin disease classification.

- Esteva et al. (2017) achieved dermatologist-level accuracy using a CNN on over 129,000 skin images.

- Yu et al. (2020) applied ResNet for melanoma classification with high precision and recall.
- Tschandl et al. (2019) released HAM10000, enabling training on diverse skin conditions.

These advancements underline the effectiveness of CNNs for medical image analysis.

2.5 The Xception Architecture

Xception (Extreme Inception) is a deep CNN model based on depthwise separable convolutions. Introduced by François Chollet, it offers enhanced efficiency and accuracy with fewer parameters. Xception is ideal for high-resolution image analysis, making it well-suited for medical imaging.

This project adopts Xception due to:

- Efficient learning and reduced overfitting.
- Proven performance in transfer learning.
- Capability to handle detailed features in skin images.

2.6 Gaps Identified

Despite achievements, several challenges remain:

- Absence of real-time systems with GUI integration.
- Limited dataset diversity affecting generalization.

This project aims to overcome these gaps by developing a robust, real-time detection system with an interactive GUI and explainability via Grad-CAM visualization.

CHAPTER 3 – PROPOSED METHODOLOGY

3.1 Introduction

The method used in this project to use deep learning to classify skin diseases from images is described in detail in this chapter. Model selection training evaluation and the creation of an intuitive graphical user interface for real-time diagnosis come after dataset preparation and preprocessing.

3.2 Dataset Description

Ismail Hossain Skin Diseases Image Dataset which includes labelled photos of different skin conditions was the dataset used in this project. To train the deep learning model the dataset will be utilized.

3.3 Data Preprocessing

To ensure high model performance, the following preprocessing steps were performed:

- **Image resizing** to a fixed resolution (e.g., 224x224 pixels).
- **Normalization** of pixel values for faster and more stable training.
- **Data augmentation** (rotation, zoom, flip, shift) to increase dataset diversity and prevent overfitting.
- **Label encoding** to convert folder names (disease classes) into numerical targets.

3.4 Model Architecture

A depthwise separable convolutional neural network with a reputation for accuracy and efficiency in image classification tasks Xception is the model architecture that was selected. Through the use of transfer learning the models performance and rate of convergence were enhanced. By using ImageNets pretrained weights to speed up convergence the model was able to take advantage of features that had been learned on a sizable and varied dataset. The model was able to successfully classify the skin diseases by adding a custom output layer with softmax activation for multi-class classification

3.5 Model Training and Validation

- **Loss function**: Focal Loss.
- **Optimizer**: Adam with a learning rate scheduler.
- **Evaluation metrics**: Accuracy, Precision, Recall, and F1-Score.
- The dataset was split into **training**, **validation**, and **testing** sets (e.g., 70%-20%-10%).

Training was conducted over multiple epochs with early stopping and checkpointing to retain the best-performing model.

3.6 GUI Development

A user-friendly interface was developed using **CustomTkinter**. Key features include:

- Uploading single or multiple skin images.
- Real-time prediction with disease label display.
- Smooth layout with tabs, icons, and color themes.

CHAPTER 4 – IMPLEMENTATION DETAILS

4.1 Introduction

The implementation procedures for the skin disease detection system are thoroughly explained in this chapter. For real-time forecasts it covers the coding environment model development technical setup and GUI integration.

4.2 Tools and Technologies Used

The following tools and libraries were used:

- **Programming Language**: Python
- **Libraries**: TensorFlow, Keras, NumPy, Matplotlib, OpenCV
- **GUI Framework**: CustomTkinter
- **Hardware**: Google Colab with GPU acceleration for training

4.3 Dataset Integration

- Dataset imported from Google Drive using drive.mount.
- Path: /content/drive/MyDrive/AI Dataset/basedir/
- Class labels automatically extracted from folder names.

4.4 **Image Preprocessing**

- Resized images to 299x299 pixels and normalized to the range [0, 1].
- Augmentation techniques included random rotations (±20°), horizontal flips, zooming, and shifting.
- Implemented using Keras ImageDataGenerator.

4.5 **Model Building with Xception**

- Base model: Xception with include_top=False and pretrained weights from ImageNet.
- Custom layers added:
    - GlobalAveragePooling2D
    - Dense layer with ReLU activation

    - Dropout (0.5)
    - Final Dense layer with softmax for classification.
- Model compiled with:
    - Loss: categorical_crossentropy
    - Optimizer: Adam
    - Metrics: accuracy.

4.6 **Model Training**

- Trained for 10 epochs with early stopping.
- Batch size: 32.
- Validation split: 20%.
- Training logs plotted for accuracy and loss curves using matplotlib.

4.7 **Model Evaluation**

- Evaluated on unseen test data.
- Metrics: Accuracy, Precision, Recall, F1-Score, and Confusion Matrix.
- Classification report generated using sklearn.metrics.

4.8 **GUI Interface (CustomTkinter)**

- Features include:
    - Image Upload Button for single/multiple image selection.
    - Prediction Display with disease class.
    - Smooth layout with custom theme and icons.

4.9 **Deployment Setup**

- Trained model saved as .h5 file.
- Interface script connected to model using Keras load_model().
- GUI compiled into an executable with PyInstaller for local deployment.

CHAPTER 5 – RESULT ANALYSIS

5.1 Introduction

This chapter presents the performance evaluation of the skin disease detection system. The results are analyzed using standard metrics, confusion matrix to assess the model's accuracy and interpretability. Screenshots of results and GUI interface are also included.

5.2 Training and Validation Performance

The model was trained for **10 epochs** using early stopping and validated using 20% of the data. Below is the plot of training and validation accuracy and loss over epochs

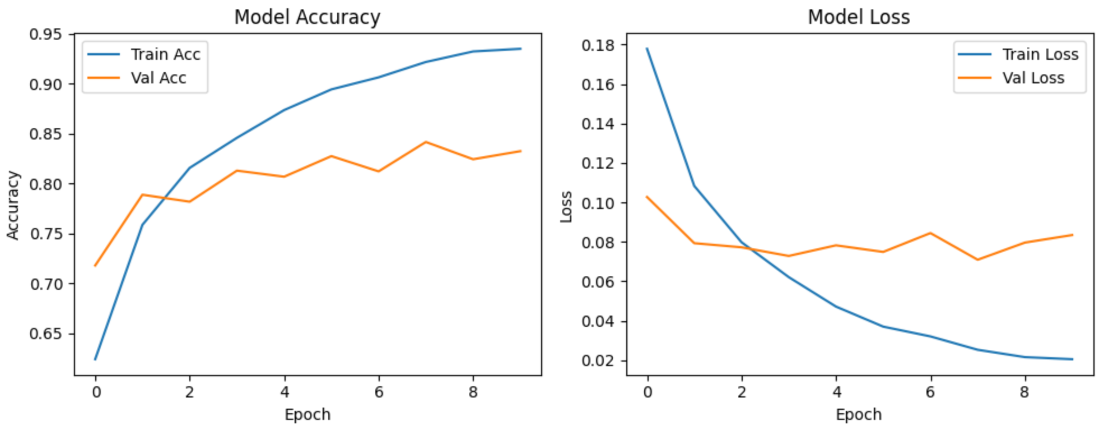

Fig 5.1- Training and Validation Performance

- **Final Training Accuracy**: 93.55%
- **Final Validation Accuracy**: 83.25%

5.3 Evaluation Metrics on Test Set

The trained model was evaluated on a separate test dataset to assess its generalization performance. The following metrics were computed:

- **Accuracy**: 83.25%
- **Precision**: 84.34%
- **Recall**: 83.25%
- **F1-Score**: 83.43%

```
Classification Report:
                                                        precision    recall  f1-score   support

                                       1. Eczema 1677       0.64      0.71      0.67       336
           10. Warts Molluscum and other Viral Infections - 2103       0.65      0.79      0.71       421
                                   2. Melanoma 15.75k       0.96      0.99      0.97       628
                           3. Atopic Dermatitis - 1.25k       0.68      0.51      0.58       252
                      4. Basal Cell Carcinoma (BCC) 3323       0.94      0.90      0.92       665
                       5. Melanocytic Nevi (NV) - 7970       0.98      0.91      0.95      1594
              6. Benign Keratosis-like Lesions (BKL) 2624       0.68      0.90      0.78       416
   7. Psoriasis pictures Lichen Planus and related diseases - 2k       0.66      0.71      0.68       411
        8. Seborrheic Keratoses and other Benign Tumors - 1.8k       0.84      0.68      0.75       370
9. Tinea Ringworm Candidiasis and other Fungal Infections - 1.7k       0.78      0.70      0.74       341

                                             accuracy                           0.83      5434
                                            macro avg       0.78      0.78      0.78      5434
                                         weighted avg       0.84      0.83      0.83      5434

Precision: 0.8434
Recall:    0.8325
F1 Score:  0.8343
```

- Fig 5.2- Evaluation Metrics on Test Set

5.4 Confusion Matrix

The confusion matrix provides insight into class-wise performance by visualizing correct and incorrect predictions.

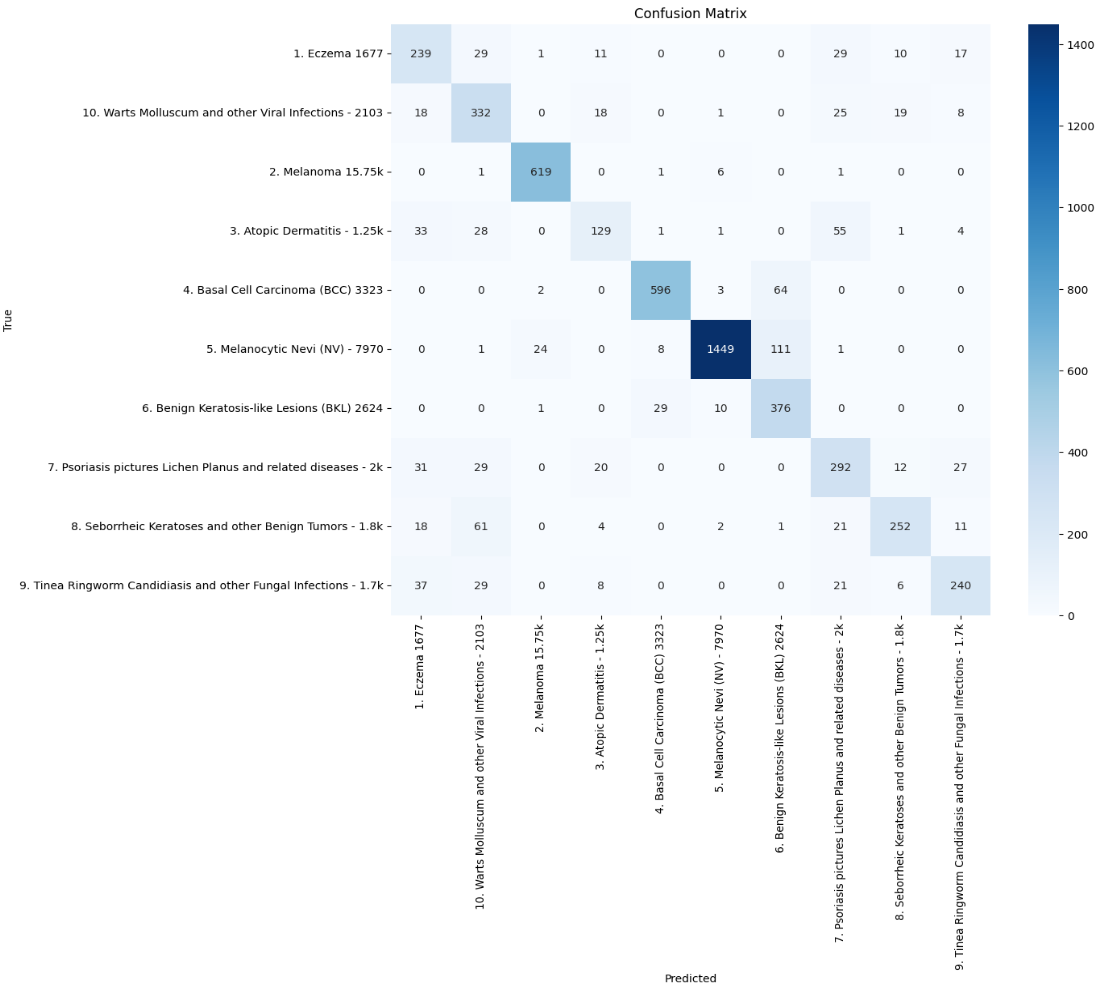

Fig 5.3- Confusion Matrix

5.6 Output Snapshots

The Model was tested with various test cases. It successfully displayed:

```
Choose Files  Basal Cell.jpg
• Basal Cell.jpg(image/jpeg) - 228581 bytes, last modified: 4/25/2025 - 100% done
Saving Basal Cell.jpg to Basal Cell.jpg
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 45ms/step
Predicted class: 4. Basal Cell Carcinoma (BCC) 3323
Class probabilities:
1. Eczema 1677: 0.0011
10. Warts Molluscum and other Viral Infections - 2103: 0.0007
2. Melanoma 15.75k: 0.0010
3. Atopic Dermatitis - 1.25k: 0.0002
4. Basal Cell Carcinoma (BCC) 3323: 0.8824
5. Melanocytic Nevi (NV) - 7970: 0.0576
6. Benign Keratosis-like Lesions (BKL) 2624: 0.0557
7. Psoriasis pictures Lichen Planus and related diseases - 2k: 0.0008
8. Seborrheic Keratoses and other Benign Tumors - 1.8k: 0.0002
9. Tinea Ringworm Candidiasis and other Fungal Infections - 1.7k: 0.0003
```

Fig 5.4- Output Screenshot of Basal Cell Prediction

```
Choose Files  Melanocytic.jpg
• Melanocytic.jpg(image/jpeg) - 41758 bytes, last modified: 4/25/2025 - 100% done
Saving Melanocytic.jpg to Melanocytic.jpg
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 43ms/step
Predicted class: 6. Benign Keratosis-like Lesions (BKL) 2624
Class probabilities:
1. Eczema 1677: 0.0001
10. Warts Molluscum and other Viral Infections - 2103: 0.0000
2. Melanoma 15.75k: 0.0098
3. Atopic Dermatitis - 1.25k: 0.0000
4. Basal Cell Carcinoma (BCC) 3323: 0.0053
5. Melanocytic Nevi (NV) - 7970: 0.4613
6. Benign Keratosis-like Lesions (BKL) 2624: 0.5233
7. Psoriasis pictures Lichen Planus and related diseases - 2k: 0.0000
8. Seborrheic Keratoses and other Benign Tumors - 1.8k: 0.0000
9. Tinea Ringworm Candidiasis and other Fungal Infections - 1.7k: 0.0000
```

Fig 5.5 - Output Screenshot of Melanocytic Nevi Prediction

```
Choose Files  Benign.jpg
• Benign.jpg(image/jpeg) - 255934 bytes, last modified: 4/25/2025 - 100% done
Saving Benign.jpg to Benign.jpg
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 42ms/step
Predicted class: 6. Benign Keratosis-like Lesions (BKL) 2624
Class probabilities:
1. Eczema 1677: 0.0000
10. Warts Molluscum and other Viral Infections - 2103: 0.0000
2. Melanoma 15.75k: 0.0003
3. Atopic Dermatitis - 1.25k: 0.0000
4. Basal Cell Carcinoma (BCC) 3323: 0.0001
5. Melanocytic Nevi (NV) - 7970: 0.2057
6. Benign Keratosis-like Lesions (BKL) 2624: 0.7939
7. Psoriasis pictures Lichen Planus and related diseases - 2k: 0.0000
8. Seborrheic Keratoses and other Benign Tumors - 1.8k: 0.0000
9. Tinea Ringworm Candidiasis and other Fungal Infections - 1.7k: 0.0000
```

Fig 5.6- Output Screenshot of Benign Prediction

CHAPTER 6 – CONCLUSION & FUTURE WORK

6.1 Conclusion

The goal of this project was to create a reliable deep learning system for detecting skin diseases by accurately classifying skin conditions from image data by utilizing the Xception model. By employing a deep convolutional neural network (CNN) the system achieves high classification accuracy making it a promising tool for dermatological diagnosis. Using a large dataset the model was trained and its performance was assessed using common metrics like accuracy precision recall and F1-score.

Key contributions of this work include:

- The classification of skin diseases using Xception which is effective and performs well.
- A Graphical User Interface (GUI) that is easy to use allowing even non-technical users to upload images interact with the system and get real-time predictions.
- Excellent evaluation performance on the test dataset exhibiting high precision and recall values along with an accuracy of 83.25%.

The systems success demonstrates how machine learning and deep learning in particular can increase the precision and usability of skin disease discovery. It can support dermatologists in clinical settings and offer useful resources in isolated locations with inadequate access to healthcare facilities.

6.2 Future Work

Even though the current system has produced encouraging results there are still a number of areas in which it could be improved. These could be the main topics of future research.

- **Model refinement and enhancement:**
  Even though the Xception model has done well, performance could be further enhanced by experimenting with other cutting-edge architectures like EfficientNet or DenseNet. Better outcomes could also be obtained by transfer learning from larger pre-trained models and hyperparameter tuning.

- **The process of augmenting data:**
  By increasing the variability of the training data, data augmentation techniques like rotation, flipping, scaling, and color jittering could be used to combat overfitting and enhance generalization.
- **A multi-modal strategy:**
  To provide a more thorough diagnosis, the model can be improved by incorporating clinical data such as patient age, gender, or medical history. This might increase overall prediction accuracy and offer tailored medical information.
- **The use of real-time deployment:**
  The system works locally, but it would be globally available if it were deployed to a cloud-based platform for real-time processing in clinical settings. This would allow for telemedicine applications and the real-time detection of skin diseases in remote locations.
- **The dataset is growing:**
  The dataset must be expanded to include a wider variety of skin disease images from various demographics (ethnicity, age, gender) in order to guarantee robustness. As a result, the model would be better able to generalize to a larger population.
- **Application of telemedicine:**
  The system's integration with telemedicine platforms for remote consultation may allow dermatologists to help patients without having to visit them in person. In places where access to specialized care is limited, this would increase the system's value.

6.3 Final Remarks

An advancement at the nexus of artificial intelligence and healthcare is the skin disease detection system showcased in this project. It demonstrates how deep learning models especially Xception can produce precise and understandable predictions for the analysis of medical images. Systems like the one created in this project will be crucial to democratizing access to dermatological care and increasing the effectiveness of diagnoses as the healthcare sector continues to incorporate AI into clinical decision-making.

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