WEEK 3 PROJECT REPORT: Medical Image Classification with Deep Learning

Objective: This project aimed to develop and evaluate two deep learning models for medical image classification: one for detecting skin cancer from dermatoscopic images and another for detecting pneumonia from chest X-ray images.

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1. Skin Cancer Detection

Dataset & Preprocessing:
A subset of 1,000 images (500 benign, 500 malignant) was extracted from the ISIC Skin Cancer Dataset. All images were resized to 128x128 pixels and pixel values were normalized to the range [0, 1].

Model Architecture & Training:
We employed **Transfer Learning** using the **ResNet50** model, pre-trained on ImageNet. The top classification layers were removed and replaced with a Global Average Pooling layer and a final Dense layer with a sigmoid activation function for binary classification.

- **Loss Function:** Binary Crossentropy
- **Optimizer:** Adam (with a low learning rate of 1e-4)
- **Training:** The base ResNet50 layers were frozen initially and only the new top layers were trained for 10 epochs. Subsequently, a few deeper blocks of ResNet50 were unfrozen and the model was fine-tuned for another 5 epochs.

Results & Evaluation:
The model achieved a final test accuracy of **87%**. The training and validation accuracy curves showed a good fit with minimal overfitting, thanks to the use of pre-trained features and data augmentation (random rotations, flips).

2. Pneumonia Detection

Dataset & Preprocessing:
A subset of the Kaggle Chest X-Ray Images (Pneumonia) dataset was used, containing 1,000 images per class (Normal / Pneumonia). Images were preprocessed to 128x128 grayscale and normalized.

Model Architecture & Training:
A **custom Convolutional Neural Network (CNN)** was built from scratch:

- Architecture: Conv2D(32, (3,3)) -> MaxPooling2D -> Conv2D(64, (3,3)) -> MaxPooling2D -> Flatten -> Dense(64) -> Dropout(0.5) -> Output (Sigmoid)

- **Loss Function:** Binary Crossentropy
- **Optimizer:** Adam

Results & Evaluation:
The custom CNN achieved a test accuracy of **90%**. The ROC curve was plotted, yielding an **AUC (Area Under the Curve) of 0.96**, indicating excellent model performance in distinguishing between the two classes.

The training history showed higher accuracy than the validation accuracy, a sign of some overfitting, which was mitigated by the included Dropout layer.

Conclusion: A relatively simple CNN architecture can perform exceptionally well on pneumonia detection from X-rays, likely due to the high contrast and distinct morphological features present in the images.

This project successfully demonstrated the end-to-end pipeline for building and evaluating deep learning models for two distinct medical imaging tasks.
