Automatic Classification of Spirulina Microscopic Observations using Deep Learning Techniques

CNN Architecture Evaluation and Pond-Level AI Monitoring

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“A picture is worth a thousand words.” — Fred R. Barnard

Question: Can we teach a computer to interpret that visual information and convert it into quantitative data?
In other words, can we create a new language in which the image begins to speak through data?

AGENDA

Automatic Classification of Spirulina Microscopic Observations Using Deep Learning Techniques

- 01 INTRODUCTION & RESEARCH PROBLEM
- 02 THEORETICAL FRAMEWORK & OBJECTIVES
- 03 AI ARCHITECTURE & EXPERIMENTAL DESIGN
- 04 MODEL EVALUATION & SELECTION
- 05 RESULTS & POND-LEVEL MONITORING
- 06 CONTRIBUTIONS, CHALLENGES & FUTURE WORK
- 07 CONCLUSIONS & FUTURE WORK

1. *Spirulina* Morphology

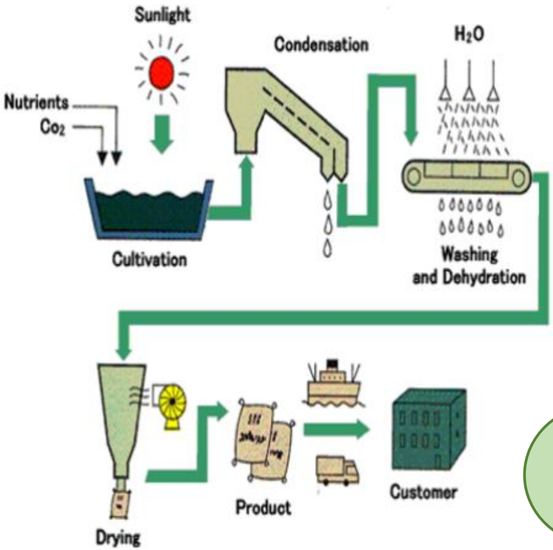
🌿 Culture Health

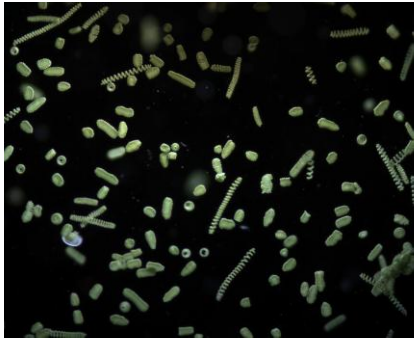
Microscopic morphology directly reflects culture stress and physiological state

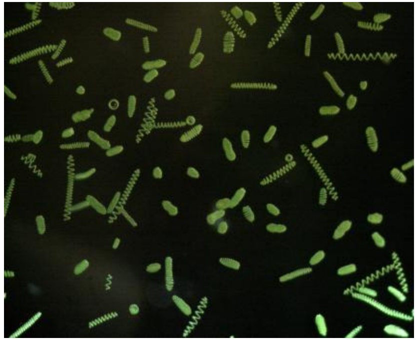
🔬 Continuous Monitoring

Industrial spirulina ponds require frequent microscopic assessment

👁️ Expert Dependency







2. The Challenge of Manual Microscopic Evaluation

Subjectivity

Interpretation varies between analysts and over time

Standardization

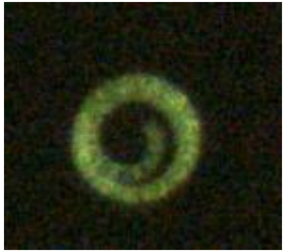
Difficult to maintain consistent criteria across observations

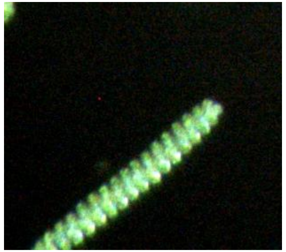
Missed Signals

Subtle morphological changes may go undetected

Limited Quantification

Pond-level tracking requires systematic, reproducible data





A standardized AI-based approach is needed to convert microscopy into actionable monitoring data.

3. Theoretical Foundation

Convolutional Neural Networks

Automatic extraction of spatial and morphological features from raw image data

Transfer Learning

Pretrained visual representations repurposed for specialized biological datasets (convergence, generalization)

Industry 5.0

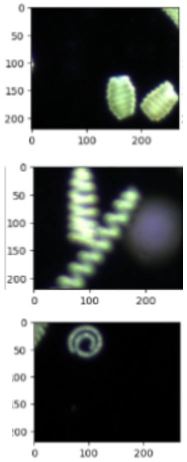
AI augments human-centered decision-making, supports, not replaces expert judgment

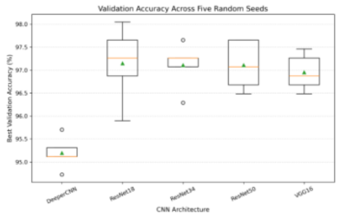
4. Research Objectives

Develop an AI-based framework for **automatic classification** and **quantitative monitoring** of *Arthrospira platensis* morphology at industrial scale.

Classify Patches

morphological classes



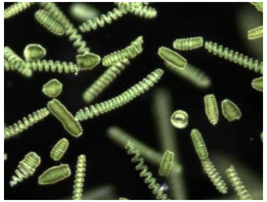


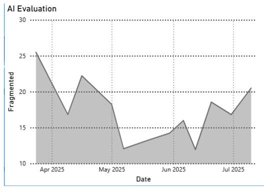
Compare CNNs

Five architectures under controls

Select Model

Choose most efficient and accurate





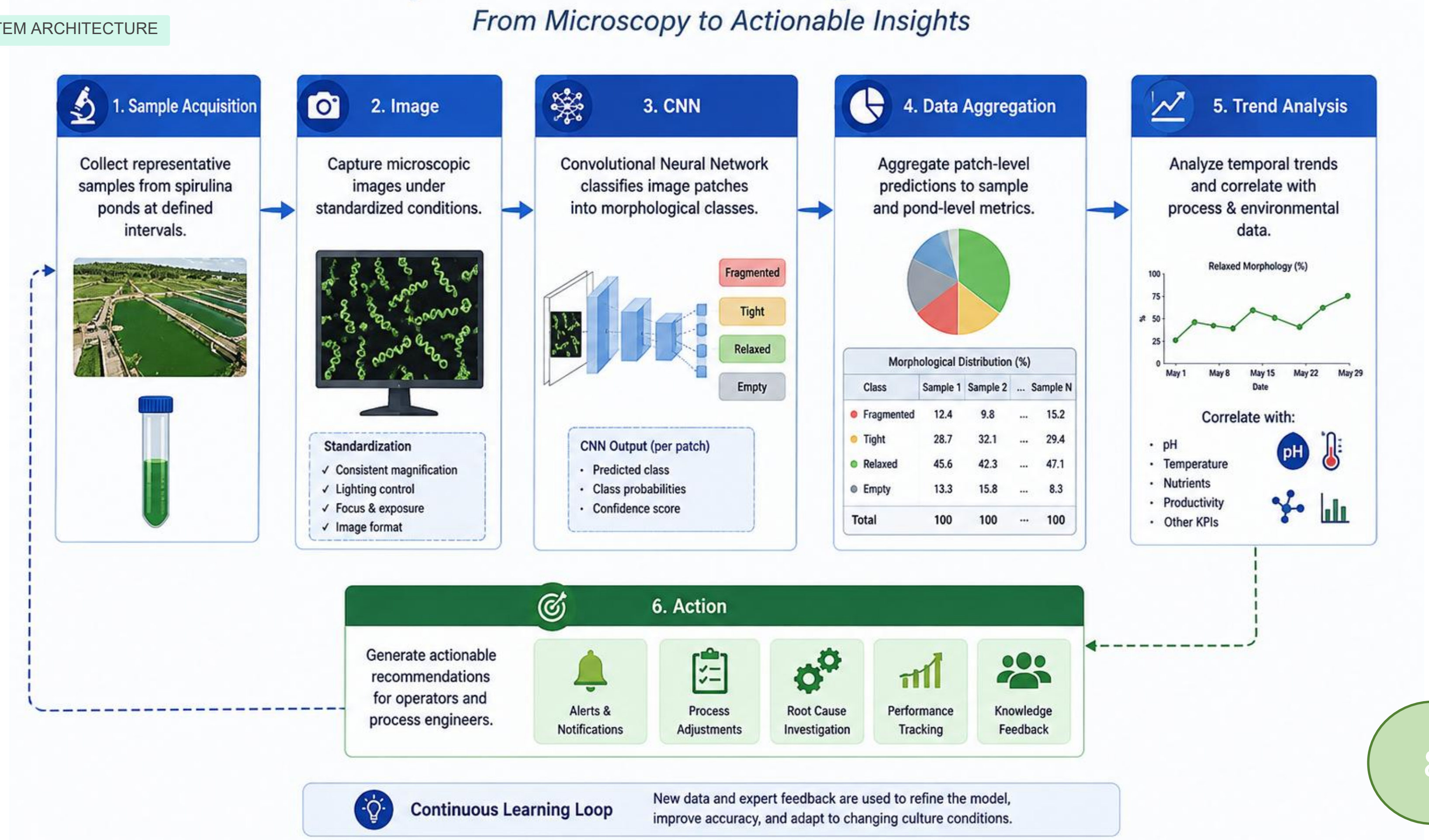
Scale Monitoring

Full-image and pond-level monitoring

Each objective builds toward a scalable, reproducible industrial monitoring pipeline.

5. Proposed Monitoring Arquitechture

SYSTEM ARCHITECTURE



6. CNN Models and Experimental Protocol

1

DeeperCNN

Custom architecture baseline

2

ResNet18

Lightweight residual network

3

ResNet34

Deeper residual variant

4

ResNet50

Full-depth residual network

5

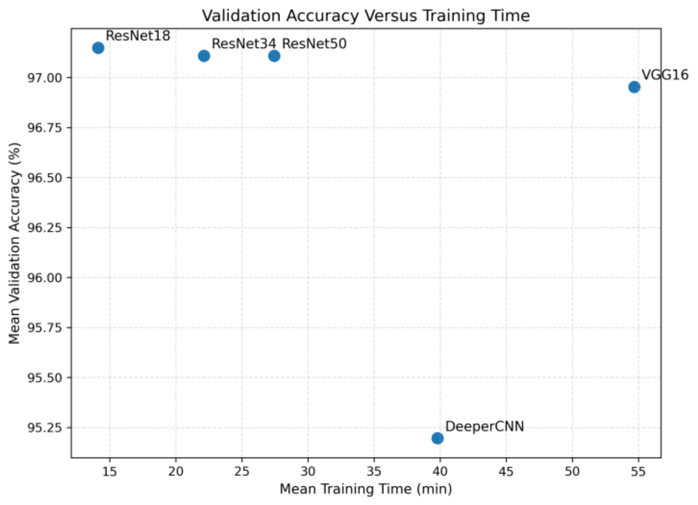
VGG16

Classic deep convolutional model

Controlled Experimental Conditions

- 5 independent random seeds per model
- Identical optimizer, learning rate, batch size, and epochs
- Same train/validation split across all runs
- Random undersampling for class balance
- Four-class classification task throughout

All five architectures compared under strictly identical conditions — ensuring fair, reproducible benchmarking.



7. Comparative CNN Performance

🏆 ResNet18 Selected

Best balance of accuracy, F1, and MCC with fewest parameters

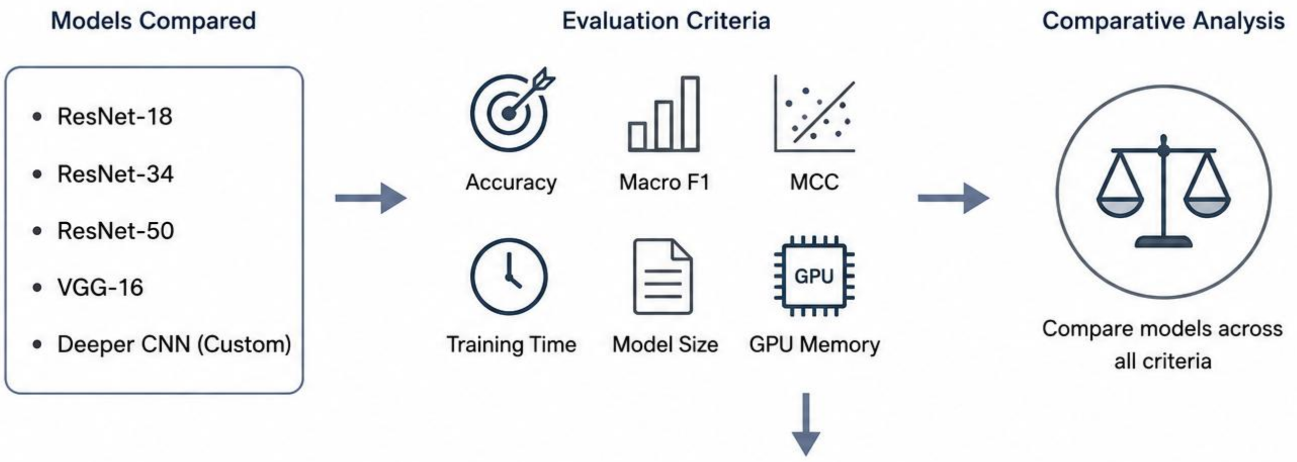
📉 DeeperCNN

Slower convergence and higher variability across seeds

⚖️ ResNet34 / ResNet50 / VGG16

No meaningful accuracy gain over ResNet18 despite greater computational cost

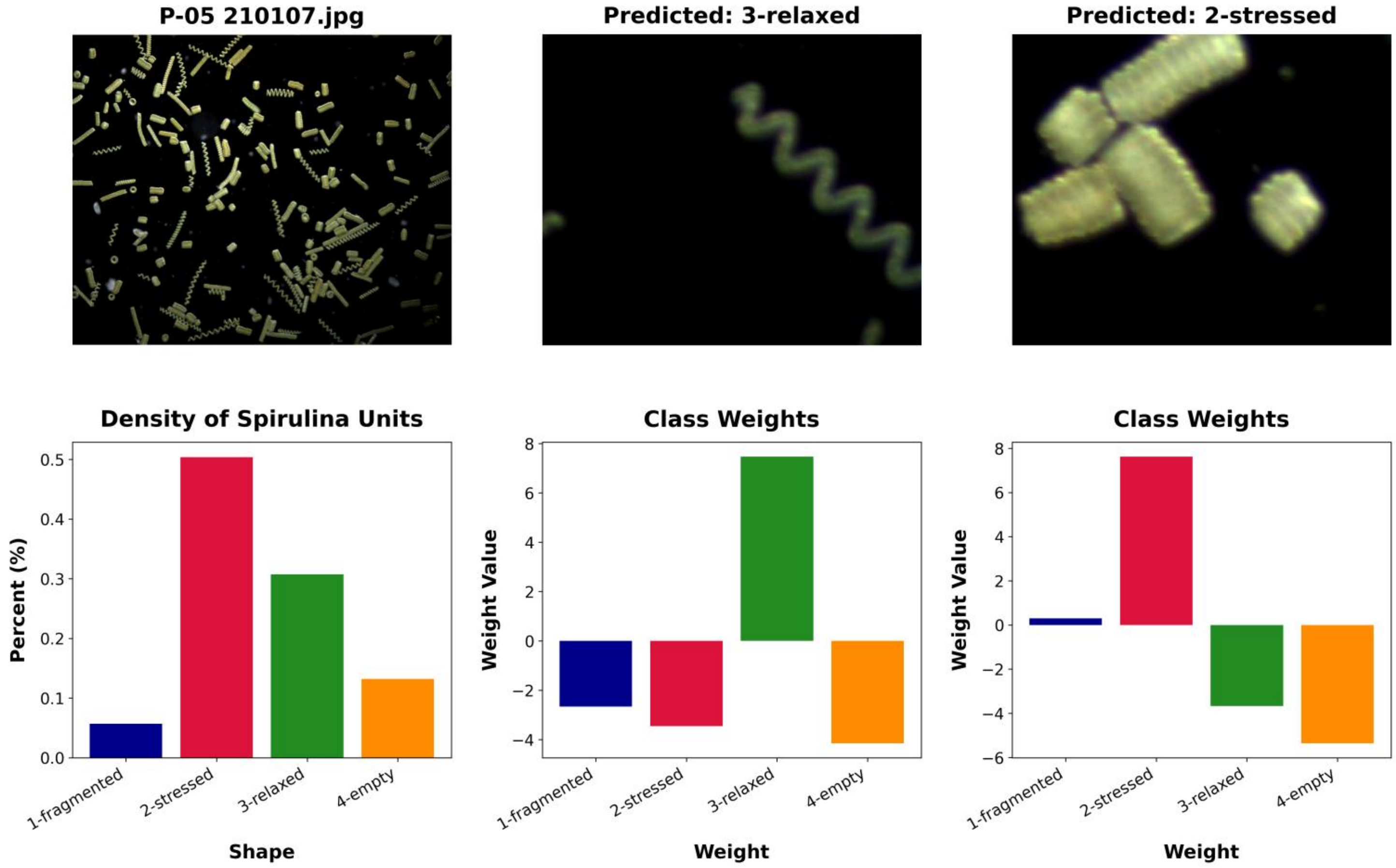
Model Selection for *Spirulina* Image Classification



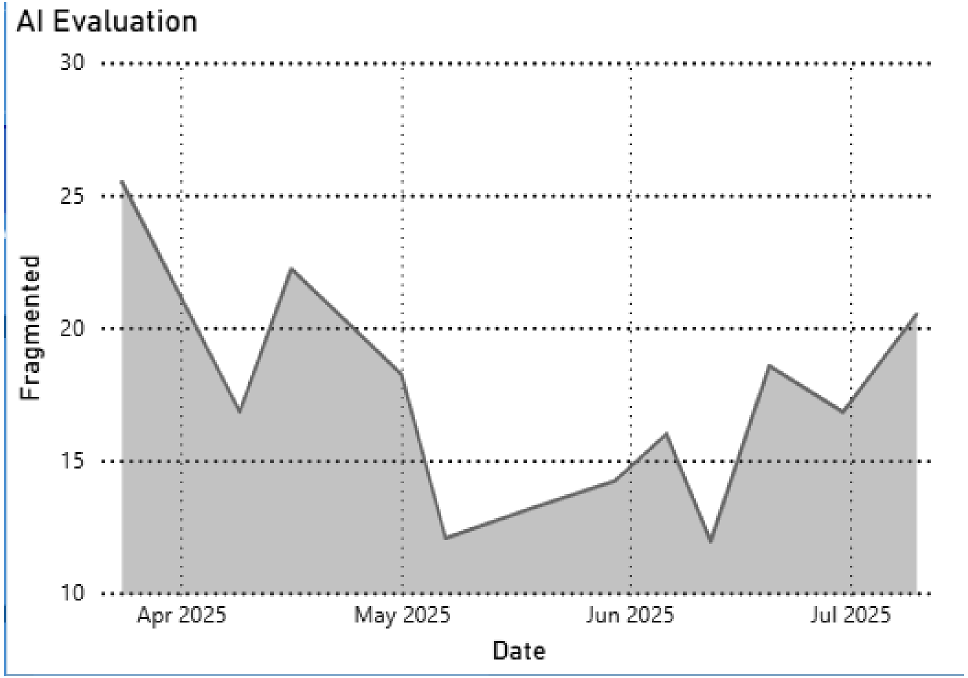
Selected Model

ResNet18 was selected as the optimal architecture based on combined evidence across all criteria.

8. Inference Results



9. From Classification to Pond-Level Monitoring / Future



Quantitative Time-Series Pipeline

AI-derived indicators can be correlated with pH, temperature, nutrients, and productivity for root-cause investigations.

10. Conclusions and Future Directions

Contributions

- Automated four-class morphology classification
- Comparative evaluation: 5 architectures, 5 seeds
- ResNet18 selected as efficient final model
- Complete-image inference and pond-level trend monitoring
- Foundation for AI-assisted root-cause analysis

Challenges

- Limited dataset size
- Manual sample preparation
- Camera and imaging automation constraints

Future Work

- Expand to six morphological classes
- Automate droplet preparation and image acquisition
- Integrate AI indicators with full production data

The framework supports **human-centered, AI-assisted monitoring** for sustainable industrial spirulina production — augmenting, not replacing, expert knowledge.

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Thank you for your attention

Q & A

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