Pollen's Profiling: Automated Classification of Pollen Grains

Team Members:

Name 1: Pitchuka Aravin **(Team Lead)**

Name 2**: Patan Sabeer Khan**

Name 3: **Parasa Kavyasree**

Name 4: **Parasa Naga Vijaya Durga**

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.

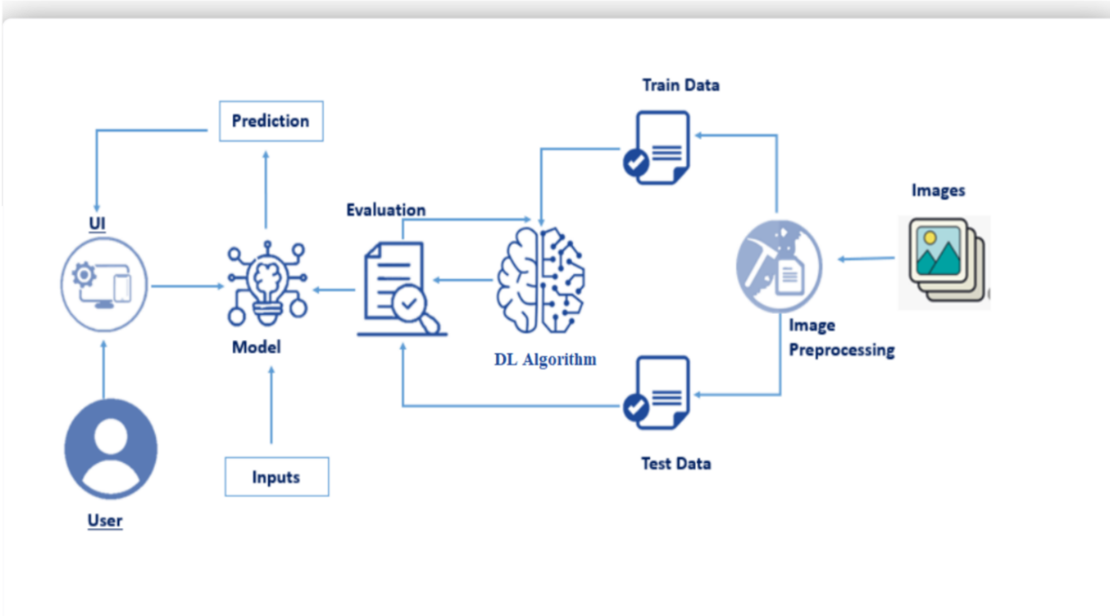
- **Key Points:**

8. **System Architecture:**

   - Input Module → Image Preprocessing

   - Classification Module → Transfer Learning

   - Output Module → Display prediction & confidence



9. **User Flow:**

   User uploads image → Preprocessing → Classification → Confidence shown → (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

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

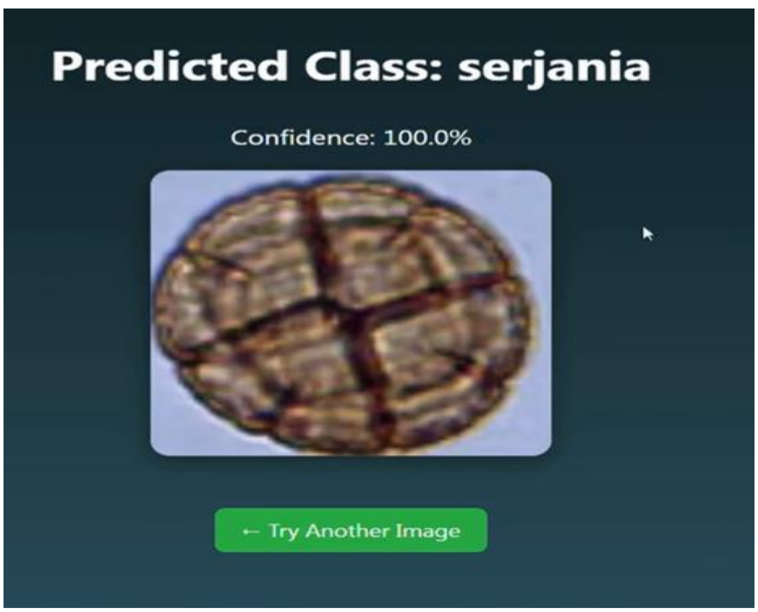
    - UI performance and clarity

    - Edge testing: blurred or out-of-focus samples

    - Device/resource usage

Phase 7: Results

- Accuracy up to ~90 to 93% achieved



- UI bugs resolved

- Alerts added for uncertain predictions

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

Phase 8: Conclusion

Pollens Profiling showcases a powerful fusion of deep learning and biological science, enabling fast, accurate pollen classification that once required expert manual work. The team— Pitchuka Aravin, Patan Sabeer Khan, Parasa Kavyasree, and Parasa Naga Vijaya Durga—navigated phases from ideation to deployment, addressing real-world issues like subtle morphological differences, dataset imbalance, and image quality.

Phase 9: Future Scope

In summary, **Pollens Profiling** not only enhances classification precision but also improves accessibility, allowing experts to redirect their time toward interpretation and strategic insight. With opportunities ahead—such as expanding datasets, boosting transparency, and exploring edge deployment—this project lays a strong groundwork for future innovation in pollen analysis.