Paper 1 –

Accuracy

MDFAN achieves an average

classification accuracy of 92.11% with two source domains and 93.02%

Limitations

1. **Soil Conditions**  
    Test how the model performs in different types of soil (e.g., dry, wet, sandy, clay).
2. **Camera Types**  
   Check if the model gives accurate results with photos from different cameras (e.g., mobile, drone, DSLR).
3. **Crop Varieties**  
    Study how well the model works for different varieties of the same crop.
4. **Other Crops**  
   Try using MDFAN on different crops, not just the ones it was trained on.
5. **Data Availability**

The model needs many labeled images to train. But in real-world farms, it's hard to collect and label that much data.

1. **Changing Field Conditions**  
   Test the model in real-life farm conditions where things like weather, sunlight, and background may vary a lot.

Paper 2 –

Accuracy

features extracted from DCNN model and input into SVM, and the accuracy achieved 97.5%.

Limitations

1. **Limited Dataset Variety**  
   Most image samples used in research are taken in controlled lab environments. These don't reflect real-world conditions in fields.
2. **Lack of Generalization**  
   Models often work well only for specific crops, locations, or seasons. They may not perform well when applied to different crops or environments.
3. **Narrow Imaging Techniques**  
   Most studies use only visible light images, but important information also exists in other types like near-infrared or multispectral images.
4. **Lack of Early Detection Research**  
   Diseases and pests are hard to detect in early stages. There is limited research focused on identifying early symptoms, which are usually unclear.
5. **Limited Real-World Dataset Collection**  
   Large, diverse datasets from natural field conditions are still missing. Current data lacks randomness and variety.
6. **High Dependency on Manual Labeling**  
   Deep learning models need a lot of labeled data, but manually labeling such data is time-consuming and requires a lot of effort.
7. **Underexplored Unsupervised Learning**  
   Most methods depend on supervised learning. Unsupervised or semi-supervised approaches are not well studied yet.
8. **Low Interpretability of Deep Learning**  
   Deep learning models act like black boxes. It is difficult to understand how the model makes decisions.
9. **Hardware Limitations**  
   Deep learning models require large memory and are slow during testing. They are hard to use on mobile devices or tools with limited processing power.
10. **Hyperparameter Sensitivity**  
    Deep learning models rely on settings like learning rate or filter size. Small changes in these can greatly affect performance.
11. **Lack of Interdisciplinary Integration**  
    Current approaches do not fully combine AI with agricultural knowledge. More collaboration between AI and plant science is needed for better results.

Paper 4 –

Limitations

**Risk of Feature Loss**  
The Selective Token Generator, while reducing computational load, may accidentally remove useful features—especially in very complex or noisy image scenarios.

**Over-Filtering in Complex Environments**  
In scenarios with a lot of redundant or overlapping information, the model might filter out too much, leading to a drop in detection accuracy.

**Trade-off Between Efficiency and Accuracy**  
Although the model is efficient, achieving a perfect balance between low computational cost and high accuracy remains a challenge—especially when used in real-time applications or with high-resolution images.

**Limited Real-Time Performance**  
The current version of the model may struggle in real-time detection tasks due to processing constraints or high-resolution data.

**Need for Better Feature Extraction**  
There is still room for improvement in how the model extracts and combines features, especially in dynamic or highly variable field environments.

Paper 5 –

Limitations

1. **Limited Dataset Diversity**  
   Many existing studies use small datasets with limited variation. There is a lack of large-scale datasets containing images from diverse geographical regions and environmental conditions.
2. **Changing Symptoms Over Time**  
   The symptoms of plant diseases can vary significantly at different stages of infection. This affects the reliability of disease detection, as models trained on one stage may not perform well on others.
3. **Dependence on Preprocessing and Segmentation**  
   Traditional methods heavily rely on effective preprocessing and segmentation. If these steps are not accurate, it significantly reduces the overall model performance.
4. **Handcrafted Feature Limitations**  
   Models based on handcrafted shape- and texture-based features tend to underperform compared to deep learning models, limiting their usefulness in practical applications.
5. **Limited Use of Lightweight Models**  
   While some lightweight deep learning models like MobileNetV2 and SqueezeNet exist, there's still a need for more optimized and reliable models for real-time use on mobile and edge devices.
6. **Lack of Early Detection Capability**  
   Although early detection is crucial for minimizing crop damage, current methods may not reliably detect diseases in their initial stages due to subtle or unclear symptoms.

Paper 6 –

Limitations

1. **Lack of Explainability in Deep Learning Models**  
   Despite their high performance, deep learning models such as EfficientNet, DenseNet, and GoogleNet are *black-box* in nature. Their internal decision-making processes are difficult to interpret, making the predictions less trustworthy.
2. **Inappropriateness for Critical Applications**  
   Black-box models are unsuitable for high-stakes domains (e.g., medicine or agriculture) where incorrect predictions can lead to serious consequences, such as crop loss or famine.
3. **Immature State of Explainable AI (XAI)**  
   Although visual-explainable techniques like LIME, GradCAM, and GradCAM++ provide some level of interpretability, the field of XAI is still in its early stages. The explanations generated are not yet sufficient for robust decision-making.
4. **Human Bias in Visual Interpretations**  
   Visual heatmaps and explanation overlays are subject to human interpretation, which can introduce bias and reduce reliability, especially in automated systems.
5. **Limited Support from Explanation Maps**  
   Current explanation maps do not always provide comprehensive or logically sound justifications for the model's decisions, limiting their utility in practical applications.
6. **Need for Verbose and Logically Sound Interpretations**  
   There's a lack of detailed, human-understandable reasoning in existing XAI methods. Future work needs to focus on generating more logical, context-aware, and verbose explanations.

Paper 7 –

Limitations

1. **Limited Background Generalization**  
   The model was trained using the PlantVillage dataset, which contains leaf images with plain black or gray backgrounds. As a result, the model may **not perform well on real-world images** with complex or natural backgrounds.
2. **Dependence on Controlled Image Conditions**  
   To achieve optimal performance, images need to be captured under **controlled conditions** similar to the dataset (i.e., isolated leaves on uniform backgrounds), which **limits practical deployment** in field environments.
3. **Limited Number of Disease Classes**  
   The model is trained to classify **only 39 plant disease classes**, which may not be sufficient for broader agricultural use cases involving a **wider variety of diseases and crops**.
4. **Performance Trade-off in Some CNN Variants**  
   While the proposed model variants (like ShuffleNet) showed a good balance between accuracy and computational cost, **other variants did not outperform** state-of-the-art models like MobileNet V2 or Xception in terms of accuracy alone.
5. **Scalability and Real-World Applicability Challenges**  
   The current model might **struggle to generalize** to images taken in natural, uncontrolled environments or across **different geographic locations**, which is critical for real-world deployment.

Paper 17 –

Limitations

 **Limited Dataset Diversity**  
There is a **lack of large, diverse datasets**, especially those containing images from **varied geographical locations**, which affects the generalization of models.

 **Variation in Disease Symptoms**  
When disease symptoms **change significantly across different infection stages**, the **reliability of detection decreases**, making it challenging to ensure consistent accuracy.

 **Dependence on Preprocessing and Segmentation**  
The accuracy of models using **handcrafted features** is highly dependent on **effective preprocessing and segmentation**, making the pipeline more complex and sensitive.

 **Limited Real-Time Applicability**  
Although deep learning models like ResNet50, InceptionV3, and DenseNet201 are accurate, they are **resource-intensive**, which limits their deployment on **low-power or mobile devices**.

 **Need for Lightweight Models**  
There is a **lack of robust lightweight CNN models** that are both accurate and suitable for **real-time applications on mobile platforms**.

 **Inadequate Representation of All Plant Diseases**  
Many studies focus on a limited set of plant diseases; thus, **existing models may not be comprehensive enough** for practical use in diverse agricultural scenarios.

Paper 16 –

 **Limited Disease Coverage**  
The study focuses only on **five primary diseases** of paddy (brown leaf spot, leaf blast, sheath rot, false smut, and bacterial blight), limiting its applicability to other rice diseases or crops.

 **Model Scope Restricted to CNN and SVM**  
Only **SVM and CNN** models were explored. The study does **not include newer or more advanced deep learning models**, which might offer better performance.

 **Limited Use of Modern Techniques**  
**Transfer learning and other advanced methods** were not used in the current work, which could potentially **boost classification accuracy and generalization**.

 **Dependence on Preprocessing**  
Achieving high classification accuracy is highly dependent on **careful selection of preprocessing techniques**, which adds complexity and may reduce scalability.

 **Lack of Integration with External Data Sources**  
The study **does not integrate geographical or seasonal data**. Including **GIS-based or temporal data** could enhance the system's ability to estimate crop yield or disease patterns.

 **Validation Limited to Accuracy Metrics**  
The evaluation relies mainly on **validation accuracy and test accuracy**, with **no mention of other performance metrics** like precision, recall, or F1-score for a more comprehensive assessment.