CSE 499A: Project Work | Section: 15 | Group: 07 Members: Amit Chandra Das (2014242042), Tanushree Das (2212225042), Ashraful Islam (2212669042)

Project Report: A Proposed Solution for Arsenic Skin Detection

1.Problem Statement

Arsenic in groundwater is a major health crisis in Bangladesh, causing visible skin lesions. Early, automated detection using smartphone images is critical for diagnosis in remote areas. This project proposes a deep learning model to classify skin images as 'infected' or 'not infected' to aid in rapid diagnosis.

2. Justification from Literature Review

Our research confirms our project is well positioned:

- **The Dataset:** We are using the "ArsenicSkinImageBD" (8,892 balanced images), the standard dataset for this problem (Paper 1). This makes our results comparable.
- **The Benchmark:** A hybrid model, "ArsenicNet," set the state-of-the-art accuracy at **97.69%** on this dataset (Paper 2). This is our target to beat.
- **The Method:** Research confirms **Convolutional Neural Networks (CNNs)** are the best method for skin image classification (Paper 3).
- **Our Goal (The Gap):** The benchmark is a complex custom hybrid. Our project will test if a different, popular architecture (ResNet50) can match or beat this score.

3. Proposed Methodology (The Plan)

Our solution follows a two-pronged comparative approach.

A. Data Preprocessing Regardless of the model, all 8,892 images will be processed identically:

1. **Load Data:** Download and extract the ArsenicSkinImageBD.zip file.
2. **Resize:** All images will be resized to a uniform **128x128 pixels** to ensure consistent input size.
3. **Format:** Images will be converted to 3-channel RGB and then into NumPy arrays.
4. **Split:** The data will be split into an 80% training set and a 20% testing set.
5. **Scale:** All pixel values will be scaled from the [0, 255] range to [0.0, 1.0] by dividing by 255. This helps the models train faster and more stably.

B. Model 1: The Baseline (A Simple CNN)

- **What:** We will first build a simple, sequential CNN from scratch.

- **Architecture:**
  - Conv2D (32 filters) -> MaxPooling2D
  - Conv2D (64 filters) -> MaxPooling2D
  - Flatten
  - Dense (128 units) -> Dropout (0.5)
  - Dense (64 units) -> Dropout (0.5)
  - Output: Dense (2 units, 'SoftMax')
- **Purpose:** This model will give us “baseline" accuracy. It tells us the minimum performance we can expect and provides a reference point to prove that our advanced model is actually better.

C. Model 2: The Advanced Model (ResNet50 + SimCLR)

- **What:** A state-of-the-art model using Transfer Learning.
- **Architecture:** Use a pre-trained **ResNet50** as a powerful feature encoder. We will add new, simple classification layers on top.
- **Enhancement:** we will explorer **SimCLR** (Contrastive Learning) to pre-train the encoder on our specific skin images, potentially improving feature extraction.
- **Purpose:** To challenge the 97.69% benchmark with a different, powerful, and well-understood architecture.

4. Evaluation Plan

We will measure success using standard metrics:

- **Primary Metric: Accuracy**
- **Secondary Metrics: Precision, Recall, and F1-Score** (to check for bias).

Success Criteria:

1. **Baseline:** Baseline CNN trains successfully.
2. **Improvement:** Model 2 (ResNet50) achieves higher accuracy than Model 1.
3. **Ultimate Goal:** The ResNet50 model's accuracy is comparable to or **exceeds the 97.69%** benchmark.

5. Expected Outcome

A final report and a trained .h5 or .pkl model file that clearly answers our research question: "Is ResNet50-based architecture a viable and effective alternative to the current 'ArsenicNet' benchmark for this specific task?"