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Topic of Research: **Melioration of Plant Science and Agriculture using Deep Learning**

FINDINGS

This thesis systematically examines the challenges associated with the application of deep learning and computer vision to real-world agricultural problems. These challenges include efficient plant identification, sustainable crop protection through the detection of diseases, pests, and weeds, and soil health assessment via Soil Organic Carbon (SOC) prediction. The findings indicate that models designed and validated using data from real-world settings can simultaneously achieve high accuracy, interpretability, and computational efficiency, and demonstrate significant generalization across diverse agricultural domains.

The first finding was facilitated by the development of the **REMEDS** dataset, a comprehensive repository comprising over 8,000 annotated images of 15 medicinal plant species captured under varied real-world field conditions. In contrast to previous collections that depended on laboratory environments or artificial backgrounds, REMEDS was specifically designed to capture natural intra-class similarities and inter-class diversity. Utilizing this dataset, the proposed **VitNas** architecture, which integrates Vision Transformer (ViT-B32) and NasNet Large representations, achieved an accuracy, precision, and recall rate of 99%, setting a new standard for the identification of medicinal plants in the real world. Furthermore, the incorporation of a Large Language Model layer for retrieving medicinal properties illustrated how classification outputs can be transformed into actionable, context-aware feedback for end users.

For plant disease detection, an explainable image classification framework built on a **Swin Transformer backbone** was validated on a real-world Robusta coffee leaf dataset (RoCoLe). A staged fine-tuning strategy combined with label smoothing, AdamW optimization, and Cosine AnnealingLR scheduling enabled the model to achieve a classification accuracy of 93.25 %. High-resolution Grad-CAM overlays generated from an advanced Swin stage further produced visually significant saliency maps that accurately localized leaf lesions, enhancing transparency and supporting agronomist trust under uncontrolled real-world imaging conditions.

For pest detection, **an ensemble learning** approach combining VGG16, VGG19, and ResNet50 through a voting classifier was validated on the large-scale IP102 dataset, which comprised over 75,000 images across 102 pest categories. The findings show that this ensemble effectively addressed class imbalance and subtle interspecies differences, achieving an accuracy of 82.5%, the highest among the tested approaches, and surpassing both classical machine learning methods and contemporary single-model deep learning benchmarks.

For weed detection in UAV-based precision agriculture, a **knowledge distillation** framework using DeepLabV3+ with a SeNet154 encoder as the teacher model and a lightweight student network was designed for real-time deployment on UAV platforms. Evaluated on the extensively annotated WeedsGalore multi-band dataset, the distilled system achieved a mean Intersection over Union (mIoU) of 71.24%, substantially surpassing the previous benchmark of 50.81%, confirming its suitability for real-time weed mapping and precision herbicide application.

Finally, for soil health analysis, the model architecture operated through a sequence of preprocessing steps focused on feature engineering, and a dense encoder-decoder with a contractive penalty (CAE) was used to develop a robust feature representation using a custom loss function. The **CAE-LSTM** stack yielded lower RMSE and greater predictive stability across large, heterogeneous spatial domains, further statistical analysis on PowerBi dashboard was also implemented

These findings collectively underscore the significance of deep learning systems that incorporate real-world dataset design, attention-driven interpretability, ensemble- and distillation-based efficiency, and multimodal potential within robust and generalizable architectures in practical settings. The proposed frameworks effectively address challenges such as heterogeneous field conditions, limited computational resources, and the need for transparent and actionable decision-making. This work establishes a solid foundation for the deployment of interpretable AI systems capable of supporting efficient plant identification, sustainable crop protection, and soil health management across diverse agricultural fields in real world settings