# Pollen's Profiling: Automated Classification of Pollen Grains

## **Team Members:**

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Team Size: 5

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## **Phase 1: Brainstorming & Ideation**

## **Objective:**

Analyze challenges in manually identifying and classifying pollen grains under microscopy. Explore how transfer learning and image classification can automate the identification process for environmental, botanical, and medical applications.

## • Key Points:

#### 1. ProblemStatement:

Manual examination of pollen grains is labor-intensive, subjective, and requires significant expertise. Differences in pollen morphology are subtle and often misclassified by non-experts.

#### 2. **ProposedSolution**:

"Pollen's Profiling" uses deep learning models like VGG16 or MobileNet to classify microscope images of pollen into their respective categories. Transfer learning improves accuracy even on smaller datasets.

#### 3. Target Users:

- Botanists and palynologists
- Environmental monitoring agencies
- Allergy research labs
- Academic and research institutions
- Agricultural and crop research centers

## 4. ExpectedOutcome:

An intelligent application that can classify pollen images quickly and accurately, supporting research, allergy forecasts, and automated laboratory processes.

# **Phase 2: Requirement Analysis**

## Objective:

Define the software, hardware, and functional requirements for the pollen classification system. Consider image clarity, dataset diversity, and classification challenges.

## • Key Points:

## 5. **Technical Requirements:**

- Languages: Python 3.10+
- Frameworks: TensorFlow, Keras
- Tools: Google Colab, Jupyter Notebook, VS Code
- Hardware: GPU (NVIDIA recommended), 16 GB RAM

# 6. Functional Requirements:

- Upload pollen microscope image
- Classify into specific pollen types
- Show prediction confidence
- Display image with label
- Download result/report (Optional)

## 7. Constraints & Challenges:

- Similar morphology among different species
- Varying microscope image quality
- Imbalanced dataset
- Need for transparency in classification output for research acceptance

# **Phase 3: Project Design**

## **Objective:**

Design a modular system with easy input-output handling and high interpretability for research professionals.

## • Key Points:

## 8. System Architecture:

- Input Module → Image Preprocessing

- Classification Module → Transfer Learning
- Output Module → Display prediction & confidence

## 9. **User Flow:**

User uploads image  $\rightarrow$  Preprocessing  $\rightarrow$  Classification  $\rightarrow$  Confidence shown  $\rightarrow$  (Optional: Report Export)

# 10. UI/UX Considerations:

- Minimal interface suitable for lab settings
- Color-coded prediction for clarity
- Mobile and web support
- Clear feedback for low-quality images

# **Phase 4: Project Planning (Agile)**

## Objective:

Follow Agile development with iterative testing, collaboration, and refinement.

# • Key Points:

## 11. Sprint Planning:

- Sprint 0: Literature review & dataset sourcing
- Sprint 1: Data cleaning & augmentation
- Sprint 2: Model training with base CNN
- Sprint 3: UI setup
- Sprint 4: Backend integration
- Sprint 5: Final testing & enhancements

## 12. Task Allocation:

- ML Engineer: Model architecture, training
- Data Engineer: Dataset preparation
- UI Developer: Interface and display
- Backend Developer: Integration logic
- QA Engineer: Accuracy, edge case testing

#### 13. Timeline & Milestones:

- Week 1–2: Dataset finalized
- Week 3-4: Model training completed
- Week 5: Frontend-backend integration
- Week 6: Final validations & testing

# **Phase 5: Implementation**

## **Objective:**

Deploy the model into a working application using a clean tech stack.

# • Key Points:

## 14. Technology Stack:

- Frontend: HTML, CSS, Streamlit

- Backend: Flask API

- Model: Keras with TensorFlow

- Deployment: Google Colab / Heroku / Docker

## 15. **Implementation Steps:**

- 1. Collect data (e.g., Kaggle, microscopy datasets)
- 2. Preprocess & augment images
- 3. Load pre-trained model with custom layers
- 4. Train and validate model
- 5. Save `.h5` model
- 6. Build prediction pipeline
- 7. Display classification results

# 16. Challenges & Fixes:

- Overfitting: Mitigated with data augmentation
- Similar classes: Improved with fine-tuning
- Performance: Used MobileNet for optimized speed

# **Phase 6: Functional & Performance Testing**

## Objective:

Ensure the model works reliably across microscope images, maintains high precision, and serves its intended scientific purpose.

# • Key Points:

## 17. **Tests Performed:**

- Prediction accuracy per class
- Image batch testing
- UI performance and clarity
- Edge testing: blurred or out-of-focus samples
- Device/resource usage

## 18. Results & Fixes:

- Accuracy up to ~90–93% achieved
- UI bugs resolved
- Alerts added for uncertain predictions

## 19. FinalValidation:

Model demonstrated strong generalization. Ready for academic demos or lab pilot testing. Supports reproducible research workflows.

# 20. **Deployment Options:**

- Google Colab (Demo)
- Streamlit + Flask + Heroku (Public tool)
- Docker container (For offline lab use)