INDIAN INSTITUTE OF INFORMATION TECHNOLOGY

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

PROJECT PRESENTATION

on

Plant Leaf Classification and Information Retrieval Using Vision Transformers and Transfer Learning

Submitted by

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Content

Background

- **Significance:** A reliable and efficient system for identifying plant species, especially in agriculture, forestry, and environmental conservation.
- **Manual Challenges:** Manual classification is time-consuming and requires expert knowledge.
- **Limitations of Existing Tools**: Existing tools may not be tailored for specific applications and often provide a broad range of results, which can be overwhelming and inaccurate.
- **Automation Benefits**: Advances in deep learning and computer vision provide faster, more reliable, and scalable plant classification.
- **Real-Time Impact**:Real-time classification, such as improving productivity for farmers and enabling rapid decision-making in critical situations like disease outbreaks in crops.

Literature review

1. Plant Species Identification based on Plant Leaf Using Computer Vision and Machine Learning Techniques[1]

- Their study focuses on automated plant species identification using plant leaf images, employing **Computer Vision** and **machine learning** techniques.
- The system involves four main steps: image acquisition, pre-processing, feature extraction, and classification using **Multiclass-Support Vector Machine (MSVM)**.
- The Swedish Leaf Dataset, containing **1,125 images** of **15 species**, was used, achieving a classification accuracy of **93.26%**.

[1] Kaur, Surleen & Kaur, Prabhpreet. (2019). Plant Species Identification based on Plant Leaf Using Computer Vision and Machine Learning Techniques. Journal of Multimedia Information System. 6. 49-60. 10.33851/JMIS.2019.6.2.49.

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2. Deep Learning for Plant Species Classification[2]

- The paper presents an automated plant species classification system using a **Convolutional Neural Network (CNN)**.
- The model includes multiple layers, such as convolutional layers for extracting detailed features, pooling layers to reduce dimensionality, and fully connected layers for the final classification.
- The process involves **image pre-processing** , **feature extraction** (texture and color), and classification with a CNN implemented using **TensorFlow**.
- The model was trained on a dataset of **17 plant species**, achieving an accuracy of **94.26%**.

[2] Kiran S.Gawli Ashwini S. Gaikwad Mtech 2nd year Student Assistant professor Department Of Computer Science & Engg. Department Of Computer Science & Engg. Deogiri Institute Of Engg.& Management Deogiri Institute Of Engg.& Management Studies, Aurangabad. Studies, Aurangabad.

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3. Alexey Dosovitskiy et al., 2021[3]

- This study explores the application of Vision Transformers (ViTs) for image classification tasks, traditionally dominated by convolutional neural networks (CNNs).
- They treat images as sequences of patches, similar to **NLP tokens**, avoiding CNN biases.
- ViTs can outperform CNNs like **ResNets** when pre-trained on large datasets (e.g., ImageNet-21k and JFT-300M).
- Achieved high accuracy: **88.55%** on **ImageNet** and **94.55%** on **CIFAR-100** with reduced computational effort.

[3] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., and Houlsby, N. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. Journal of Images. viii, 4, 12

Shortcomings

- It uses a dataset of limited number of **plant species**, which restricts the model's ability to generalize effectively across a larger, more diverse range of plants.
- The dataset appears to be captured under controlled conditions, which might not accurately reflect the challenges of real-world environments, like different lighting and backgrounds.
- The research does not focus on real-time classification, which could limit the usability of the system in practical scenarios where immediate results are required.
- It lacks comparison to newer deep learning models, which could provide better performance and robustness.

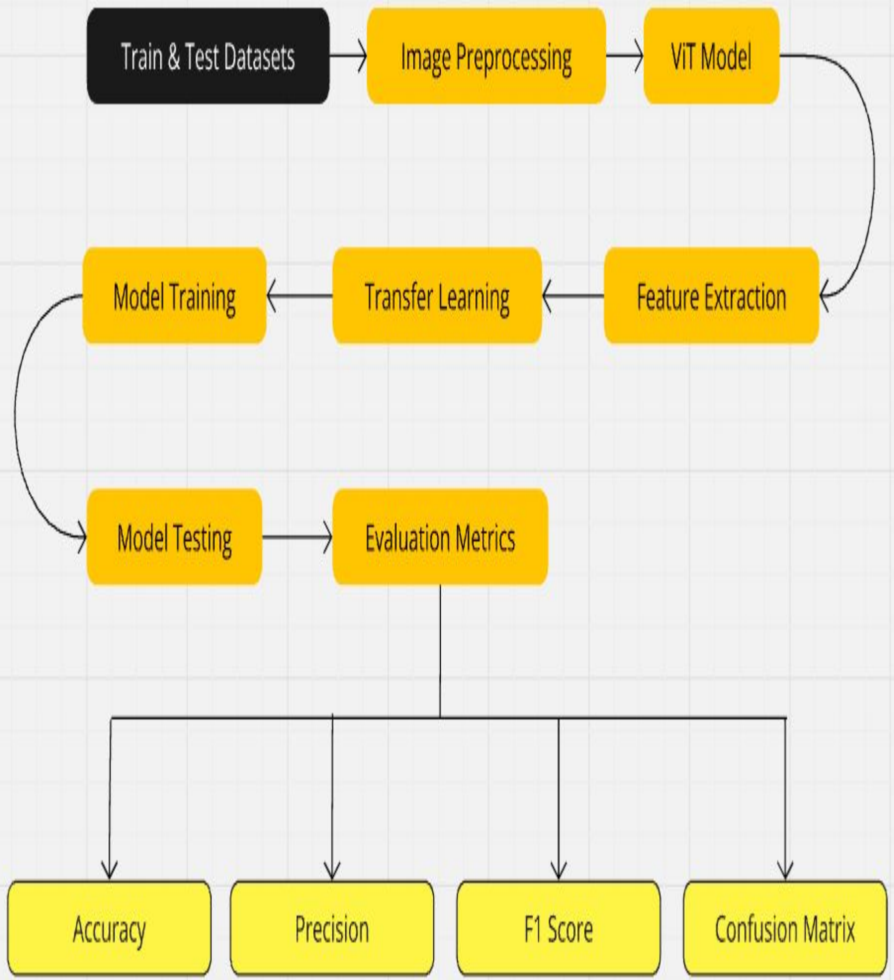
Problem Formulation

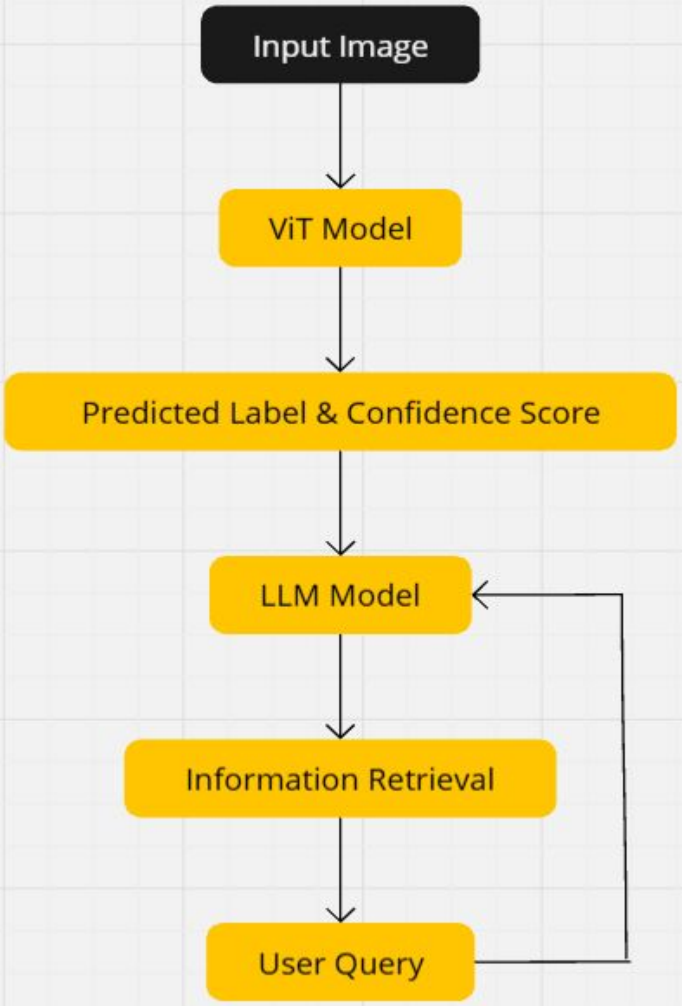
- Current plant leaf classification systems, including CNNs, struggle to capture **global features**, often overfit on limited datasets, and lack adaptability to varying scales, leading to reduced accuracy and practical usability.
- This project develops a real-time plant leaf classification system using **Vision Transformers (ViTs)[3]** and **transfer learning** for accurate species identification.
- ViTs use a **self-attention** mechanism to capture **global image features**, overcoming CNN limitations and improving adaptability across varying scales.
- By leveraging pretraining and transfer learning, ViTs reduce overfitting, allowing the model to achieve high performance with less data.
- An integrated chatbot powered by **Google Gemini Pro AI** enhances user experience by providing instant, detailed information on identified plant species.

Methodology

Building an advanced plant species classification system, integrating deep learning, transfer learning, and AI-driven information retrieval.

- **Model :** Fine-tuned Vision Transformer (ViT) for plant classification using transfer learning.
- **AI-Powered Chatbot:** Google Gemini Pro LLM provides detailed plant insights interactively.
- **Streamlit Interface:** Real-time plant classification via a user-friendly GUI.


Train & Test Datasets
Image Preprocessing
ViT Model
Feature Extraction
Transfer Learning
Model Training
Model Testing
Evaluation Metrics
Accuracy
Precision
F1 Score
Confusion Matrix


Input Image
ViT Model
Predicted Label & Confidence Score
LLM Model
Information Retrieval
User Query

Algorithm

- **Image Preprocessing:** Automate data handling with resizing, normalization, and augmentation (rotations, flips, shifts) for better generalization.
- **Feature Extraction:** Utilize Vision Transformers (ViT) pre-trained on ImageNet by dividing images into patches, removing top layers, and adding a custom classifier for plant species classification.
- **Transfer Learning:** Freeze initial layers of ViT, add a custom classifier (Linear layer (512 units) → ReLU activation → Dropout (0.5) → Output layer (matching number of classes)) and fine-tune final layers on the plant dataset for enhanced accuracy and faster convergence.
- **Model Training:** Employed Adam optimizer (learning rate 0.001), Cross-entropy loss, learning rate scheduler (0.1 reduction every 5 epochs), and early stopping (patience of 3 epochs) to optimize model performance and prevent overfitting.

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- **Model Testing:** The model was evaluated on the test dataset using batch processing to calculate validation loss and accuracy, achieving a final accuracy score based on correct predictions against the total samples.
- **Generative AI Integration:** Utilizes Google Generative AI to provide detailed information on plant leaves, seamlessly integrated with a chatbot powered by Gemini Pro LLM for real-time interaction.
- **Streamlit GUI Integration:** Provides an interactive, web-based interface for users to upload plant leaf images.

TECHNOLOGY SUMMARIZATION

- **Framework:** PyTorch
- **Python Version:** 3.11.5
- **Key Libraries:** torch, torchvision, transformers, scikit-learn, matplotlib, seaborn
- **Generative AI Integration:** langchain-google-genai, langchain[openai,all], langchain-community, sentence-transformers
- **Hardware:** NVIDIA A100 GPUs with CUDA
- **GUI Development:** Streamlit

Results

Model Training Result

```
Epoch 1/20, Training Loss: 2.1874
Validation Loss: 0.9478, Accuracy: 0.8452
Epoch 2/20, Training Loss: 0.8483
Validation Loss: 0.4636, Accuracy: 0.8677
Epoch 3/20, Training Loss: 0.5456
Validation Loss: 0.3156, Accuracy: 0.9403
Epoch 4/20, Training Loss: 0.4128
Validation Loss: 0.2514, Accuracy: 0.9484
Epoch 5/20, Training Loss: 0.3164
Validation Loss: 0.2217, Accuracy: 0.9403
Epoch 6/20, Training Loss: 0.2795
Validation Loss: 0.1996, Accuracy: 0.9597
Epoch 7/20, Training Loss: 0.2570
Validation Loss: 0.1911, Accuracy: 0.9532
Epoch 8/20, Training Loss: 0.2506
Validation Loss: 0.1873, Accuracy: 0.9581
Epoch 9/20, Training Loss: 0.2501
Validation Loss: 0.1845, Accuracy: 0.9597
Epoch 10/20, Training Loss: 0.2447
Validation Loss: 0.1826, Accuracy: 0.9581
Epoch 11/20, Training Loss: 0.2372
Validation Loss: 0.1783, Accuracy: 0.9597
Epoch 12/20, Training Loss: 0.2412
Validation Loss: 0.1798, Accuracy: 0.9597
Epoch 13/20, Training Loss: 0.2375
Validation Loss: 0.1775, Accuracy: 0.9597
Epoch 14/20, Training Loss: 0.2353
Validation Loss: 0.1796, Accuracy: 0.9597
Epoch 15/20, Training Loss: 0.2330
Validation Loss: 0.1806, Accuracy: 0.9597
Epoch 16/20, Training Loss: 0.2372
Validation Loss: 0.1768, Accuracy: 0.9597
Epoch 17/20, Training Loss: 0.2330
Validation Loss: 0.1780, Accuracy: 0.9597
Epoch 18/20, Training Loss: 0.2379
Validation Loss: 0.1785, Accuracy: 0.9597
Epoch 19/20, Training Loss: 0.2311
Validation Loss: 0.1768, Accuracy: 0.9597
Early stopping triggered.
```

```
Precision: 0.96, Recall: 0.96, F1 Score: 0.96
```

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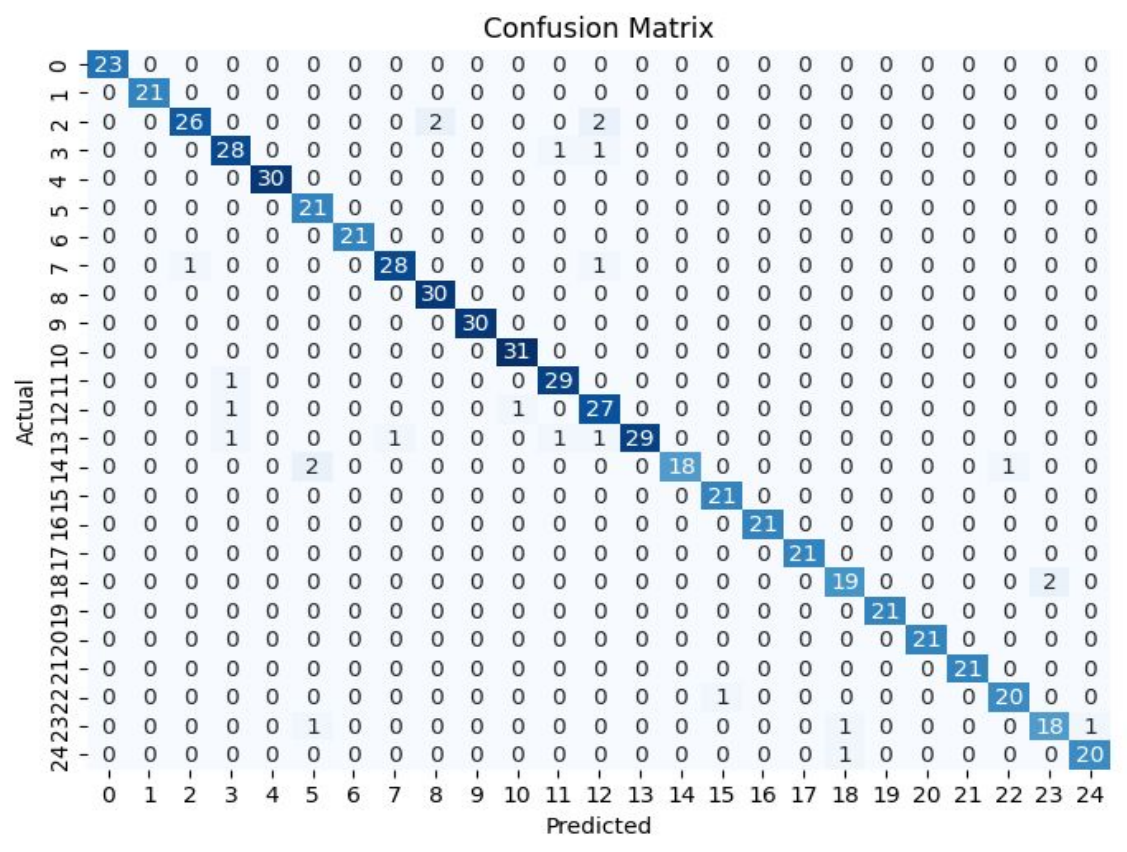

Conclusion

The model trained on a dataset of **25 classes** with a total of **1,875 images**, achieved a high accuracy of **95.97%**, with precision, recall, and F1-score each at **0.96**, demonstrating the effectiveness of **Vision Transformers and transfer learning** in automating plant leaf classification. This significantly reduces manual effort in species identification.

Additionally, integrating a chatbot powered by Google Generative AI (Gemini Pro) enriches user interaction by delivering real-time, informative insights about identified plant species, enhancing both accessibility and engagement.

Future Works

- **Multilingual Support:** Implementing multiple language options in both the classification model and chatbot to broaden accessibility, especially in regions critical to plant conservation and research.
- **Disease Detection:** Expanding the model to identify plant diseases from leaf symptoms, enabling early intervention in agriculture and aiding conservation efforts.

References and Links :

[1] Kaur, Surleen & Kaur, Prabhpreet. (2019). Plant Species Identification based on Plant Leaf Using Computer Vision and Machine Learning Techniques. Journal of Multimedia Information System. 6. 49-60. 10.33851/JMIS.2019.6.2.49.

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[3] Dosovitskiy, A., Beyer, L., Kolesnikov, A., Weissenborn, D., Zhai, X., Unterthiner, T., Dehghani, M., Minderer, M., Heigold, G., Gelly, S., Uszkoreit, J., and Houlsby, N. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. Journal of Images. viii, 4, 12

THANK YOU