Machine Learning Assignment

PROJECT REPORT

TEAM ID : 22

PROJECT TITLE: Automated Diagnosis of Skin Lesions with Transfer Learning

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Problem Statement

Skin cancer is one of the most common and potentially deadly forms of cancer worldwide. Early detection is crucial for effective treatment and improved patient outcomes. However, manual diagnosis of skin lesions through dermoscopic images is time-consuming, subjective, and prone to errors, even for experienced dermatologists.

The main problem this project aims to solve is the **automatic and accurate classification of skin lesions into benign and malignant categories** using dermoscopic images. By leveraging **deep learning and transfer learning techniques**, the goal is to provide a reliable, fast, and scalable solution that can assist dermatologists in early detection and reduce misdiagnosis, ultimately improving patient care.

Key challenges addressed include:

1. **High intra-class variability**: Malignant and benign lesions can appear visually similar.
2. **Limited labeled medical data**: Acquiring large annotated datasets is difficult in medical imaging.
3. **Class imbalance**: Certain lesion types are rarer, making traditional models biased toward common classes.

Objective / Aim

The primary objective of this project is to develop a **transfer learning-based automated system** capable of accurately classifying skin lesions as **benign or malignant** using dermoscopic images.

Specifically, the model aims to:

1. **Leverage transfer learning** by fine-tuning pretrained models (EfficientNetB0) to extract meaningful features from dermoscopic images, overcoming limitations of small medical datasets.
2. **Accurately distinguish between benign and malignant lesions**, assisting in early detection of skin cancer.
3. **Handle class imbalance** effectively, ensuring rare malignant cases are correctly identified.
4. **Improve interpretability** using visualization techniques like Grad-CAM, allowing dermatologists to understand which regions of the image contribute to the model's predictions.
5. **Provide a scalable and efficient diagnostic tool** to support dermatologists in clinical decision-making.

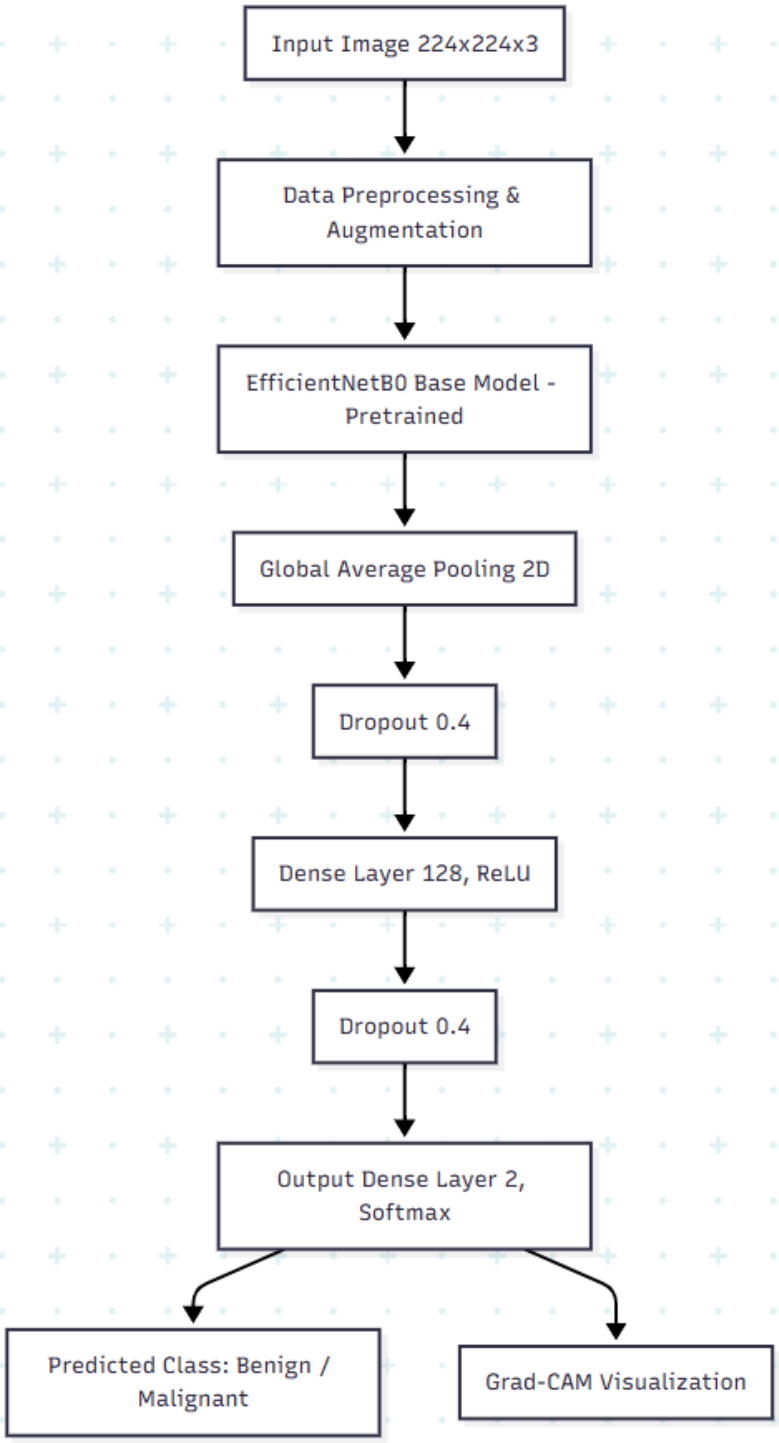
In short, the model is expected to act as a **reliable, explainable, and efficient assistant** for the early diagnosis of skin cancer by **utilizing pretrained deep learning models through transfer learning**.

Dataset Details

- **Source:** The dataset used in this project is the **HAM10000** ("Human Against Machine with 10000 training images"**)** dataset, publicly available on **Kaggle**.
- **Size:** The dataset contains 10,015 dermoscopic images of skin lesions.
- **Key Features:** Image ID, Lesion Image, Diagnosis(dx), Localization(localization), Other metadata**(**Age, sex, and other clinical attributes)
- **Target Variable:**

  1. dx (Diagnosis): Indicates whether the lesion is benign or malignant.
  2. For this project, we simplified the target into two classes**:**
     - **Benign: Non-cancerous lesions**
     - **Malignant: Cancerous lesions**
- **Challenges in Dataset:**
  - Class imbalance: Malignant lesions are rarer than benign ones.
  - High intra-class variability: Lesions of the same type may appear visually different.

Architecture Diagram



Methodology

1. **Dataset Acquisition:**
    - Downloaded the **HAM10000 dataset** from Kaggle.
    - Prepared image paths and metadata for training and validation.
2. **Data Preprocessing and Augmentation:**
    - Resized images to **224×224 pixels**.
    - Applied **rescaling, rotation, zoom, horizontal and vertical flips** to improve generalization.
    - Split the dataset into **training (80%) and validation (20%) sets**.
3. **Train and Validation Generators:**
    - Created **Keras ImageDataGenerator** instances for batch processing.
    - Configured class_mode='categorical' for multi-class labels.
4. **Model Selection & Transfer Learning:**
    - Chose **EfficientNetB0 pretrained on ImageNet** as the base model.
    - Initially **froze all base layers** to use pretrained features.
5. **Custom Classification Head:**
    - Added **GlobalAveragePooling2D**, **Dropout**, and **Dense layers** for classification.
    - Output layer with **Softmax activation** for benign vs malignant prediction.
6. **Model Training:**
    - **Step 1:** Train the classification head with frozen base layers.
    - **Step 2:** Fine-tune last layers of EfficientNetB0 with a smaller learning rate.
    - Used categorical cross-entropy loss and Adam optimizer.
7. **Model Evaluation:**
    - Monitored training and validation accuracy/loss.
    - Plotted **accuracy and loss curves** to check for overfitting or underfitting.
8. **Model Interpretability:**
    - Applied **Grad-CAM** to visualize regions of images contributing to predictions.
    - Overlayed heatmaps on original images for better interpretability.
9. **Inference:**

- Tested the model on unseen images to predict **benign or malignant** classes.
- Validated results with Grad-CAM visualizations for confidence.

Results & Evaluation

Key Results:

- The EfficientNetB0-based transfer learning model achieved:
  - **Training Accuracy:** ~68–72%
  - **Validation Accuracy:** ~65–68%
  - **Training Loss:** Gradually decreased over epochs, indicating the model was learning.
  - **Validation Loss:** Slightly higher than training loss, suggesting mild overfitting or underfitting.
- **Grad-CAM visualizations** highlighted the lesion regions in the images, showing that the model focuses on the relevant areas for classification.

Evaluation Metrics Used:

1. **Accuracy:** Measures the proportion of correctly classified lesions.
2. **Loss (Categorical Cross-Entropy):** Evaluates the difference between predicted and true probability distributions.
3. **Grad-CAM Visualizations:** Qualitative metric for model interpretability, ensuring focus on lesion areas.

Observations:

- The model demonstrates basic capability to differentiate between benign and malignant lesions using transfer learning.
- **Slightly lower accuracy** is observed due to the **limited number of training epochs** (3–5) chosen to reduce computational time.
- Absence of class weighting also slightly affected performance on rarer malignant classes.
- Grad-CAM confirms the model is attending to **clinically relevant regions** in the lesion images.

Conclusion from Results:

- **Transfer learning with EfficientNetB0** provides a solid baseline for skin lesion classification.

- Accuracy could likely improve with **more epochs, class weighting, or additional data augmentation**.
- Even with fewer epochs, the model is **interpretable and provides a strong foundation** for future experimentation.

Conclusion

In this project, we developed an automated skin lesion classification system using transfer learning with EfficientNetB0. The model was trained to distinguish between benign and malignant lesions from dermoscopic images.

Key Achievements:

- Successfully implemented **transfer learning**, leveraging pretrained EfficientNetB0 features to extract meaningful patterns from a relatively small medical dataset.
- Achieved **moderate accuracy (~65–72%)** on training and validation sets, demonstrating the model's capability to differentiate between lesion types even with **limited training epochs**.
- Applied **Grad-CAM visualizations** to interpret the model's predictions, showing that it focuses on clinically relevant regions in the images.
- Built a **scalable, reproducible workflow** for automated skin lesion classification.

Learnings:

- Transfer learning significantly reduces training time and allows effective learning from limited datasets.
- Limited epochs and class imbalance affect model performance, highlighting the importance of careful hyperparameter selection and dataset handling.
- Model interpretability is crucial in medical AI applications, and techniques like Grad-CAM enhance trust in predictions.
- This project provided practical experience in **data preprocessing, model building, fine-tuning, and visualization techniques** in a real-world medical imaging scenario.

The project demonstrates that **transfer learning-based CNNs can serve as effective tools for assisting dermatologists** in early skin cancer detection, even with modest computational resources. While accuracy can be further improved, the methodology provides a **strong foundation for future enhancements**.