Abstract:

Crop pests and diseases significantly impact agricultural productivity and food security, necessitating efficient detection and management methods. Traditional identification techniques, which are often manual and time-intensive, are prone to inaccuracies, highlighting the need for automated solutions. This study introduces a method that combines the Kolmogorov-Arnold Network (KAN) with DenseNet201 and other convolutional neural networks (CNNs) for crop pest and disease classification. Our investigation reveals that the combination of KAN with DenseNet201 achieves the highest classification accuracy among all tested architectures, demonstrating superior performance in both feature extraction and generalization. Additionally, the inclusion of a KAN Linear layer enhances the model's ability to capture complex patterns in diverse datasets. Comprehensive evaluations using metrics such as accuracy, precision, recall, and F1 score confirm the effectiveness of our approach. These findings underscore the potential of KAN-enhanced deep learning frameworks to provide scalable and efficient solutions for automated pest and disease monitoring systems, significantly reducing dependency on manual methods while improving agricultural decision-making.

1. Introduction:

Pests and diseases pose a significant challenge to agriculture, leading to substantial crop losses and threatening global food security. These threats not only reduce crop yield and quality but also increase costs for farmers due to the need for pest control and recovery from crop damage. Traditional identification methods, such as manual inspection and instrument-based detection, are often labor-intensive, time-consuming, and prone to human error, which can result in delayed responses and ineffective interventions. The growing scale of modern agriculture, coupled with the increasing variability of pest populations due to climate change, has made the need for automated, accurate, and efficient pest and disease detection systems more urgent than ever [1][2].

Deep learning, particularly through convolutional neural networks (CNNs), has emerged as a powerful tool for tackling image-based classification tasks, including crop pest and disease identification. Pretrained CNN models, trained on large datasets and then fine-tuned for specific tasks, offer significant advantages by leveraging transfer learning. This approach reduces the computational resources and time required for training while improving model performance on specialized datasets [3].

In this study, we fine-tuned several state-of-the-art pretrained CNN architectures, including DenseNet201, ResNet18, MobileNetV3Large, ResNet34, and VGG19, for the task of crop pest and disease classification. These models were selected for their diverse architectures, offering varying strengths in feature extraction, computational efficiency, and scalability. These models were trained and evaluated using the CCMT: Dataset for Crop Pest and Disease Detection, which consists of high-quality images categorized into multiple pest and disease classes. The dataset includes diverse images capturing variations in lighting, angles, and environmental conditions, ensuring robust model performance. Performance metrics such as accuracy, F1 score, recall, and precision were used to assess their effectiveness in both training and testing phases [4].

Furthermore, we explore the integration of the Kolmogorov-Arnold Network (KAN) Linear layer with CNN architectures to enhance their feature extraction capabilities and improve the ability to capture intricate, non-linear patterns in data. KAN offers a novel approach that complements existing models, enabling more accurate classification when applied in targeted scenarios. While DenseNet201 and other CNN architectures serve as strong baselines for pest and disease classification, the incorporation of KAN is strategically applied to address specific challenges where traditional models may fall short.

The fine-tuning of pretrained models, combined with the selective use of KAN, highlights the critical role of advanced machine learning techniques in overcoming the limitations of traditional methods. By improving the speed and accuracy of pest and disease classification, these advancements have the potential to transform agricultural practices, reduce crop losses, and contribute to the resilience and sustainability of global food systems [5][6][7].

2. Problem Statement:

Crop pests and diseases pose a significant threat to agricultural productivity, resulting in substantial crop losses and economic burdens for farmers. Traditional methods for detecting pests and diseases, such as manual inspection and instrument-based detection, are often:

- Time-consuming: The process of manual observation across large agricultural fields requires considerable effort and time.
- Labor-intensive: Skilled labor is needed to accurately identify various pest and disease types, increasing operational costs.
- Error-prone: Human error in identification can lead to delayed interventions and improper pest control measures.

These limitations become more severe in the context of modern agriculture, which operates on a large scale and faces increasing challenges due to the unpredictable effects of climate change on pest populations. This creates an urgent need for automated, efficient, and accurate pest and disease detection systems to support timely decision-making.

This project seeks to address these challenges by leveraging advanced deep learning techniques, particularly through fine-tuning pretrained Convolutional Neural Networks (CNNs) and integrating the Kolmogorov-Arnold Network (KAN) Linear layer. The goal is to develop a robust system capable of accurately classifying various crop pests and diseases, enabling early detection and effective management in real-world agricultural environments.

Proposed Solution

- **Integration of Deep Learning Models:**
- Utilize pretrained CNN architectures such as DenseNet201, ResNet18, and MobileNetV3 Large to enhance feature extraction and classification accuracy.
- Fine-tune these models on a comprehensive agricultural dataset to optimize performance for crop pest and disease detection.
- **Incorporation of KAN:**
- Integrate the Kolmogorov-Arnold Network (KAN) to improve their ability to capture complex, non-linear patterns in pest and disease images. Enhance the generalization capabilities of the models for diverse and dynamic agricultural conditions.

- Comprehensive Dataset Utilization:
- Use the CCMT dataset, containing high-quality, annotated images of various pests and diseases across multiple crops.
- Resizing the images.
- **Evaluation Using Key Metrics:**
- Assess model performance with metrics such as accuracy, precision, recall, F1 score, and confusion matrix analysis.
- Compare different CNN architectures to determine the most effective model for the classification task.
- **Development of an Automated System:**
- Design a scalable and efficient solution for real-world agricultural applications, capable of early detection and intervention.
- Reduce dependency on manual inspection and traditional methods, improving response times and decision-making in pest management.
- **Potential for Real-Time Application:**
- Adapt the system for deployment on mobile or embedded devices, enabling real-time pest and disease monitoring in the field.
- Ensure low computational cost and high accuracy for practical usage by farmers and agricultural organizations.

3. Literature Survey:

Crop pest disease classification has witnessed significant progress with the integration of deep learning methods, addressing limitations inherent in traditional manual inspection and classical machine learning approaches, which often depended on hand-crafted feature extraction. These conventional techniques were limited in their ability to scale and adapt to large, diverse datasets. The emergence of Convolutional Neural Networks (CNNs) has revolutionized the field by enabling automated feature learning and improving the accuracy and efficiency of pest disease identification systems [8].

Among the popular pretrained deep learning models, DenseNet201 has shown remarkable performance due to its dense connectivity, where each layer is directly connected to every other layer in a feed-forward fashion. This architecture improves feature reuse and gradient flow, resulting in enhanced classification performance, especially on complex image datasets [9]. Similarly, ResNet18 leverages residual connections, which help train deeper networks by resolving the vanishing gradient problem. It effectively captures complex patterns in crop images, making it a strong candidate for identifying various crop pest diseases [10]. MobileNetV3-Large, known for its efficiency, employs depth wise separable convolutions, significantly reducing the model's computational requirements, making it well-suited for real-time applications, particularly on mobile and resource-limited devices [11].

The dataset used for crop pest disease classification in this study consisted of a comprehensive collection of 102,976 RGB images across 22 classes, including both healthy and pest-damaged crops. The images were sourced from the CCMT dataset, which offers a diverse and well-annotated collection of pest-affected crop images, facilitating robust model training and evaluation. To ensure consistency, input images were resized to a standard resolution of 224x224 pixels. Data augmentation techniques, such as rotation, flipping, and scaling, were applied to enhance model generalization and mitigate overfitting. This preprocessing strategy proved essential in improving the model's robustness and accuracy.[12]

4. Dataset Description:

The dataset used in this study is **CCMT: Dataset for crop pest and disease detection** which is a publicly available dataset and is an extensive collection tailored for multi-class classification, detection, and recognition tasks in crop pest and disease detection. This dataset consists of a total of 24,881 raw images and 102,976 augmented images, all captured in high resolution, with dimensions ranging from 400×400 to 4032×3024 pixels. The diversity of resolutions provides a realistic representation of varied field conditions and allows flexibility in model training and optimization. It is divided across four primary crop categories—Cashew, Cassava, Maize, and Tomato—each further divided into several subcategories representing unique pest and disease conditions relevant to each crop. For instance, the Cashew category includes classes such as Anthracnose, Gummosis, Healthy, Leaf miner, and Red rust, while the Maize category contains classes like Fall armyworm, Grasshopper, and Streak virus, among others. This multi-level categorization helps in building a comprehensive dataset that mirrors real agricultural challenges in pest and disease detection across crops.[12]

In our work, we exclusively used the augmented images due to their enriched variability, which supports robust model generalization. To prepare this dataset for deep learning classification, we combined all classes into two folders for training and testing purposes. Subsequently, the training folder was split into a new training set and validation set as shown in fig.1, ensuring an optimal balance between model training and validation while preserving a representative sample of each pest and disease class. This structure provides our model with a rich variety of labelled examples across all classes, allowing it to effectively learn to identify and distinguish between numerous pest and disease conditions across different crops. The augmented dataset, through its structured organization and high volume, aims to enhance the model's classification accuracy by capturing subtle visual patterns indicative of specific pest and disease conditions. The images taken from the dataset are shown in fig.2.

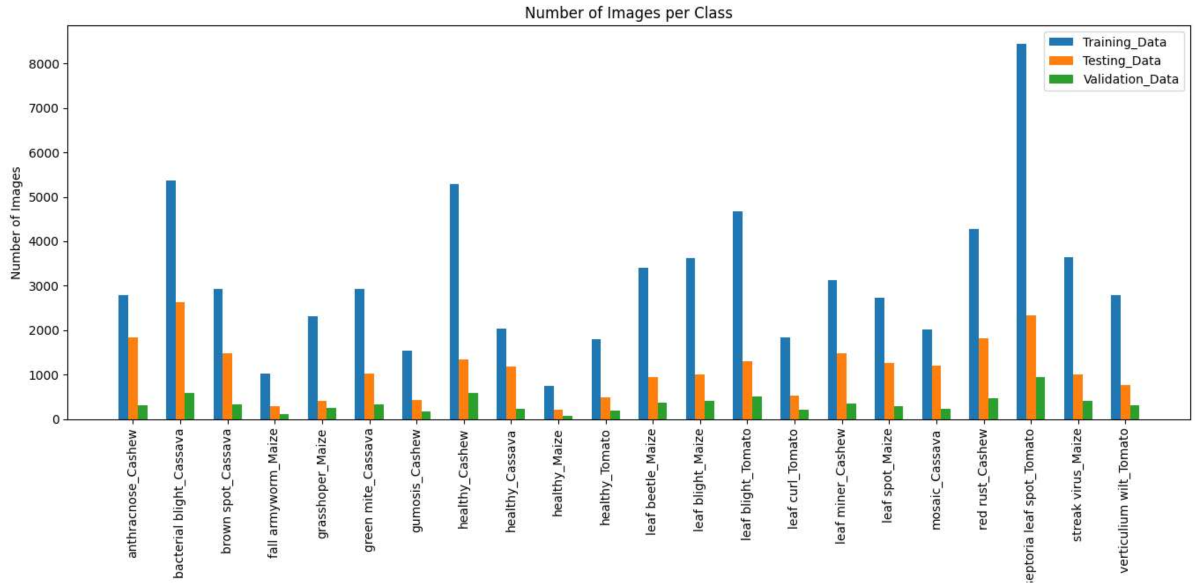


Fig.1 Augmented Dataset Description

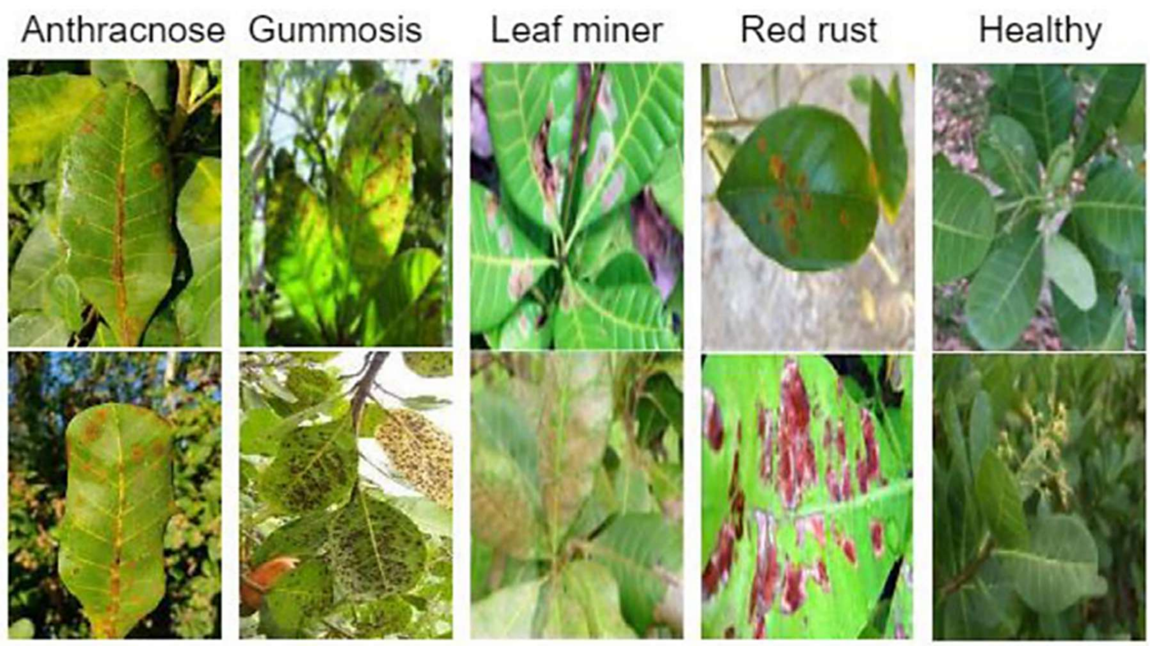


Fig.2 Images from the CCMT Dataset

5. Methodology:

The methodology for this project involved several key steps, including data preparation, model selection, training, and evaluation. Each step was carefully designed to ensure that the models generalized well and were capable of accurately classifying crop pest diseases. We employed a range of advanced pre-trained deep learning models, each with distinct architectural features and strengths. These models, trained on large-scale image datasets like ImageNet, provide robust feature extraction capabilities that are crucial for accurate classification in complex scenarios, such as crop pest disease identification.

1. **DenseNet201** is part of the DenseNet family, characterized by densely connected layers where each layer is directly connected to every other subsequent layer. This unique architecture allows for efficient feature reuse, as feature maps from all preceding layers are used as inputs for each subsequent layer. The design reduces the number of parameters, alleviates the vanishing gradient problem, and enhances the propagation of features across the network. DenseNet201's ability to learn rich representations from complex data makes it a strong candidate for image classification tasks involving intricate patterns and textures [9].

2. **ResNet18** is a lightweight model from the ResNet family, known for introducing the concept of residual connections. These residual (or skip) connections help mitigate the vanishing gradient problem by allowing the network to learn identity mappings, thus making the training of deeper models more stable and efficient. ResNet18 consists of 18 convolutional layers, structured with a series of residual blocks. The model is effective at capturing hierarchical features from input images, making it a preferred choice for applications requiring a balance between depth and computational efficiency [10].

3. **MobileNetV3 Large** is an efficient and compact model designed for mobile and embedded applications, focusing on low latency and reduced computational cost. It employs depthwise separable convolutions, which separate spatial and depthwise operations to minimize the number of parameters. Additionally, the use of squeeze-and-excitation modules helps recalibrate channel-wise feature responses, enhancing the model's capacity to capture important features. The lightweight design of MobileNetV3

Large makes it well-suited for real-time applications without sacrificing accuracy [11].

4. **ResNet34** builds upon the ResNet architecture, featuring 34 layers with deeper residual blocks. This additional depth enables ResNet34 to capture more detailed features from input images. The residual connections in ResNet34 further enhance the training process, making it capable of learning complex representations effectively. The model's deeper architecture and efficient training strategy make it suitable for datasets with a high level of feature complexity, such as crop pest disease images [13].

5. **VGG19** is part of the Visual Geometry Group (VGG) network family and is known for its deep architecture with 19 layers. The network uses a simple and uniform design, consisting of sequential convolutional layers followed by max-pooling layers. Despite its straightforward architecture, VGG19 is effective at capturing intricate image features due to its depth. However, the model's large number of parameters makes it computationally intensive. Nevertheless, VGG19 remains a popular choice in image classification tasks for its strong performance and ability to learn fine-grained features [14].

These pre-trained models were chosen based on their proven capabilities in handling diverse and complex datasets. By leveraging their feature extraction strengths, we aimed to enhance the classification accuracy of our crop pest disease identification system.

In this work, we modified the standard DenseNet201 architecture by removing its fully connected (FC) layer and replacing it with the **Kolmogorov-Arnold Network (KAN) Linear layer**. DenseNet201's original design employs densely connected convolutional layers that facilitate efficient feature reuse and improved gradient flow. However, the traditional FC layer at the end of the network can sometimes limit the model's ability to capture complex, non-linear relationships in the feature space. To overcome this, we introduced the KAN Linear layer, which is capable of learning non-linear mappings and enhances the model's ability to capture intricate patterns in the data. This integration improves DenseNet201's generalization capabilities, making it better suited for the diverse and complex nature of crop pest and disease classification tasks while preserving the network's efficiency.

6. Kolmogorov Arnold Network:

The **Kolmogorov-Arnold Network (KAN)** is an innovative neural network architecture based on the **Kolmogorov-Arnold Representation Theorem**, which asserts that any continuous multivariate function can be expressed as a combination of univariate functions. Unlike conventional neural networks that rely on fixed, non-adaptive activation functions, KANs utilize learnable univariate functions for approximation. The theorem specifies that any function f:[0,1]n→R can be represented as:

$$f(x) = \sum_{q=1}^{2n+1} \Phi_q \left(\sum_{p=1}^{n} \phi_{q,p} \left(x_p\right) \right)$$

Where $\phi_{q,p}$ and Φ_q are univariate functions. This unique formulation allows KANs to decompose complex functions into simpler, composable parts, thereby facilitating better generalization and function approximation [15].

KANs introduce the use of **B-splines** as activation functions, replacing traditional neural network weights with learnable spline parameters. The integration of B-splines offers dynamic and adaptable activation functions, enabling KANs to effectively capture complex, non-linear patterns within data. Unlike typical neural networks that employ fixed activation functions like ReLU or Sigmoid at the nodes, KANs feature **learnable activation functions on the edges**, enhancing their capacity to model intricate data distributions. This setup allows KANs to approximate functions with higher precision, making them suitable for applications requiring fine-grained pattern recognition [16].

The architecture of KANs, characterized by layers composed of matrices of univariate functions, is advantageous for modelling tasks with compositional structures. The learnable spline functions allow the network to dynamically adjust activation shapes during training, providing greater flexibility and interpretability. KANs have demonstrated superior performance compared to traditional Multi-Layer Perceptron's (MLPs) due to their ability to model complex functional dependencies. In scientific applications, KANs have been effectively employed for tasks like solving partial differential equations and discovering mathematical laws, highlighting their utility in scenarios that require accurate function approximation [15][16].

KANs have also made notable strides in computer vision tasks. The **KAN-Mixer** architecture, an adaptation for image processing, has shown competitive results on benchmark datasets like MNIST, CIFAR-10, and CIFAR-100. By processing non-overlapping image patches and employing both channel and token mixing, KAN-Mixer maintains spatial resolution while capturing dependencies across spatial and channel dimensions. This architecture has outperformed traditional MLP-Mixer models in certain settings, demonstrating the potential of KANs in capturing structured representations required for complex vision tasks [17].

The flexibility of KANs in using learnable, data-driven activation functions, combined with their theoretical foundation, positions them as a powerful alternative for modelling non-linear functions. Their effectiveness in vision tasks and scientific computing highlights their versatility and robustness, making them a promising approach for applications like crop pest disease classification, where capturing detailed and intricate data patterns is crucial.

7. Experimental Implementation

Hardware Requirements

To ensure optimal performance and efficient execution of the project, the following hardware components are required:

- **Processor:** Intel Core i5 (12th Gen) or higher, with a clock speed of 2.5 GHz or more.
- **GPU:** NVIDIA RTX A4000 with 16 GB VRAM for accelerated deep learning model training and evaluation.
- **RAM:** Minimum of 32 GB to handle large datasets and ensure smooth model training.
- **Storage:** At least 1 TB SSD for storing datasets, model checkpoints, and results.
- **Display:** High-resolution monitor for visualizing dataset samples and model outputs.
- **Additional Peripherals:** Keyboard, mouse, and high-speed internet for research and software installation.

Software Requirements

The project relies on a range of software tools and frameworks for development, training, and evaluation:

- **Operating System:** Windows 10/11 or Ubuntu 20.04 LTS (64-bit) for compatibility with deep learning frameworks.
- **Programming Language:** Python 3.8 or higher.
- **Development Environment:**
  - Jupyter Notebook or Visual Studio Code for code development and debugging.

- **Deep Learning Framework:**
  - PyTorch 2.0 or higher for implementing and fine-tuning CNN models and integrating the KAN.
- **Additional Python Libraries:**
  - NumPy, Pandas, and Matplotlib for data manipulation and visualization.
  - Scikit-learn for performance evaluation metrics.
- **Hardware Drivers:** Latest NVIDIA drivers and CUDA Toolkit for GPU support.

8. Results:

In our experiments, we fine-tuned several pretrained models and experimented DenseNet201 with KAN layer on the **CCMT: Dataset for Crop Pest and Disease Detection** to assess their performance in pest and disease classification. The models tested included **DenseNet201 with KAN**, **DenseNet201, ResNet18**, **MobileNetV3Large**, **ResNet34**, and **VGG19**. Below are the testing accuracies for each model:

- **DenseNet201 with KAN:** Testing Accuracy: **94.85%**
- **DenseNet201**: Testing Accuracy: **94.64%**
- **ResNet18**: Testing Accuracy: **94.45%**
- **MobileNetV3Large**: Testing Accuracy: **94.38%**
- **ResNet34**: Testing Accuracy: **92.89%**
- **VGG19**: Testing Accuracy: **86.85%**

DenseNet201 integrated with the KANLinear layer achieved the highest testing accuracy of 94.85%, as well as the highest validation accuracy, as shown in Figure-3. Its superior performance is attributed to the combination of DenseNet201's densely connected layers and the KANLinear layer's ability to enhance feature representation. The dense connections in DenseNet201 facilitate efficient feature learning and reuse across layers, while the KANLinear layer adds the capability to model complex non-linear relationships, further boosting the model's precision and recall. This synergy enables the model to effectively capture intricate patterns in crop pest and disease images, making it the best-performing model in our experiments.

These results demonstrate that newer, advanced architectures like DenseNet201, when integrated with innovative layers such as the KANLinear layer, outperform traditional models like VGG19 in both classification accuracy and feature extraction. The performance differences are rooted in architectural efficiency, with DenseNet201's dense connections and the KANLinear layer's enhanced feature extraction working together for superior accuracy. Ongoing efforts involve further optimizing the integration of the KANLinear layer into state-of-the-art architectures to continue improving classification accuracy and robustness.

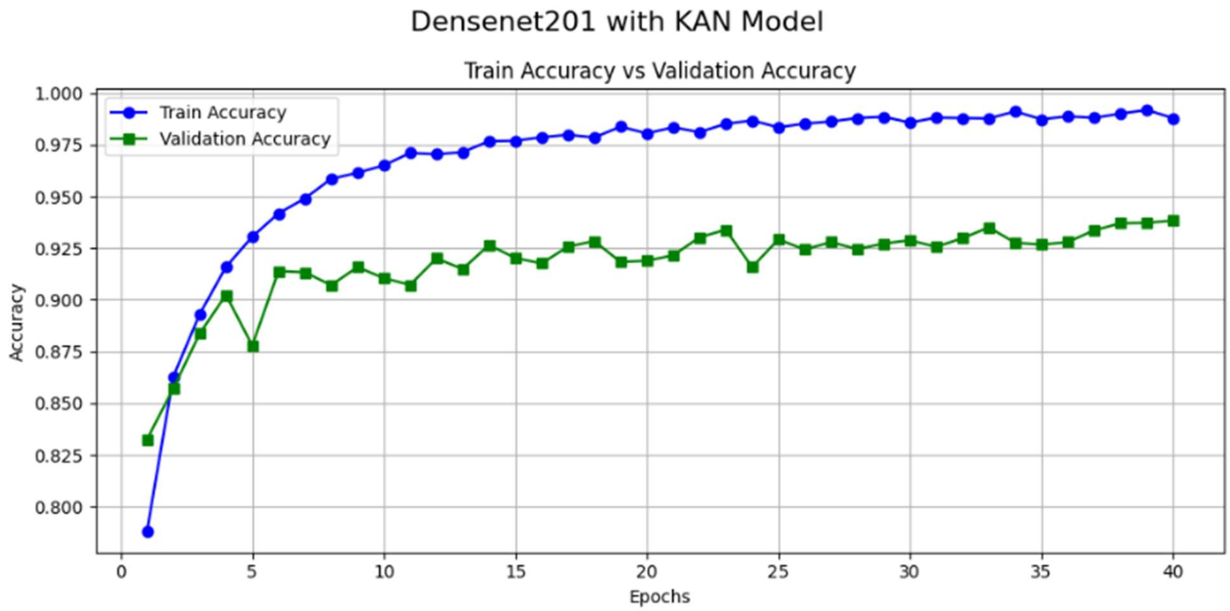


Fig.3 Validation Graphs

The confusion matrix for DenseNet201+KAN, as shown in Figure-4, highlights strong performance for classes such as *healthy_Cassava*, *leaf blight_Maize*, and *green mite_Cassava*, where true positive counts dominate. For instance, *healthy_Cassava* achieved 1149 correct predictions, and *leaf blight_Maize* attained 967 true positives. These results showcase the model's ability to accurately identify distinct and well-represented classes.

However, misclassifications are observed in visually similar categories, such as *anthracnose_Cashew* misclassified as *bacterial blight_Cashew* and *red rust_Cashew*. Similarly, there are notable confusions between *leaf blight_Maize* and *leaf spot_Maize*, which may stem from shared visual features or class overlap. Classes such as *streak virus_Maize* and *verticillium wilt_Tomato* exhibit higher misclassification rates, indicating challenges in distinguishing subtle disease patterns or addressing underrepresented classes.

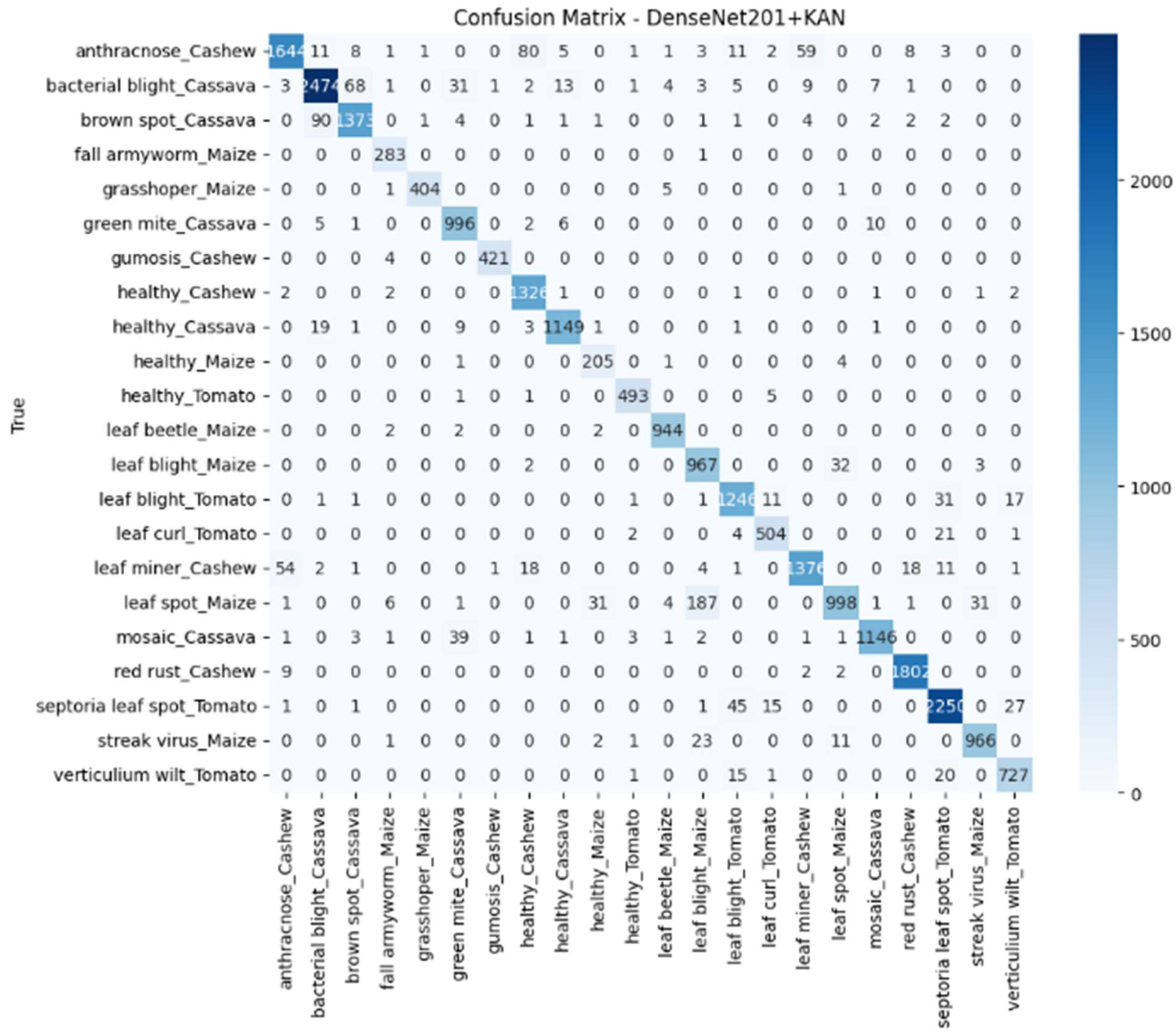


Fig.4 Confusion Matrix

We have also conducted a comprehensive evaluation of various Convolutional Neural Network (CNN) architectures to benchmark their performance on the crop pest and disease classification task. The models included in our analysis were DenseNet201 with KAN, DenseNet201, MobileNetV3Large, ResNet18, ResNet34, VGG19, and a Custom CNN model. Each model was trained using an input image of size 224*224 pixels. The training duration varied, with some models trained for up to 40 epochs, while others were stopped earlier based on early stopping criteria to prevent overfitting. Among the evaluated models, VGG19 demonstrated the lowest classification accuracy at 86.85%, whereas

DenseNet201+KAN achieved the highest accuracy of 94.85%. This result highlights the effectiveness of integrating the KANLinear layer into DenseNet201, which enhances its ability to capture complex features through efficient feature extraction.

While other high-performing models like DenseNet201, MobileNetV3Large, and ResNet18 achieved notable accuracies, they were still outperformed by DenseNet201 with KAN. The integration of KAN played a crucial role in improving the model's feature learning capabilities, enabling it to deliver superior results. The overall performance comparison is detailed in Table-1, showcasing the robustness of DenseNet201 with KAN in achieving state-of-the-art classification accuracy.

Model Name	Image Size	Epochs	Testing Accuracy
DenseNet201 with KAN	224*224	40	0.9485
DenseNet201	224*224	40	0.9464
Resnet18	224*224	20	0.9445
MobileNetV3Large	224*224	40	0.9438
Resnet34	224*224	40	0.9289
VGG19	224*224	40	0.8685

Table-1 Performance Comparison of CNN models with the proposed model

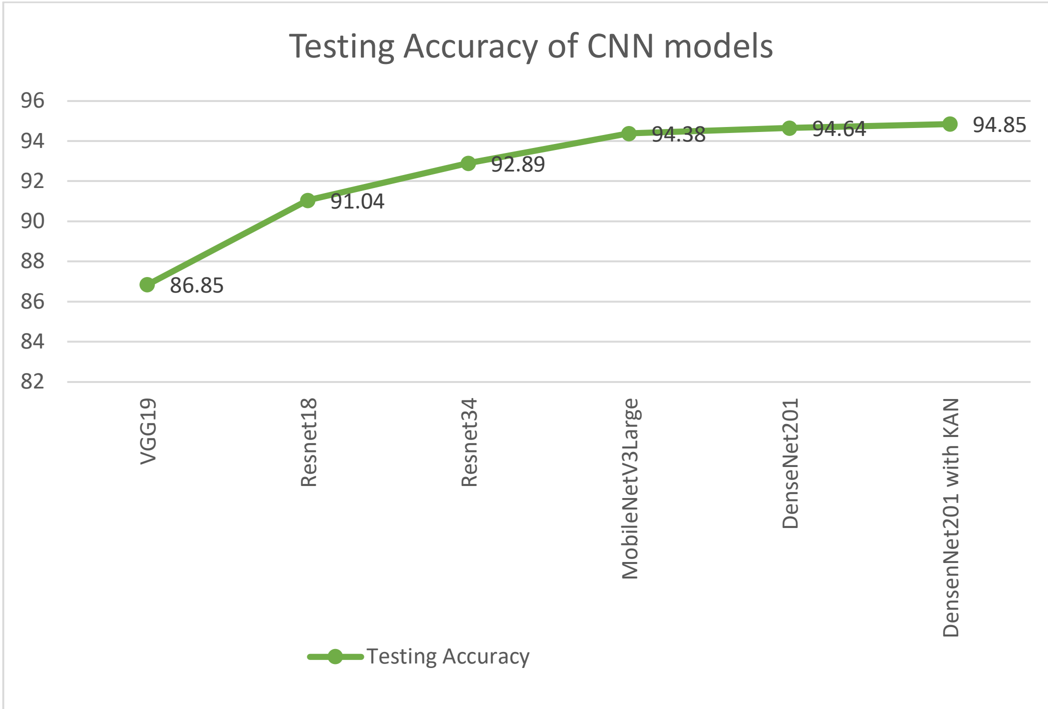


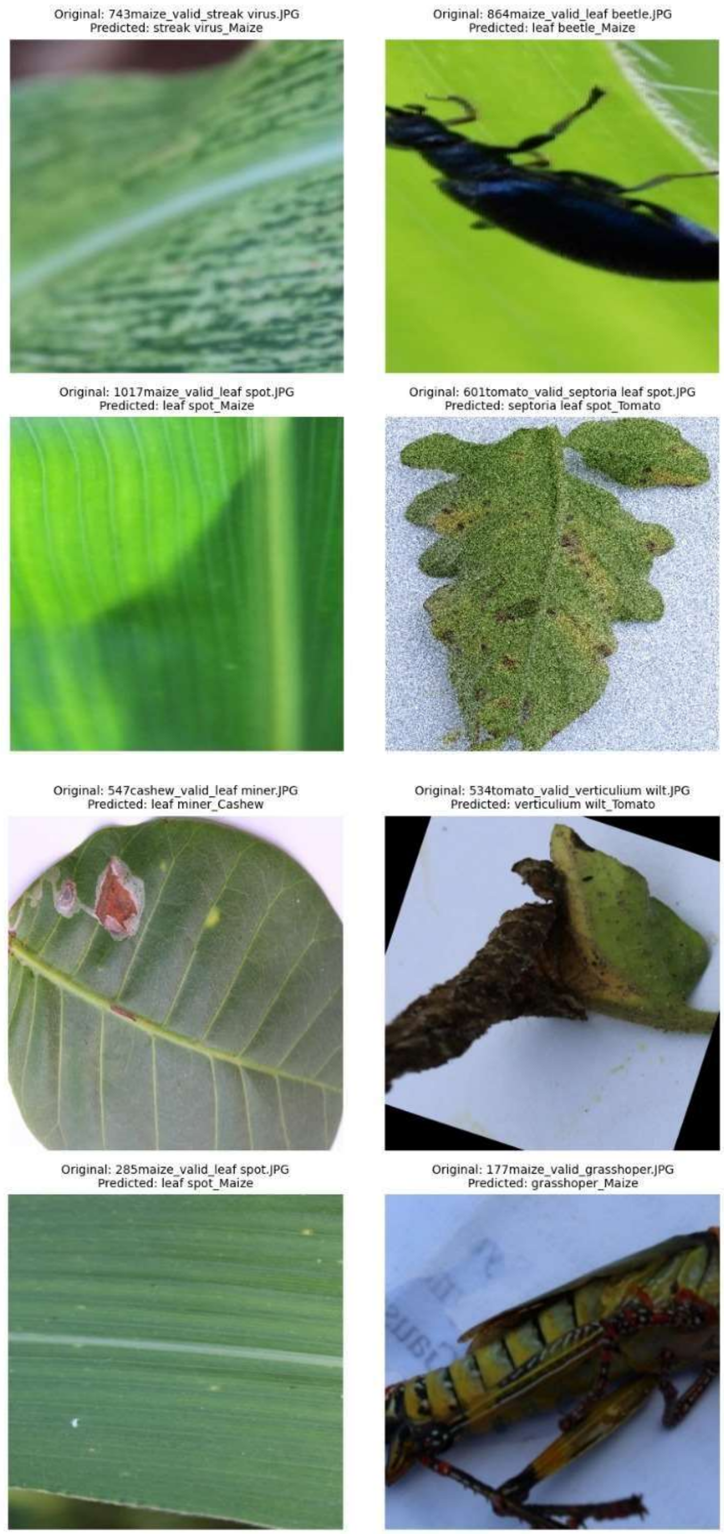
Fig.5 Testing Accuracy of Pre-trained models

Performance Evaluation for the pre-trained models was also conducted in this study including the metrics like Precision, Recall, F1 Score and Mean Intersection over Union (IoU). Densenet201 with KAN performed well than the other models as shown in table-2.

Model Name	Precision	Recall	F1 Score	IoU
Densenet201 with KAN	0.9499	0.9485	0.9483	0.9068
DenseNet201	0.9481	0.9464	0.9461	0.9036
Resnet18	0.9453	0.9445	0.9442	0.9015
MobileNetV3Large	0.9456	0.9438	0.9435	08994
Resnet34	0.9308	0.9289	0.9287	0.8769
VGG19	0.8723	0.8685	0.8678	0.7796

Table-2 Evaluation metrics report for the Models

Snapshots of Predicted Images:




Original: 528tomato_valid_leaf blight.JPG
Predicted: leaf blight_Tomato
Original: 346maize_valid_grasshoper.JPG
Predicted: grasshoper_Maize
Original: 374cassava_valid_gmite.JPG
Predicted: green mite_Cassava
Original: 192maize_valid_farmyw.JPG
Predicted: fall armyworm_Maize
Original: 513tomato_valid_leaf curl.JPG
Predicted: leaf curl_Tomato
Original: 466tomato_valid_verticulium wilt.JPG
Predicted: verticulium wilt_Tomato
Original: 696cashew_valid_leaf miner.JPG
Predicted: leaf miner_Cashew
Original: 784maize_valid_leaf beetle.JPG
Predicted: leaf beetle_Maize

Conclusion:

In this study, we fine-tuned several pre-trained deep learning models—DenseNet201, ResNet18, MobileNetV3Large, ResNet34, and VGG19—on the CCMT: Dataset for Crop Pest and Disease Detection to evaluate their performance in accurately classifying crop pests and diseases. Among these, **DenseNet201**, when integrated with the **Kolmogorov-Arnold Network (KAN) Linear layer**, achieved the highest testing accuracy of 94.85%, surpassing the performance of DenseNet201 alone as well as the other models. This enhancement in performance highlights the potential of the KAN Linear layer to improve feature learning and generalization, allowing the model to capture complex patterns more effectively. DenseNet201's original architecture, with its densely connected layers, enabled it to learn rich representations, but the addition of KAN further refined its ability to model intricate relationships in the data. While **ResNet18** and **MobileNetV3Large** showed strong performance, they slightly lagged behind DenseNet201 with KAN in terms of accuracy and precision. **VGG19** performed the least effectively, likely due to its older architecture and lower feature reuse. These results underscore the importance of wisely selecting and modifying architectures for complex agricultural tasks, where advanced feature extraction is crucial.

References:

1. Kasinathan, T., & Uyyala, S. R. (2021). Machine learning ensemble with image processing for pest identification and classification in field crops. Neural Computing and Applications, 33, 7491-7504.
2. Nagar, H., & Sharma, R. S. (2020). A comprehensive survey on pest detection techniques using image processing. Proceedings of the 2020 4th International Conference on Intelligent Computing.
3. Varma, A. K., & Agarwal, P. (2024). Advancements in Plant Pests Detection: Leveraging Convolutional Neural Networks for Smart Agriculture. MDPI Engineering Proceedings, 59(1), 201.
4. ResearchGate (2023). Challenges in automated pest and disease detection using image processing.
5. Salehin, S. et al. (2021). Pest and Disease Identification in Agriculture Using Machine Learning. International Journal of Computer Science.
6. Sharma, R. et al. (2022). Sustainable Agricultural Practices via Deep Learning Techniques. AI in Agriculture.
7. Kumar, A. et al. (2024). Convolutional Neural Network Applications in Agricultural Pest Detection. International Conference on AI and Agriculture.
8. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. Computers and Electronics in Agriculture, 147, 70-90.
9. Huang, G., Liu, Z., Van Der Maaten, L., & Weinberger, K. Q. (2017). Densely connected convolutional networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 4700-4708).
10. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 770-778).
11. Howard, A. G., Sandler, M., Chen, B., Wang, W., Chen, L. C., Tan, M., ... & Adam, H. (2019). Searching for MobileNetV3. In Proceedings of the IEEE/CVF International Conference on Computer Vision (pp. 1314-1324).
12. Mensah, P. K., Akoto-Adjepong, V., Adu, K., Ayidzoe, M. A., Bediako, E. A., Nyarko-Boateng, O., ... & Amu-Mensah, F. (2023). CCMT: Dataset for crop pest and disease detection. Data in Brief, 49, 109306.

13. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. arXiv preprint arXiv:1512.03385.
14. Simonyan, K., & Zisserman, A. (2014). Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.
15. Liu, Z., Wang, Y., Vaidya, S., Ruehle, F., Halverson, J., Soljačić, M., ... & Tegmark, M. (2024). Kan: Kolmogorov-arnold networks. arXiv preprint arXiv:2404.19756.
16. Liu, Z., Ma, P., Wang, Y., Matusik, W., & Tegmark, M. (2024). Kan 2.0: Kolmogorov-arnold networks meet science. arXiv preprint arXiv:2408.10205.
17. Cheon, M. (2024). Demonstrating the efficacy of kolmogorov-arnold networks in vision tasks. arXiv preprint arXiv:2406.14916.