CSE 311 – ARTIFICIAL INTELLIGENCE

Project Report

1. Skin Cancer Classification Using Deep Convolutional Neural Networks

Course Code: CSE 311
Course Name: Artificial Intelligence
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2. ABSTRACT

Skin cancer is one of the most rapidly increasing cancers worldwide, and early detection is critical for patient survival. This project presents a deep learning–based approach for classifying skin lesion images into seven diagnostic categories using a custom-built Convolutional Neural Network .The goal is to build an AI model capable of assisting dermatologists by automatically identifying skin cancer type .

3. INTRODUCTION

Skin cancer is one of the most common forms of cancer globally. Traditional diagnosis requires trained dermatologists and specialized equipment, which is not always accessible in rural or resource-limited regions. As a result, automated detection using Artificial Intelligence has become an important area of research.

This project implements a **custom CNN model** for classifying skin lesions into seven classes using image data. The motivation behind the project includes:

- Reducing the workload on medical professionals
- Providing early detection support
- Ensuring consistent and scalable diagnosis
- Applying AI concepts learned in the course to a real-world healthcare problem

4. PROBLEM STATEMENT AND OBJECTIVES

Problem Statement

To develop an AI-based system capable of classifying skin lesion images into seven diagnostic categories using a Deep Convolutional Neural Network, with high accuracy and robustness despite challenges like class imbalance and variability in images.

Objectives

- To preprocess and augment the skin lesion dataset to improve robustness.
- To design and train a custom CNN architecture for multi-class classification.
- To handle class imbalance using weighted sampling and weighted loss functions.
- To evaluate the model using confusion matrix, accuracy, and loss metrics.
- To analyze results and identify improvements for practical deployment.

6. PROPOSED METHODOLOGY

6.1 Dataset Description

- **Dataset Source:** Skin lesion dataset stored in the directory skin_data/ (7 classes).
- **Number of Classes:** 7
- **Image Type:** Dermoscopic RGB images
- **Image Size:** Resized to 128×128
- **Split Ratio:**
    - 80% Training
    - 10% Validation
    - 10% Testing

Preprocessing & Augmentation

To improve robustness and reduce overfitting, the following transformations were applied:

- Resize → 128×128
- Random Rotation (±45°)
- Random Resized Crop
- Horizontal & Vertical Flips
- Color Jitter (brightness, contrast, hue)
- Random Perspective Distortion

- Gaussian Noise Addition
- Normalization using ImageNet mean/std

These augmentations simulate real-world variability in skin images

6.2 CNN Architecture Description

The CNN used for this project is fully custom-designed.
It consists of:

Convolution Blocks

- **Block 1:**
    - Conv2D (64 filters)
    - BatchNorm
    - ReLU
    - Conv2D (64 filters)
    - BatchNorm
    - ReLU
    - MaxPool
    - Dropout (0.25)
- **Block 2:**
    - Conv2D (128 filters)
    - BatchNorm
    - ReLU
    - Conv2D (128 filters)
    - BatchNorm
    - ReLU
    - MaxPool
    - Dropout (0.3)
- **Block 3:**
    - Conv2D (256 filters)

- BatchNorm
- ReLU
- Conv2D (256 filters)
- BatchNorm
- ReLU
- MaxPool
- Dropout (0.4)

Adaptive Average Pooling

Ensures fixed-size output regardless of input image size.

Fully Connected Layers

- Flatten
- Linear → 512
- BatchNorm
- ReLU
- Dropout (0.5)
- Linear → 7 output classes

Activation Function

- ReLU in all convolution and FC layers
- Softmax applied implicitly by CrossEntropyLoss

Loss Function

- CrossEntropyLoss with class weights (to handle imbalance)

Optimizer

- AdamW optimizer
- Learning rate = 0.001
- Weight decay = 0.01

Learning Rate Scheduler

- OneCycleLR for dynamic warmup & cooldown scheduling

Pipeline of workflow

Input Images ----> Preprocessing & Augmentation ---- > Train / Val Split ---->CNN Training

Final Model (Deployment Read) < -------- Model Evaluation

7. EXPERIMENTAL SETUP AND RESULTS

Hardware

- GPU-enabled system (CUDA if available)
- Python 3.10
- PyTorch
- Matplotlib, NumPy, scikit-learn, tqdm

Training Configuration

- Epochs: 50
- Batch size: 10
- Scheduler: OneCycleLR
- Weighted sampling

Metrics Used

- Training Loss
- Training Accuracy
- Validation Loss
- Validation Accuracy
- Confusion Matrix

8. DISCUSSION AND ANALYSIS

The CNN performed well given the complexity of the dataset. The following observations were made:

Strengths

- Strong generalization due to heavy augmentation
- Mixup and dropout significantly prevent overfitting

- Balanced sampling improved minority class accuracy
- Adaptive pooling enables flexible image input sizes

Challenges

- Some classes remain difficult due to visual similarity
- Dataset imbalance impacts precision for rare classes
- Training time is high because of heavy augmentation

Comparison With Existing Works

Standard baseline CNNs usually achieve 70–80% accuracy on small skin cancer datasets. Our model performs competitively due to:

- Multi-block CNN
- Data augmentation
- Weighted loss
- Modern LR scheduling

9. APPLICATIONS AND FUTURE SCOPE

Applications

- Assist dermatologists in early skin cancer diagnosis
- Integrate into mobile health applications
- Use as a screening tool in remote regions
- Reduce diagnostic errors in clinical workflow

Future Enhancements

- Use pre-trained models (ResNet, EfficientNet, Vision Transformers)
- Deploy as an Android app with FastAPI backend
- Expand dataset with more diverse lesion categories
- Implement Grad-CAM for visual explanation
- Apply semi-supervised or self-supervised learning

10. CONCLUSION

This project successfully implemented a Deep Convolutional Neural Network for classifying skin cancer images into seven categories. The model achieved good performance through optimized architecture, robust augmentation, and advanced training techniques.
The work demonstrates the potential of AI in medical image analysis and lays the foundation for a clinical decision-support system. With further improvements and real-world testing, this model can significantly contribute to early cancer detection and improved healthcare accessibility.