LITERATURE REVIEW & PROJECT CONTEXT: ARSENIC SKIN DETECTION USING MACHINE LEARNING

CSE 499A: Project Work | Section: 15

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INTRODUCTION

Our Project Goal: To develop a machine learning model using Convolutional Neural Networks (CNNs) to accurately classify skin images as either affected or unaffected by arsenic poisoning.

Literature Review Purpose: To understand the existing work – specifically the available dataset, common methods, and the best current results (the benchmark) – to guide and position our project.

PAPER 1 - ESTABLISHING THE DATASET

Paper: Khan, A.H., et al. "ArsenicSkinImageBD: A Novel Dataset..." (*Processes*, 2023).

Their Contribution: Created and shared the first public dataset of 8892 arsenic vs. non-arsenic skin images from Bangladesh (ArsenicSkinImageBD).

Relevance to Our Project: We are using this exact dataset

This ensures our work is directly comparable to others using this data.

Our notebook confirms the dataset is balanced (4446 images per class).

PAPER 2 - SETTING THE BENCHMARK: ARSENICNET

Paper: Khan, A.H., et al. "A Hybrid DCNN Model..." (*Diagnostics*, 2024).

Their Contribution: Developed "ArsenicNet," a complex hybrid model (Xception + InceptionV3), specifically for the ArsenicSkinImageBD dataset.

Their Result: Achieved a high accuracy of **97.69%**.

Relevance to Our Project: This is the **target performance** we aim to compare our models against

It shows that high accuracy *is possible* on this dataset with advanced CNNs.

PAPER 3 - VALIDATING THE GENERAL APPROACH

Paper: Al-Masni, M.A., et al. "A Survey on Machine Learning Methods in Skin Disease Recognition." (*Diagnostics*, 2020).

Their Contribution: Reviewed many papers on skin disease image analysis.

Their Finding: Confirmed that **CNNs** (like VGG, ResNet, Inception) are the standard and most successful method for this type of image classification task.

Relevance to Our Project: This review **justifies our choice** to use CNN-based architectures.

Our baseline CNN and our planned ResNet50 model are appropriate methods according to this survey.

SYNTHESIZING THE LITERATURE

What We Know:

- The ArsenicSkinImageBD dataset is the standard for this problem (Paper 1).
- CNNs are the best tool for the job (Paper 3).
- A hybrid (Xception+InceptionV3) model achieved 97.69% accuracy (Paper 2).

DEFINING OUR PROJECT'S FOCUS

Our project explores a different approach:

Baseline: We've built a standard CNN to establish a basic performance level on this data.

Advanced Model: We are implementing **ResNet50** (another powerful and widely used CNN architecture, possibly enhanced with SimCLR (to see if it can match or beat the ArsenicNet benchmark using a different design.

Goal: Compare the performance of our baseline CNN and ResNet50 against the 97.69% benchmark on the same dataset.

OUR PROJECT CURRENT STATUS

Data Acquired & Prepared:

Downloaded and extracted the 8892-image ArsenicSkinImageBD dataset.

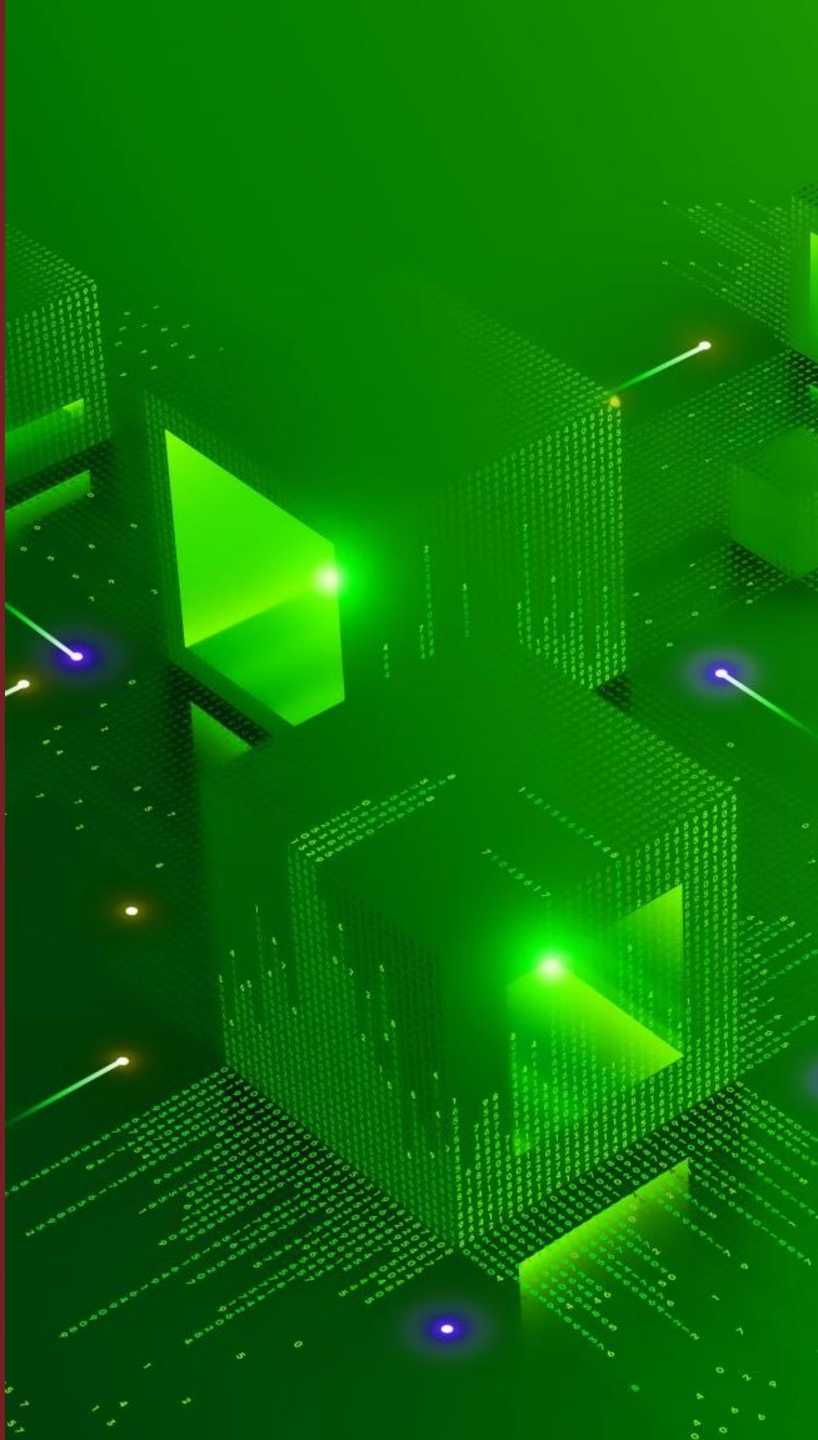
Confirmed dataset is balanced (4446 infected / 4446 not infected).

Loaded all filenames and created corresponding numerical labels (1/0).

Visually verified sample images from each class.

Libraries Imported: All necessary libraries (OS, NumPy, Matplotlib, PIL, Sklearn) are ready.

Initial Workflow Defined: Code structure for preprocessing, splitting, and model building is in place



NEXT STEPS

Run Preprocessing: Execute image resizing (128x128), RGB conversion, and NumPy array transformation.

Split & Scale Data: Perform Train/Test split (80/20) and scale pixel values to [0, 1].

Train & Evaluate Baseline CNN:

Build, compile, and train the defined CNN model.

Evaluate its accuracy on the test set and visualize performance.

Implement & Test ResNet50/ SimCLR:

Debug and run the advanced model implementation.

Evaluate its accuracy.

Compare & Conclude: Compare model results against the 97.69% benchmark from literature.

End slides