Team 3

Machine Learning Model for Colorimetric Change Assessment of a Biomaterial

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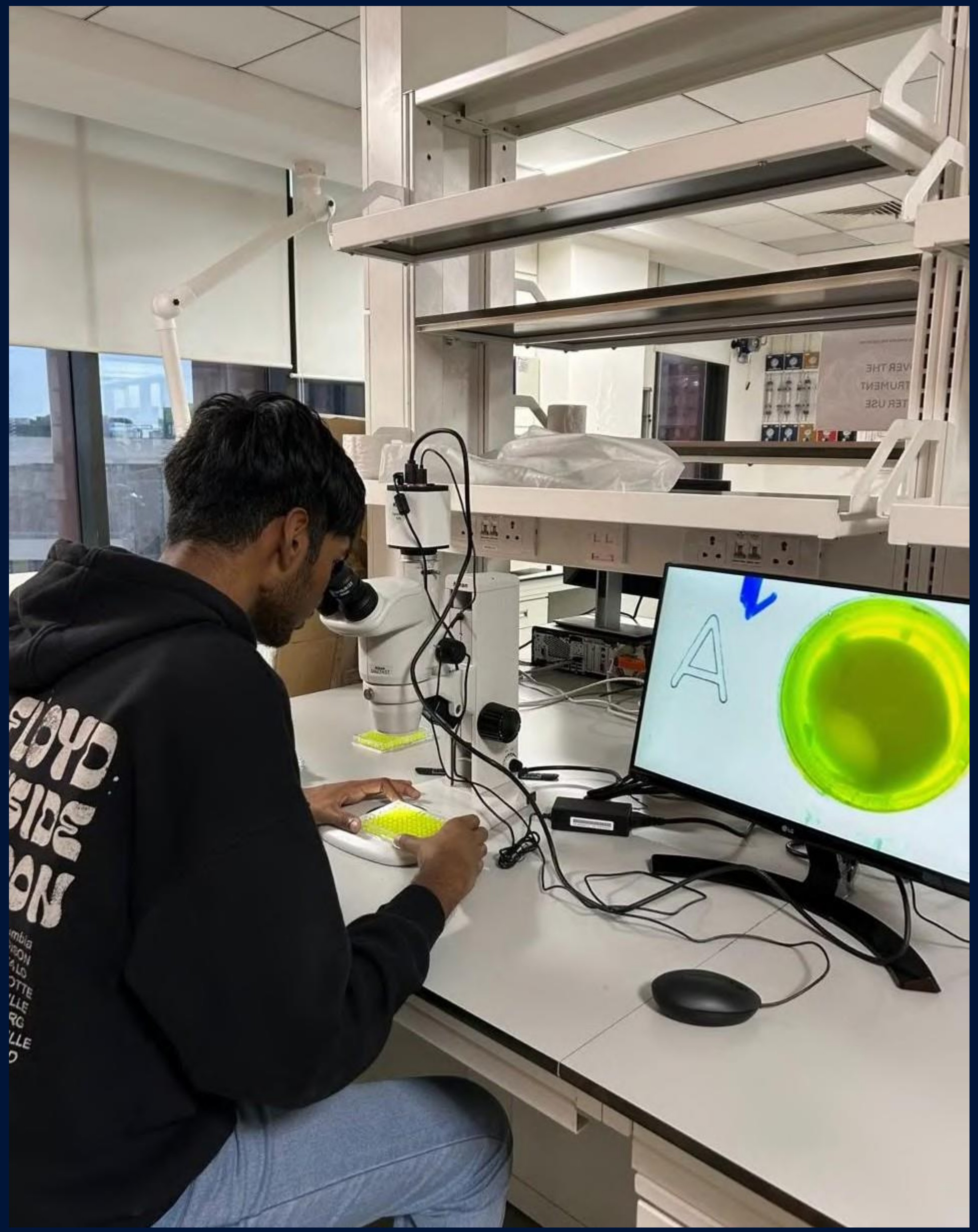
Data Collection

Equipment & Dataset:

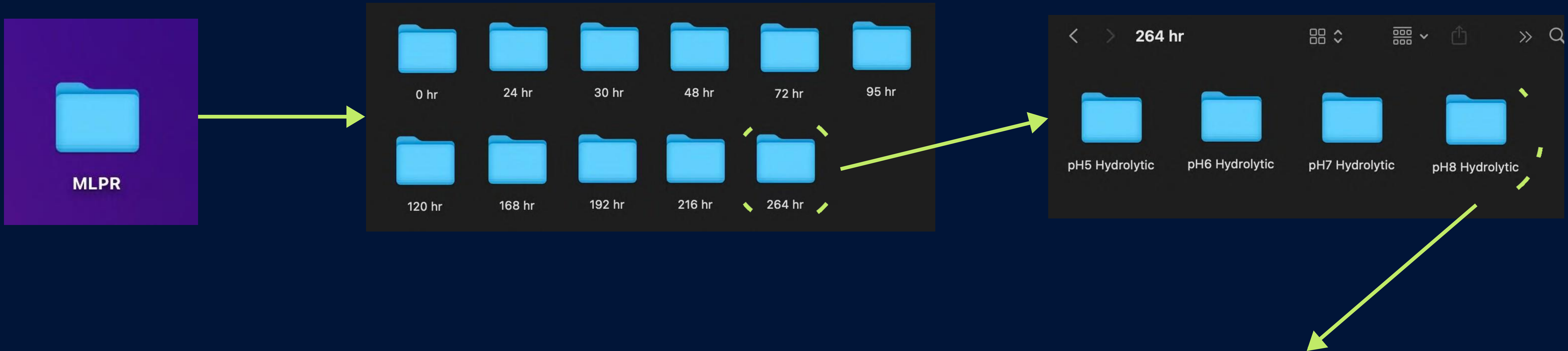
- Used Stereomicroscope for high-resolution imaging.
- Tracked the color & hydrogel change over the time of 10 days (~264 hrs).
- Images gathered : 2,112
- Classes → 4 Based on biology 11 based on timestamps

Precautions while taking readings :

1. Ensure consistent lighting across images.
2. Distance setup for consistent imaging.
3. Maintained incubation temperature of wells.
4. Taking readings at proper time intervals.

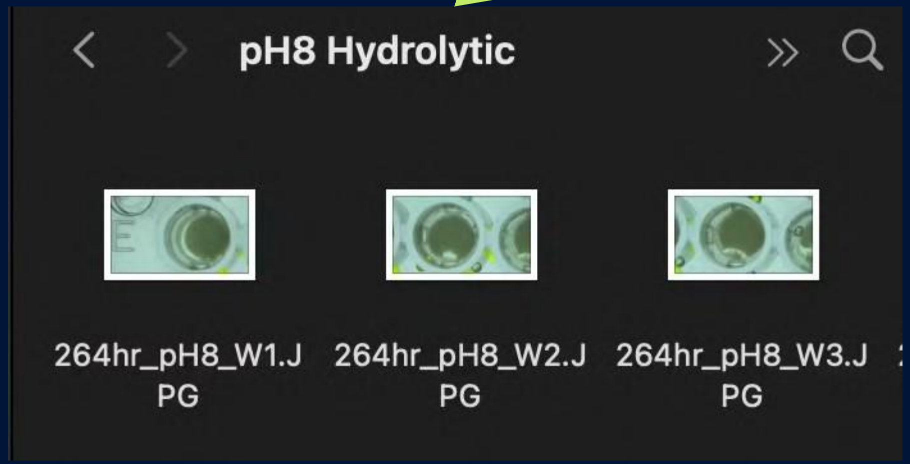


Data Collection



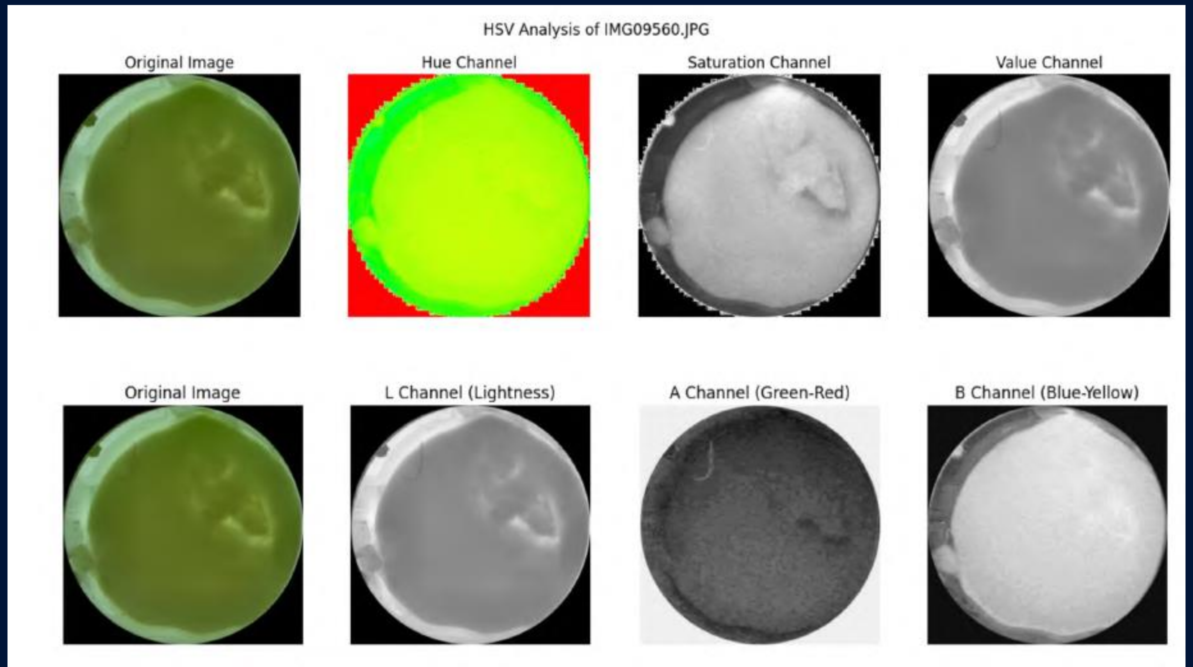
Storing and Labelling

- Folder-based arrangement of images
- Usage of a Python script for renaming images for access

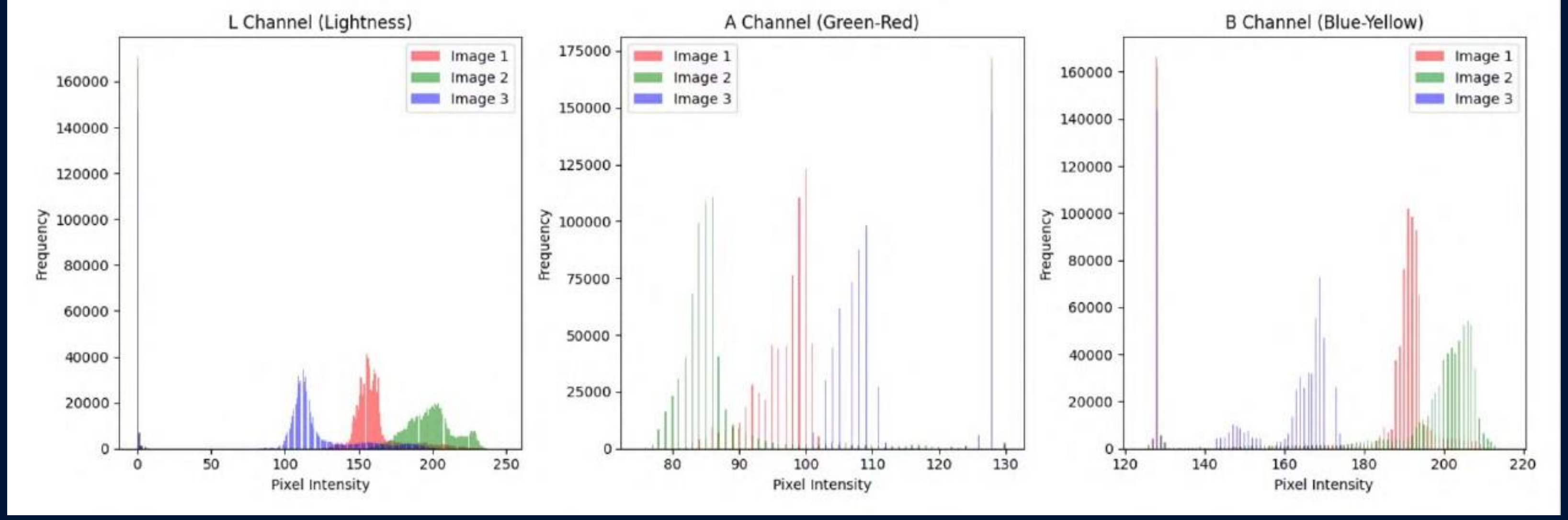


Exploratory Data Analysis

1. Images in LAB and HSV Colour Spaces



2. Detecting variations through Colour Histograms



3. Kernel Experimentations for Feature Extraction

Gaussian Blur Kernel

4. Kernel Experimentations for Colour based Feature Extraction

Sobel X Kernel

Sobel Y Kernel

Preprocessing & Exploratory Data Analysis

1

Capturing **Region of Interest** with **Binary Mask** and **Bounding Circle**

2

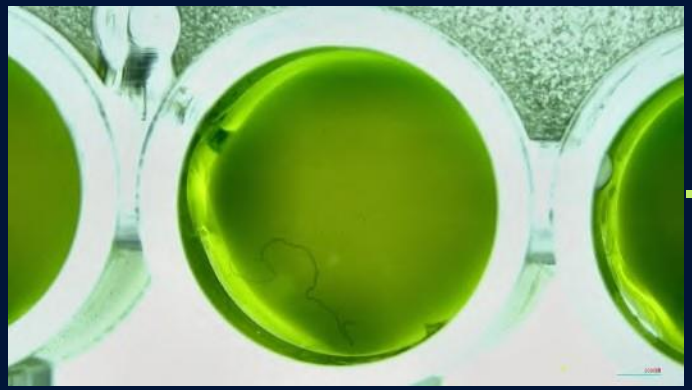
Background Subtraction: **Morphological Operations**

3

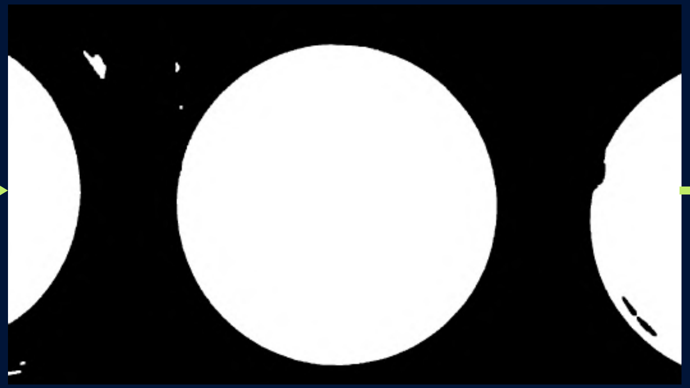
Size Reduction: OpenCV - Inter_Area

Preprocessing

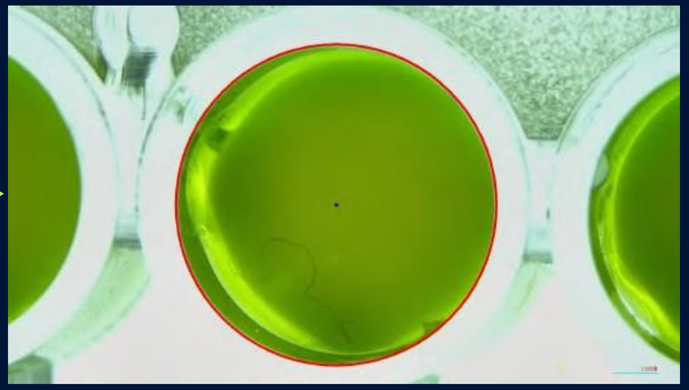
Problem: Neighbouring wells are also captured in images!



Original Image



Binary Mask
(or Thresholding)



Contour Detection and
Circle Fitting

Circular Masking
and Cropping

1. Capturing **Region of Interest** with **Binary Mask** and **Bounding Circle**

&

2. Background Subtraction: **Morphological Operations**

Explaining the approach !

Binary Mask → To isolate the green regions by **thresholding in HSV space.**

- [ ] **Morphological Operations** → To **remove noise** and fill small gaps using closing and opening.

- [ ] **Contour Detection** → To **detect the circle** enclosing a contour.

Circularity Calculation → To **filter out non-circular objects** based on shape properties.

Applying Circular Mask → To **extract only the region of interest.**

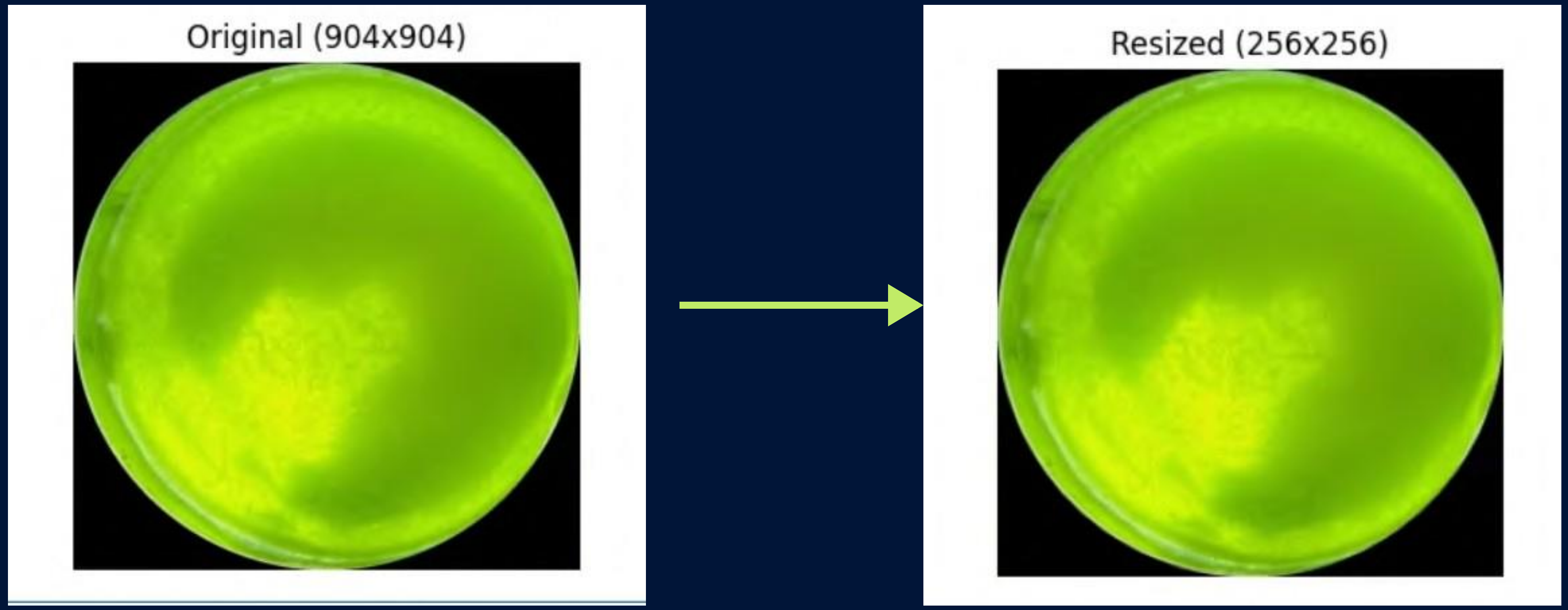
1 Capturing **Region of Interest** with **Binary Mask** and **Bounding Circle**

&

2 Background Subtraction: **Morphological Operations**

Doğru, D., Özdemir, G.D., Özdemir, M.A. *et al.* An automated in vitro wound healing microscopy image analysis approach utilizing U-net-based deep learning methodology. *BMC Med Imaging* **24**, 158 (2024). https://doi.org/10.1186/s12880-024-01332-2

Preprocessing



Reasons for Re-sizing:

1. Reducing image size lowers memory consumption, allowing models to process more images at once.
2. **Standardization** → Our inputs initially had varying dimensions, in order to bring them to the same size.

3

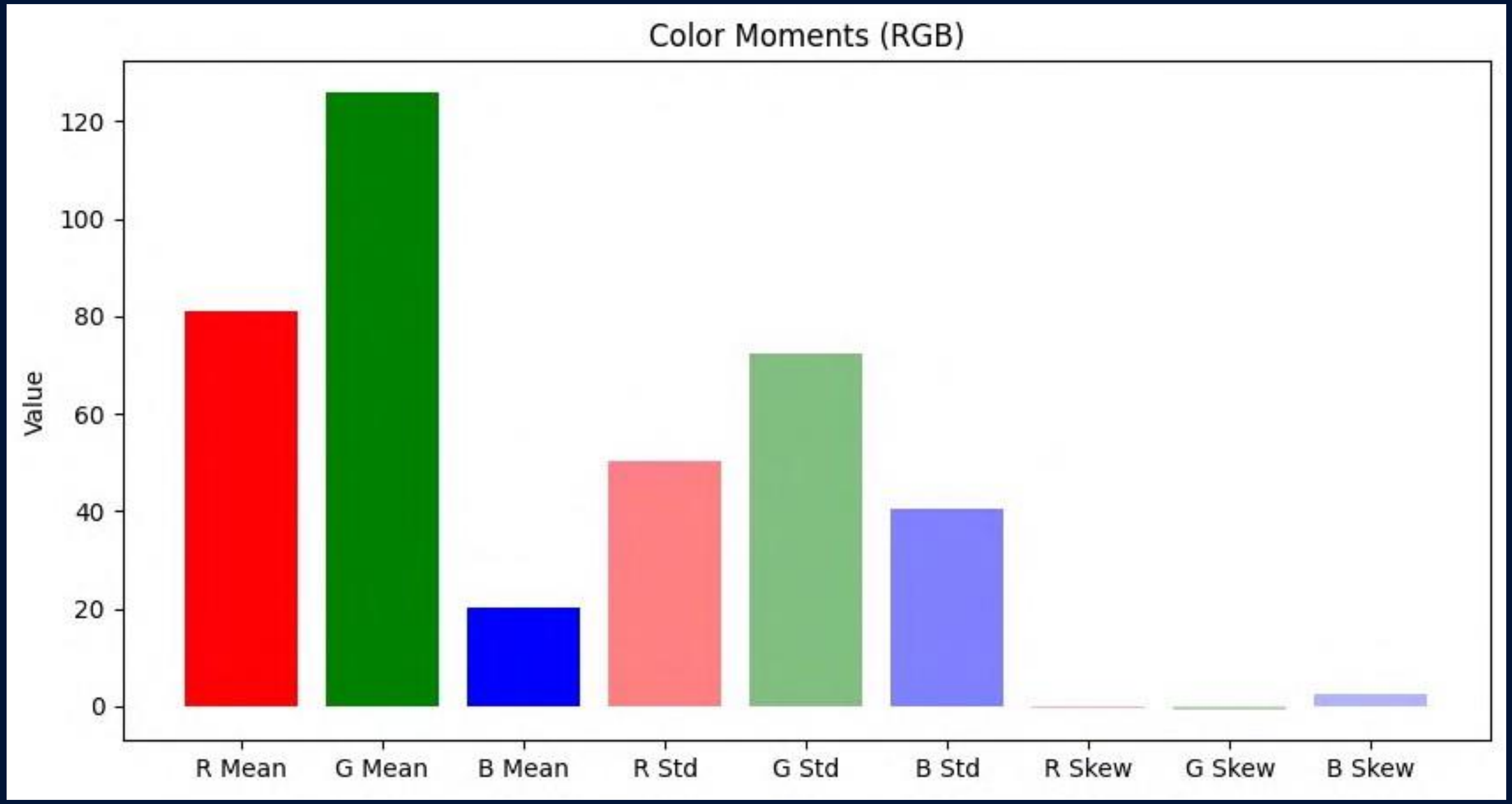
Size Reduction:
OpenCV - Inter_Area

Doğru, D., Özdemir, G.D., Özdemir, M.A. *et al.* An automated in vitro wound healing microscopy image analysis approach utilizing U-net-based deep learning methodology. *BMC Med Imaging* 24, 158 (2024). https://doi.org/10.1186/s12880-024-01332-2

Feature Extraction

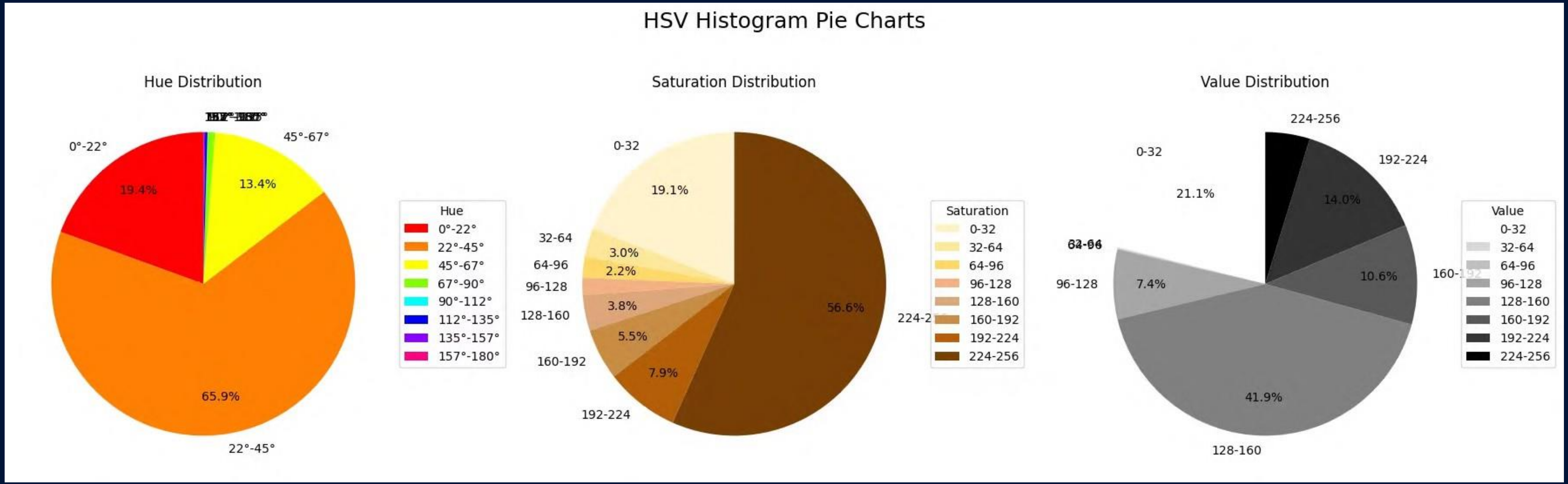
1. RGB Histogram

- **3 statistical moments** (**mean, standard deviation, skewness**) across the Red-Blue-Green (RGB) color channels of the image
- **3 (RGB) * 3 (statistical) = 9 features**



Feature Extraction

2. **HSV Histogram**



8 (Range) * **3** (Hue, Saturation, Value)
= **24 Features**

Feature Extraction

→ **Total Features:**

9 + 24 = 33 Features

RGB HSV

Target Variable = Physiological value of interest

Models Trained

→ Classical Programming

→ Machine Learning : 1. KNN
2. SVM
3. Random Forest

→ Convolutional Neural Network: **Random Forest + CNN**

→ Transfer Learning : 1. Resnet18
2. Resnet18 + Random Forest

→ Long - Short Term Memory: **Resnet18 + LSTM**

ML Models

→ Classical Programming

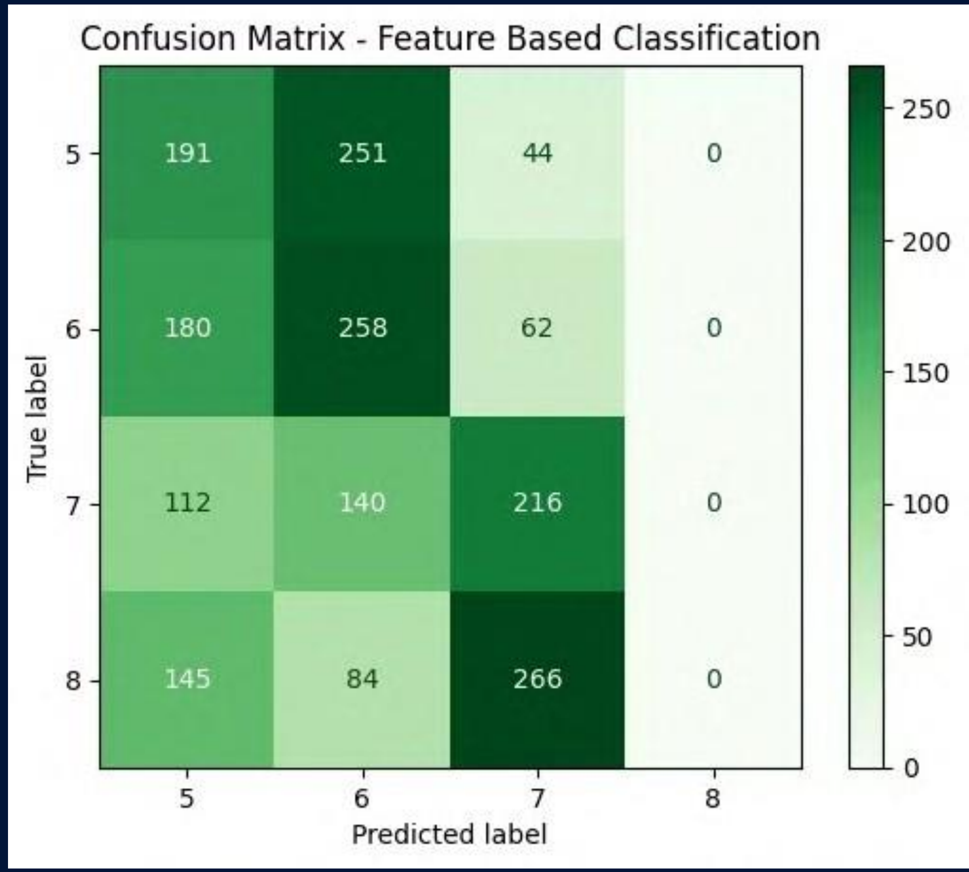
Rule-based Classification Logic:

- **Calibrated green channel intensity thresholds (mean_g values of 60, 75, and 90)**

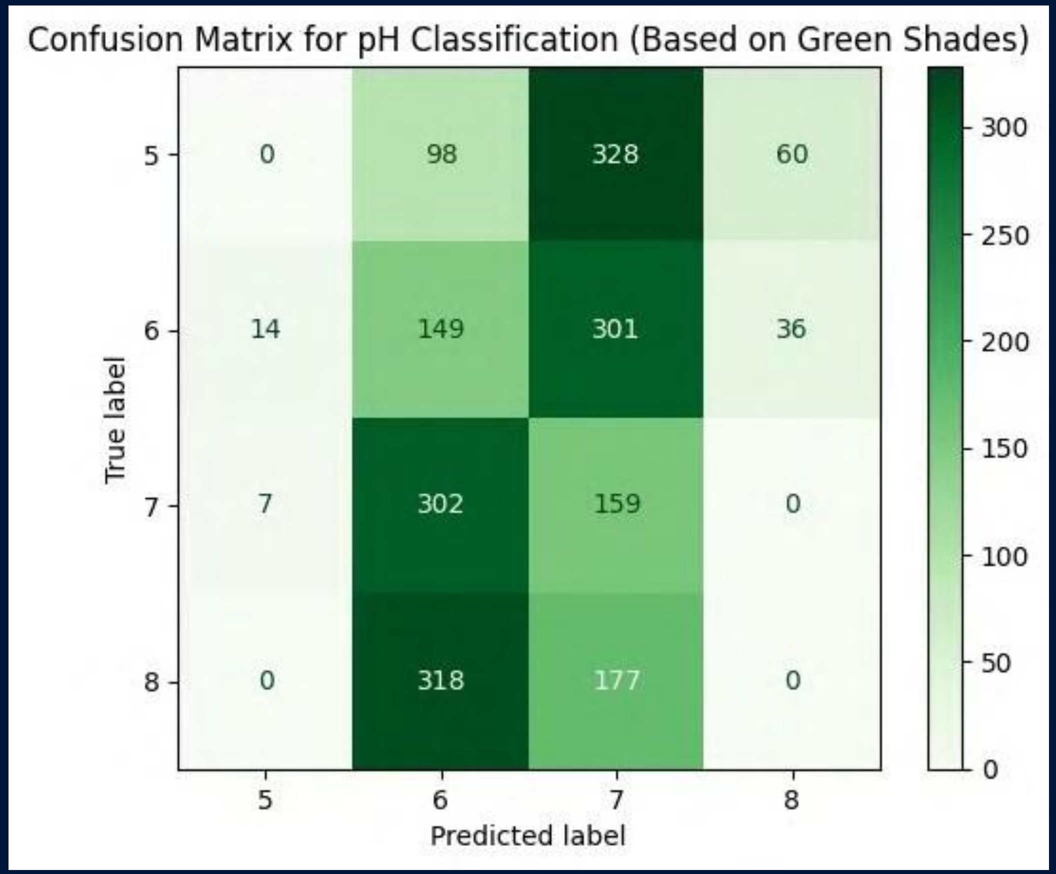
Shortcomings:

- **pH indicators does not exhibit distinct color transitions at specific pH levels**
- **Model becomes biased towards the specific mean_g value**

Accuracy: 34.12%



Accuracy: 14.85%

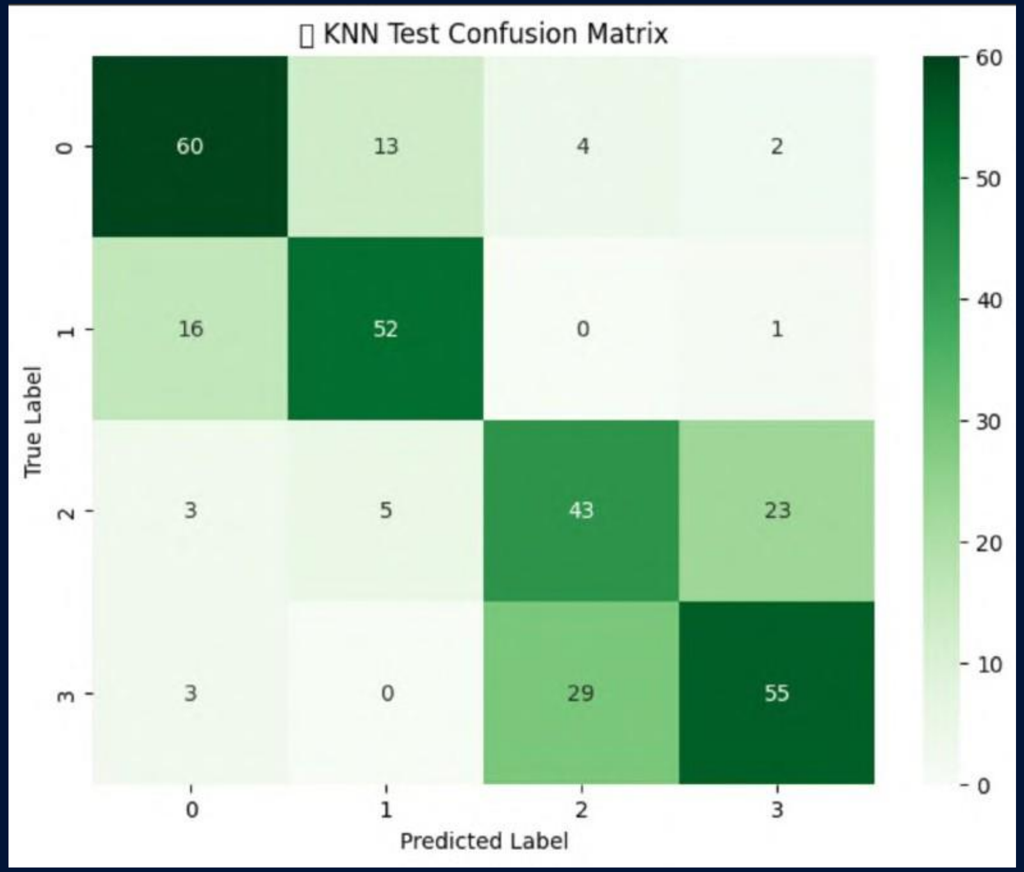


ML Models

→ Machine Learning :

1. KNN

- Accuracy: 0.679



2. SVM

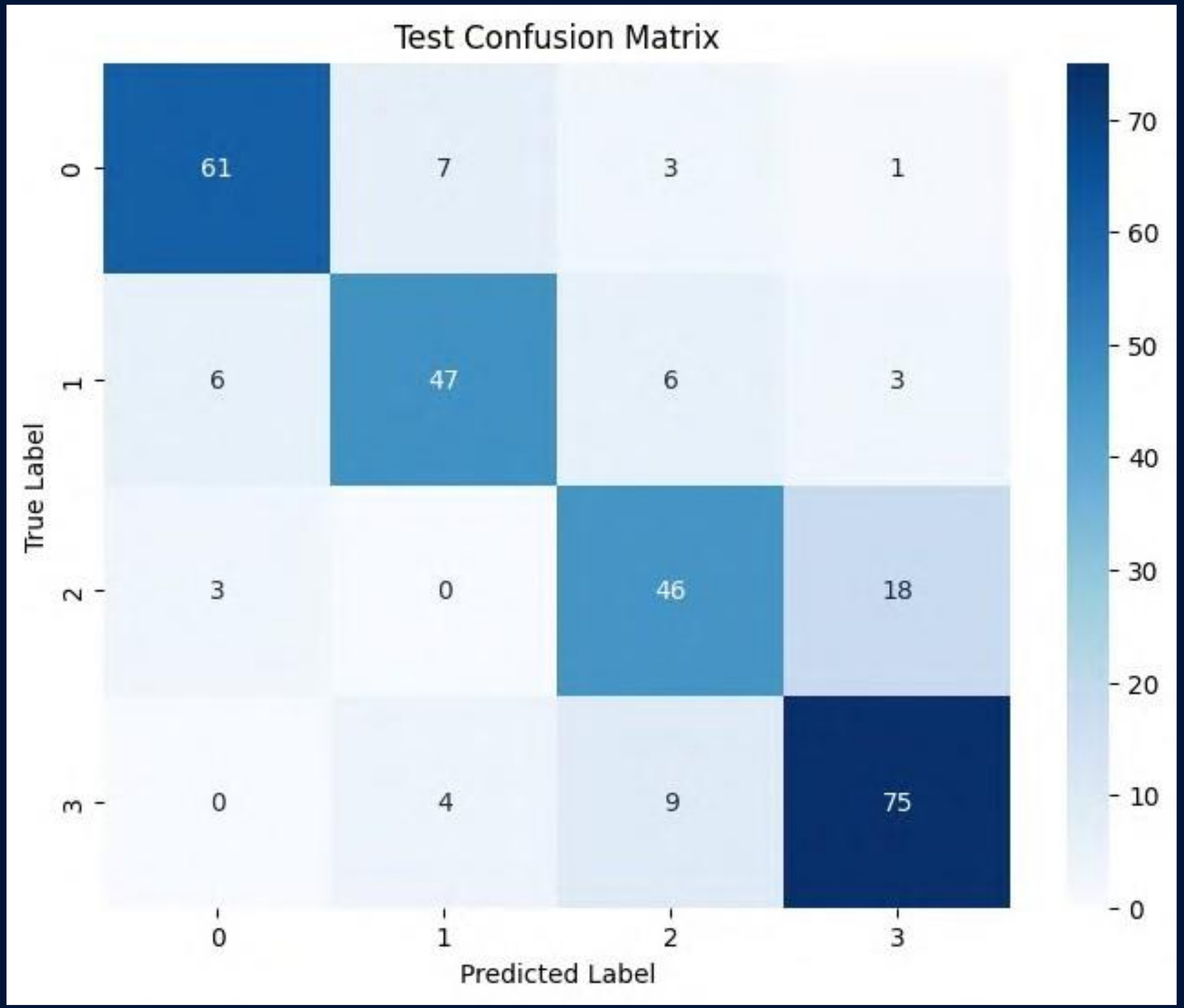
- Accuracy: 0.737

ML Models

→ Machine Learning :

3. Random Forest

- Test Accuracy: 0.792
- Training Process:
  - Feature Selection: It selects a subset of features at each split, ensuring diverse decision-making.
  - Tree Construction: Each decision tree is trained on a random subset of the training data.
  - Voting Mechanism: The final classification is based on majority voting across multiple trees.



Shortcoming: Model is becoming **biased towards pH 5 & 6** as It is not able to extract enough features.

Challenge we faced: Model was initially giving 99% accuracy but we noticed data leakage!

Try Pitch

Important Learnings

Random Forest

Shortcoming: Model is becoming **biased towards pH 5 & 6** as It is not able to extract enough features.

Challenge we faced: Model was initially giving 99% accuracy but we noticed data leakage!

The problem was with the way using which we split the data → Silly mistake!

❌ Initially : Randomly split all images as train and validation set (80%) and test set (20%).
Causing images of the same well sample to be in train and test (at different timestamps!)

✅ New technique : Divided sample-based sequential data into train and test sets this time!

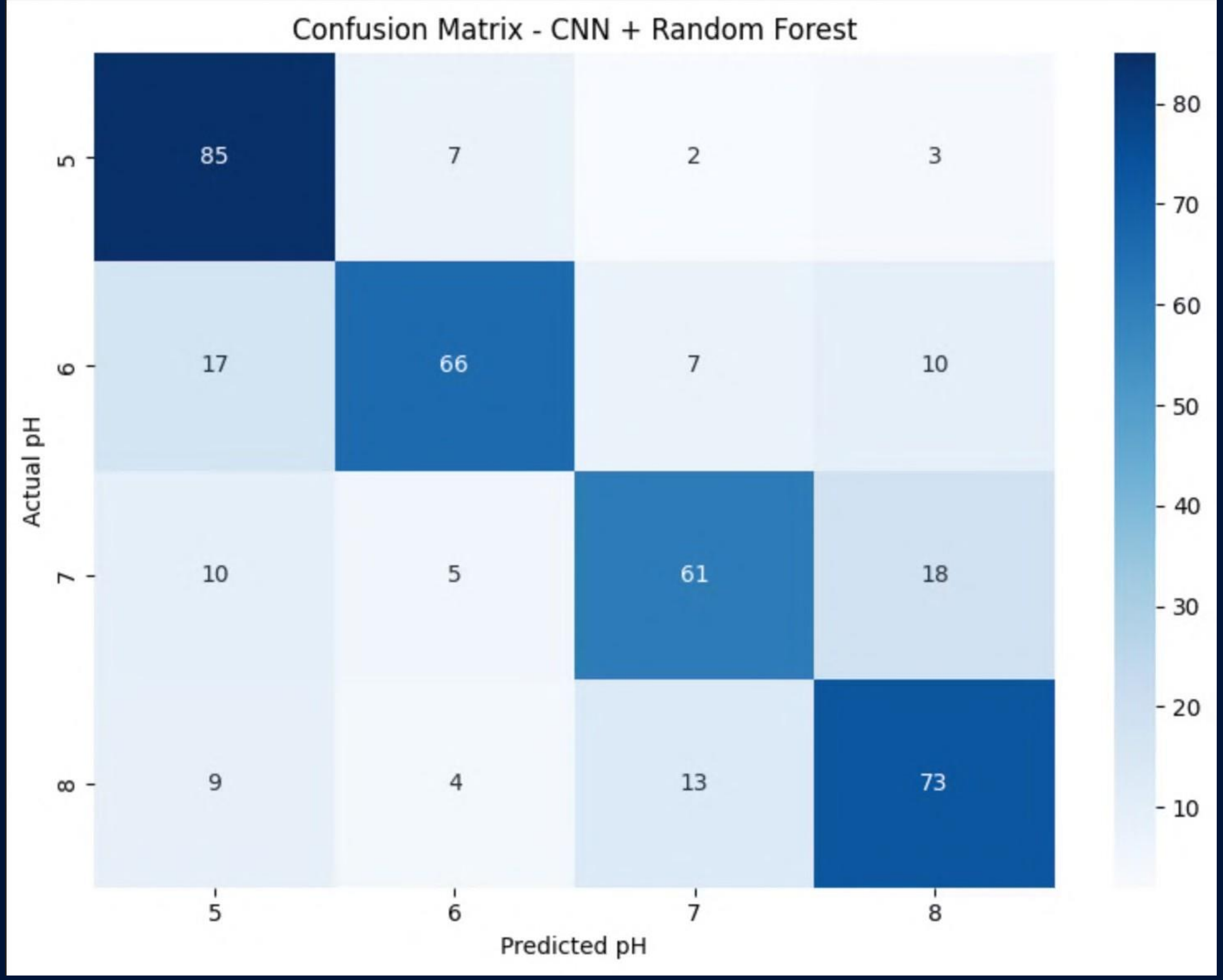
ML Models

→ Convolutional Neural Networks :

1. Random Forest + CNN

- Test Accuracy: 0.73
- We are extracting features using CNN and training Random Forest on those features.

Shortcoming: Accuracy is low as features extracted using CNN are not fine-grained enough to capture subtle image differences.



Try Pitch

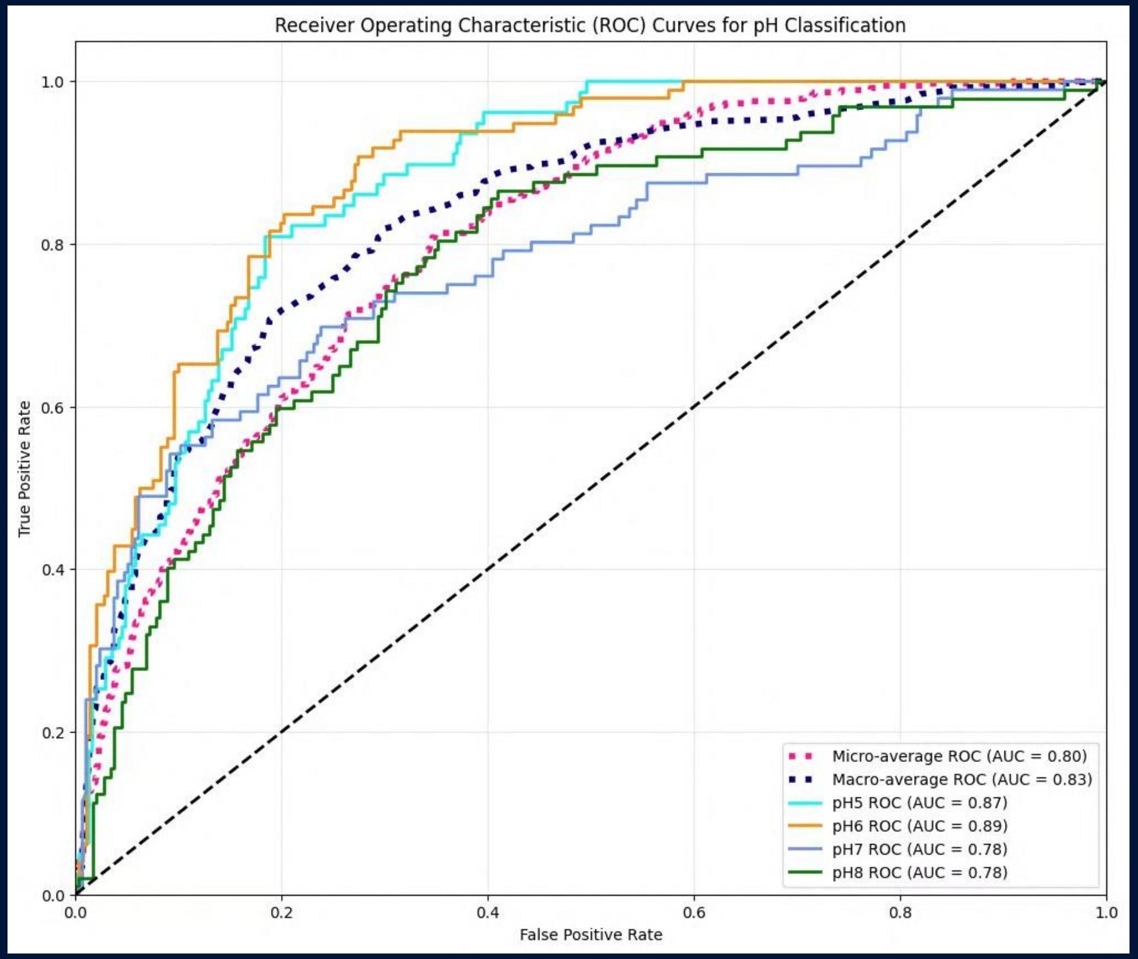
ML Models

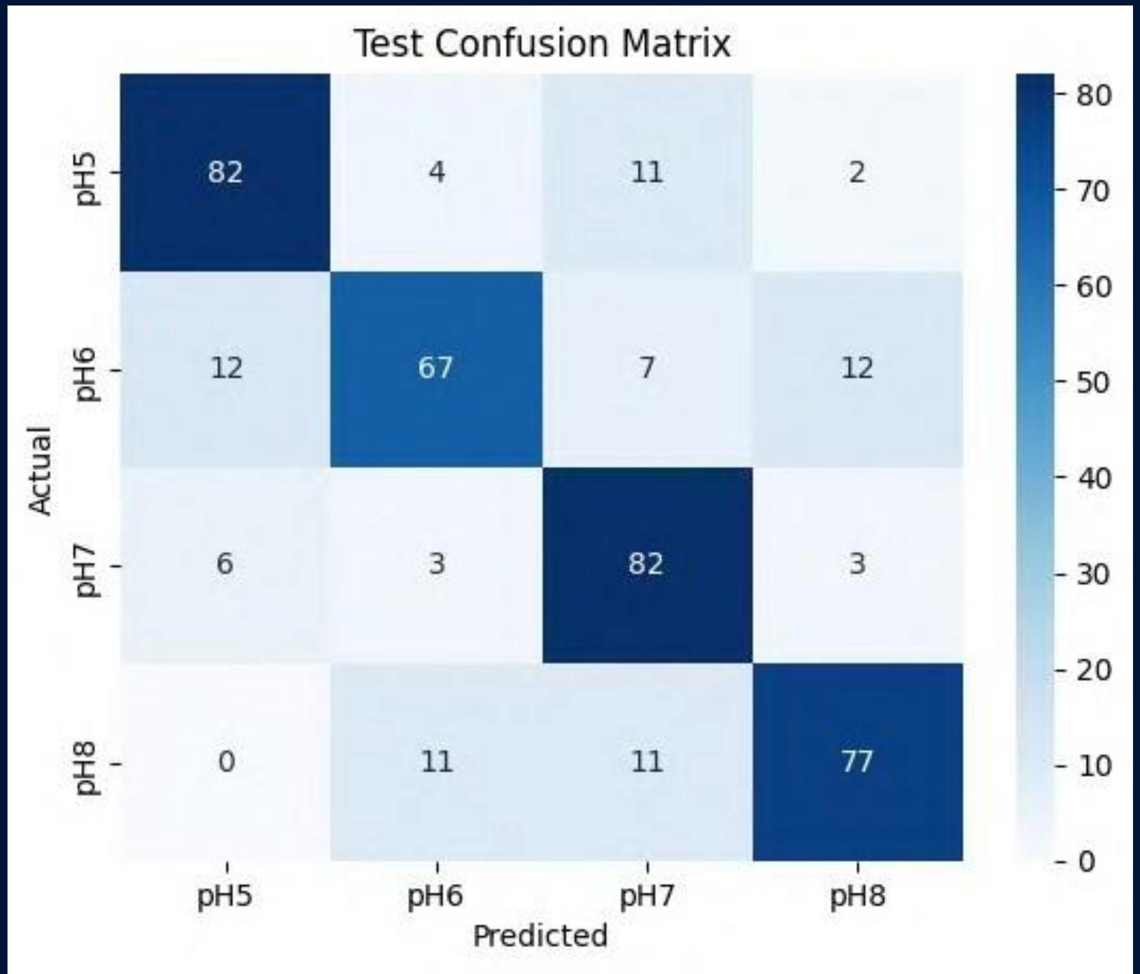
→ Transfer Learning?

1. Resnet18

- **Accuracy :** 0.79
- **Approach : Froze all but the last layer and replaced it for our dataset with 4 classes**

→Precision - 0.79
→Recall - 0.78
→F1 score - 0.80





Isohanni, J. (2025). Customised ResNet architecture for subtle color classification. *International Journal of Computers and Applications*, *47*(4), 341-355. https://doi.org/10.1080/1206212X.2025.2465727

ML Models

→ Transfer Learning:

2. Resnet18 + Random Forest

Resnet18

- Input images were resized, normalized, and fed into the ResNet-18 model.
- It consists of convolutional layers with residual connections, followed by a global average pooling and a final linear layer (modified to output 4 classes).
- Training used mini-batch gradient descent with backpropagation over 15 epochs.

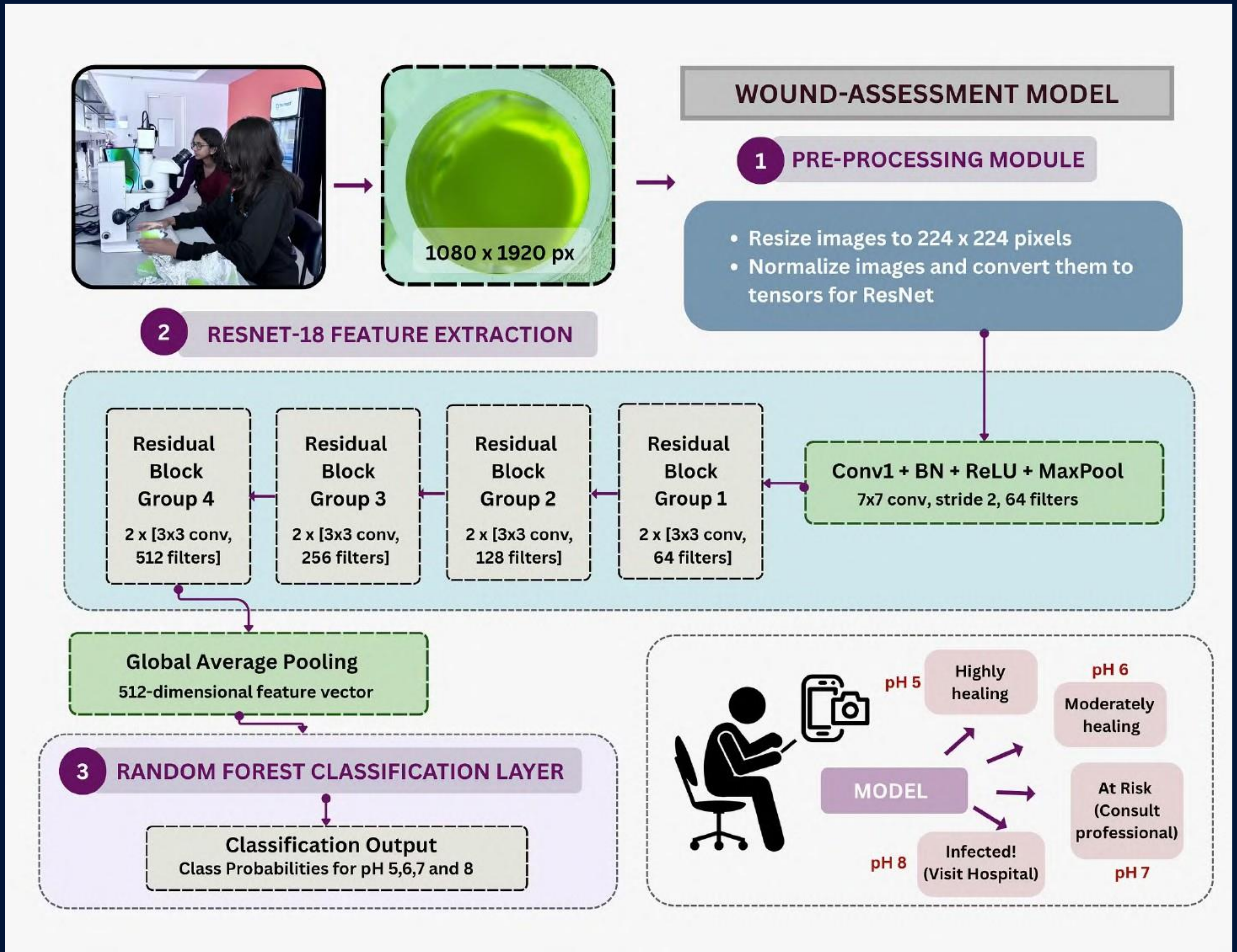
→

Random Forest

- Feature vectors were extracted from the last layer of ResNet-18.
- These vectors were flattened and passed into the RF model for classification.
- The RF model uses an ensemble of decision trees, each trained on a random subset of features, and combines their predictions for final output.

Architecture

2. Resnet18 + Random Forest



→ 32-image mini-batches: to optimize memory usage and computational efficiency.

→ Adaptive learning rates per parameter: Combines benefits of AdaGrad and RMSProp to accelerate convergence and improves model performance.

→ Multi-class Error Minimization: Utilized CrossEntropyLoss function to effectively quantify classification errors across 4 l levels, enabling precise parameter adjustments during each training iteration.

→ Normalization using ImageNet statistics, and data augmentation techniques to enhance model generalization across [redacted] levels.

Try Pitch

Performance Metrics

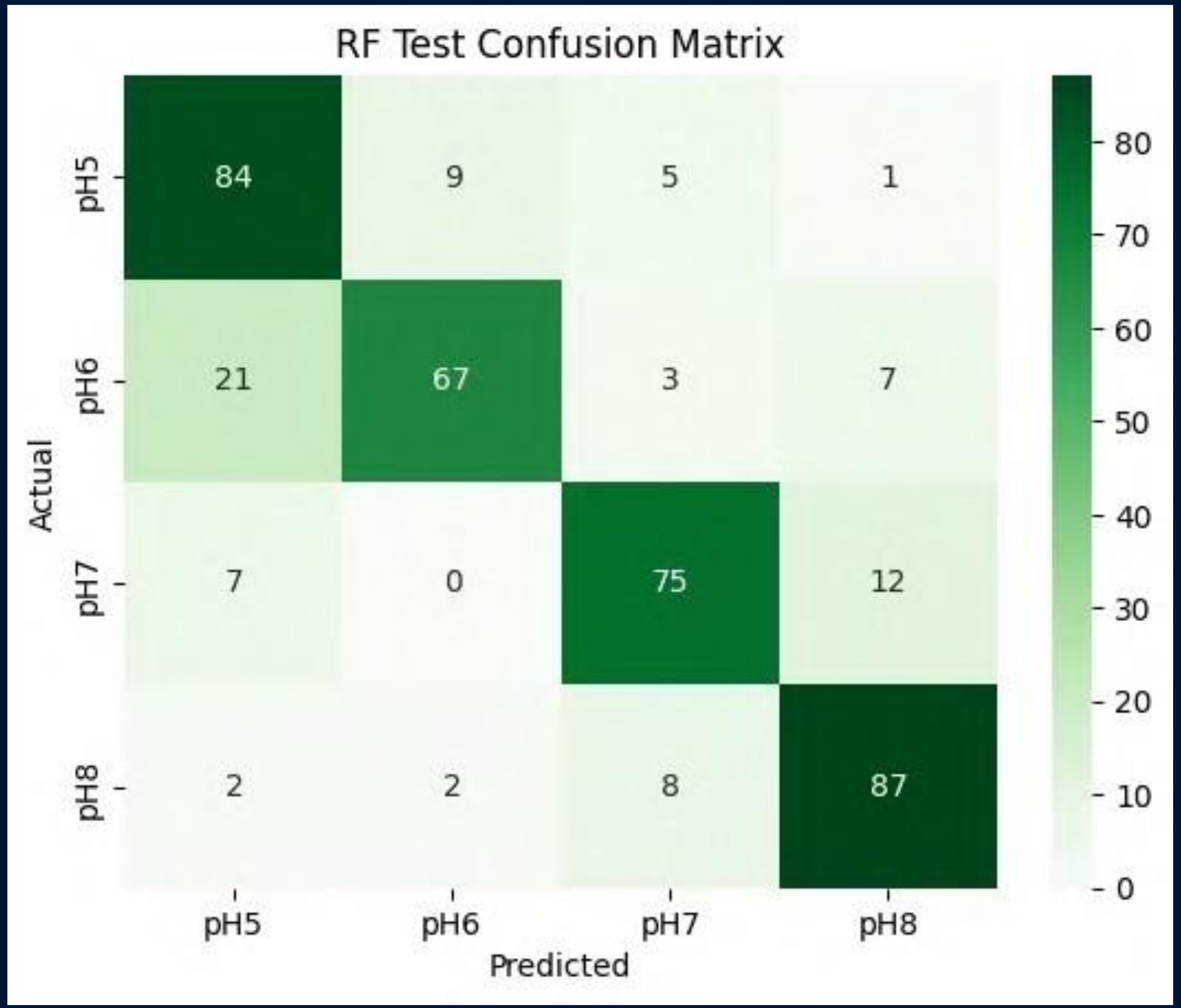
2. Resnet18 + Random Forest

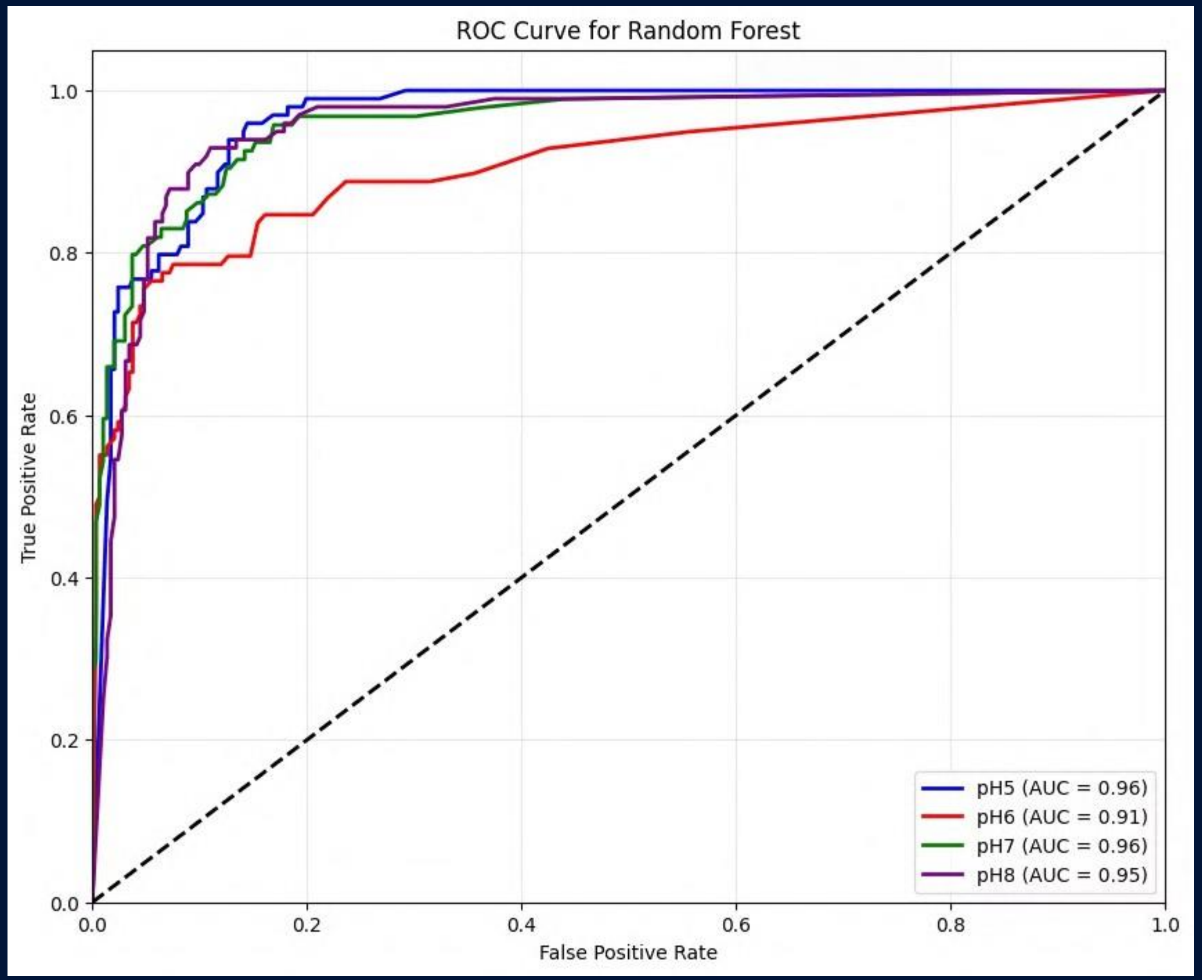
→Accuracy - 0.80
→Precision - 0.81
→Recall - 0.80
→F1 score - 0.80

1. **Higher Classification Accuracy: 80% accuracy, 0.80 F1-score with balanced precision and recall, demonstrating effective [redacted] level discrimination.**

2. **Relatively less Biased**

3. **Relatively Strong Discriminative Power: In ROC curve high AUC values (0.91-0.96), indicating that the model is more robust in distinguishing different [redacted] images.**



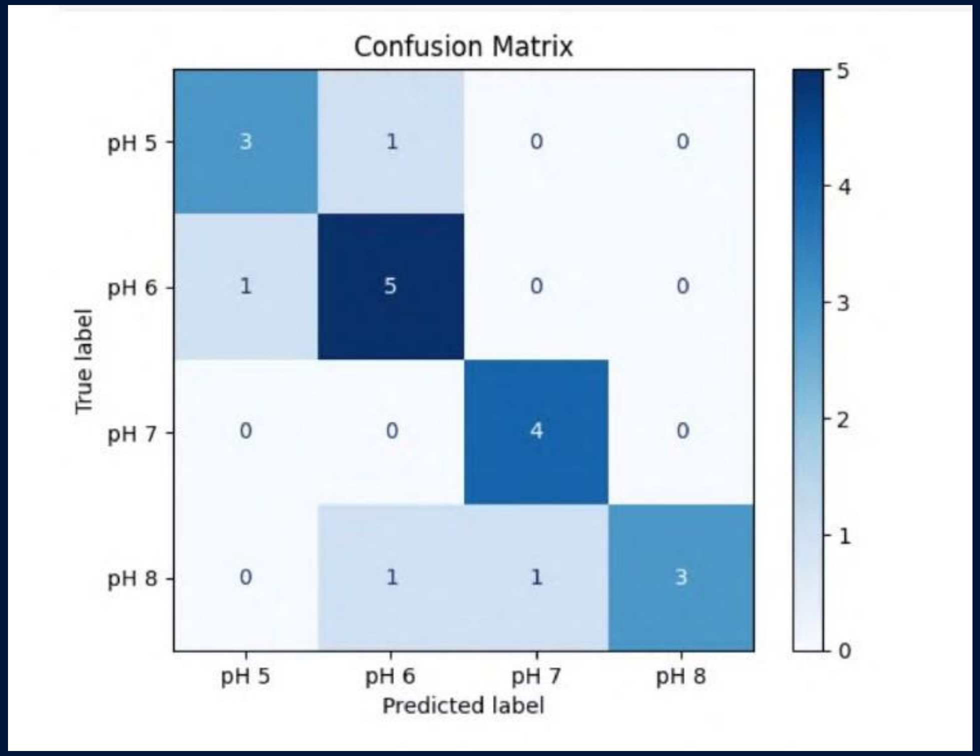


ML Models

1. ResNet-18 + LSTM → **Accuracy - 0.79**

Sequential Analysis Using LSTM

- **Simple CNN and LSTM gave a low accuracy of 31 % →** `Validation Accuracy: 0.3125`



	precision	recall	f1-score	support
5	0.75	0.75	0.75	4
6	0.71	0.83	0.77	6
7	0.80	1.00	0.89	4
8	1.00	0.60	0.75	5
accuracy			0.79	19
macro avg	0.82	0.80	0.79	19
weighted avg	0.82	0.79	0.79	19

Classification Report

Approach

- **Input:**
  Sequence of 11 images per sample
  (Each image corresponds to one of the 11 observation time points for a given well.)
- **Output:**
  Predicted a class based on color evolution in the bandage over time.

1. ResNet-18 + LSTM

Approach

1 Input

Sequence of 11 images per sample (Each image corresponds to one of the 11 observation time points for a given well.)

2 Feature Extraction (Spatial)

Each image is passed through a pre-trained ResNet-18 (without final FC layer)
→ Outputs a 512-dimensional feature vector per image.

3 Sequence Modeling (Temporal)

The 11 feature vectors (one per timestamp) are stacked into a sequence
→ Passed to an LSTM (input size = 512, hidden size = 256)

4 Prediction (Classification)

The final hidden state from the LSTM is passed through a fully connected (FC) layer
→ Outputs logits [redacted]

5 Output

Predicted [redacted] class based on color evolution in the bandage over time.

Limitations of Our Solution

1. **Errors in data collection:** Inconsistent lighting, angle, or background during imaging may affect RGB feature extraction and [redacted] classification accuracy.
2. **Less data:** Small sample size reduces model generalizability and increases the risk of overfitting
3. **Lack of temporal analysis:** The model evaluates each image independently, without considering wound progression over time.
4. Key biochemical markers (e.g., Protease XIV) that strongly correlate with infection and healing are not yet incorporated, **limiting diagnostic depth**.
5. **Did not correlate the RGB values with absorbance values/ fluorescence** intensity using a spectrometry/fluorometer readings to realize the full potential of fluorescence.

Thank you