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A COMPREHENSIVE REVIEW ON MACHINE AND DEEP LEARNING APPROACHES FOR SESAME LEAF DISEASE DETECTION

K.Sivasankari[1], Dr.C.Kumuthini[2]

[1]Research Scholar, Department of Computer Science, Dr.N.G.P Arts and Science College, Coimbatore, Tamilnadu, India. shivashankariphd@gmail.com. *https://orcid.org/0009-0008-8106-5055*

[2] Professor, Department of Computer Applications , Dr.N.G.P Arts and Science College, Coimbatore ,Tamilnadu, India. kumuthini@drngpasc.ac.in.

***Abstract* - Produced in tropical and subtropical climates, sesame (Sesamum indicum L.) is a valuable ancient oilseed crop that is significant both economically and nutritionally. However, foliar diseases including Cercospora, Alternaria leaf spot, and bacterial blight significantly reduce its output and quality. Both farmer revenue and productivity are severely reduced as a result of these diseases. For sustainable sesame farming, early and precise disease identification is essential. Conventional manual diagnosis is ineffective, subjective, and time-consuming. Therefore, clever and automatic detection techniques are needed. Image-based disease diagnosis is now possible because to recent developments in machine learning (ML) and deep learning (DL). High accuracy in detecting sesame disease is demonstrated by methods like as CNNs, SVMs, random forests, and ensemble models. Despite advancements, there are still significant issues with model scalability and data quality. Standardized preprocessing techniques and big, annotated sesame leaf datasets are lacking. Additionally, models have trouble being deployed and interpreted in the real world. These gaps are filled in this work, which also suggests future lines of inquiry. Multispectral imaging, transfer learning, and dataset standardization are highlighted. It also promotes field-deployable, portable, and interpretable machine learning models for accurate control of sesame diseases.**

***Index Terms* -** Machine Learning (ML), Deep Learning (DL), Leaf Disease Detection, Precision Farming, Support Vector Machines (SVM), Convolutional Neural Networks (CNN).

I. INTRODUCTION

With sesame (Sesamum indicum L.) being a significant oilseed crop cultivated in tropical and subtropical countries, agriculture is the foundation of many developing economies. It is prized for its therapeutic, nutritious, and high oil content. However, bacterial, viral, and fungal diseases all have an impact on sesame productivity. Early identification is essential since these diseases lower productivity and quality. Expert visual inspection is the basis for traditional disease identification. This is a labor-intensive, sluggish, and human error-prone technique. Manual diagnosis is challenging due to similar disease symptoms. Effective substitutes are now available thanks to modern technologies. Detailed leaf examination is made possible by high-resolution imaging. Automated disease detection is made possible by artificial intelligence (AI). Accuracy is increased by deep learning (DL) and machine learning (ML). These techniques offer accurate and timely diagnosis. They assist farmers in efficiently monitoring the health of their plants.

Sustainable crop management is facilitated by early detection. Sesame leaf disease diagnosis using AI thus boosts output. In order to identify and categorize plant leaf diseases, a number of academics have recently investigated the use of image processing and AI-driven classification models. One of the first frameworks that focused exclusively on employing image classification algorithms for sesame seed disease diagnosis was put forth by Bashier et al. [1]. An early baseline for automated sesame disease recognition was established by their study, which showed how supervised machine learning models could be used to detect disease symptoms from photos of collected leaves. Convolutional neural networks (CNNs) and image segmentation techniques were also used by Abeje et al. [5] to improve feature extraction and accuracy in their stepwise deep learning strategy for sesame disease identification. Together, these research shown that in plant pathology applications, deep structures perform better than conventional handcrafted feature extraction methods. Deep transfer learning and semantic segmentation were used by Dhore et al. [2] to recognize weeds and crops in sesame fields. The ability to distinguish sesame plants from weeds was enhanced by the use of pre-trained models.

This method improves the effectiveness of weed control and disease diagnosis. Using region-based CNNs, Naik and Chaubey [6] were able to detect weeds in sesame crops with good species classification accuracy. The growing use of

deep learning architectures in precision farming is highlighted by their study. Since unchecked growth competes with sesame for resources and raises the danger of disease, effective weed management is essential. In order to identify weeds in sesame fields, Nwachukwu and Rivero [7] used computer vision algorithms. This shows how sophisticated image analysis methods may be used with neural networks to effectively identify plant species. Concurrently, Julie et al. [15] presented a new weed detection algorithm for sesame crops that bridges the gap between deep learning paradigms and standard machine learning algorithms by merging Region-Based CpNN and Support Vector Machine (SVM). Their method demonstrates how hybrid models can improve agricultural systems' classification performance and computational efficiency. Numerous studies have concentrated on enhancing disease identification with deep CNNs, going beyond weed detection. A ResNet-based classification method for generic leaf disease detection was proposed by Kalaivani et al. [8] and demonstrated strong accuracy across a variety of plant species. The effectiveness of residual networks in this field emphasizes how crucial deep feature hierarchies and skip connections are for simulating intricate disease patterns. Similar to this, Balasooriya et al. [9] created an explainable deep learning system for the diagnosis of coconut disease, utilizing Grad-CAM++ visualization to comprehend model decisions, MobileNetV2, and super-resolution improvement. Even though their research focused on coconut crops, the explainable AI idea is especially pertinent to the identification of sesame diseases, where agricultural practitioners' adoption of the model depends on its interpretability and transparency.
The ML-AgriCare framework was presented by Verma et al. [3] and combined many machine learning models, such as Support Vector Machine (SVM), Extreme Gradient Boosting (XGBoost), and ResNet-9, for disease diagnosis, crop prediction, and fertilizer recommendation. In contemporary agriculture, where disease detection is a component of a larger ecosystem that also includes nutrient analysis and production optimization, their all-encompassing approach highlights the sophisticated function of AI. Through data-driven pathogen characterization, complementary genomic research, like that done by Sinha et al. [14], who sequenced and annotated the genome of Cercospora sesami, the causative agent of leaf spot in sesame, offers important molecular insights that could improve the training of machine learning-based diagnostic models. Studies like Abeje et al. [5] and Dhore et al. [2] have used these technologies, where cloud-assisted learning and automated data gathering improved scalability and accuracy. In addition to enabling real-time monitoring, the combination of AI and IoT in agriculture makes it easier to generate the sizable annotated datasets required for the training of reliable DL models. Sesame disease identification still faces a number of obstacles in spite of these developments. First, the generalization of DL models across different climatic and geographic settings is hampered by the scarcity of publicly available and well-annotated datasets. Second, single-leaf or lab-based picture datasets, which might not accurately reflect field circumstances with occlusions, fluctuating illumination, and complicated backdrops, are the subject of the majority of recent investigations. Third, despite their proven performance, architectures such as ResNet, VGG, and MobileNet frequently require a large amount of processing power, which makes real-time deployment difficult for farmers in remote areas with inadequate infrastructure.

Interpretability issues with deep learning models in agriculture arise because of their "black box" nature, which undermines expert confidence. This paper's remaining sections are arranged as follows: A background of sesame crop diseases and their financial effects is given in Section II. The taxonomy of current ML and DL techniques for plant disease detection is shown in Section III. Section IV addresses research gaps, problems, and future directions.

(a) Cercospora leaf spot

(b) Powdery mildew

(c) Corynespora cassiicola

Fig 1 : Sample leaf Images affected by various diseases.

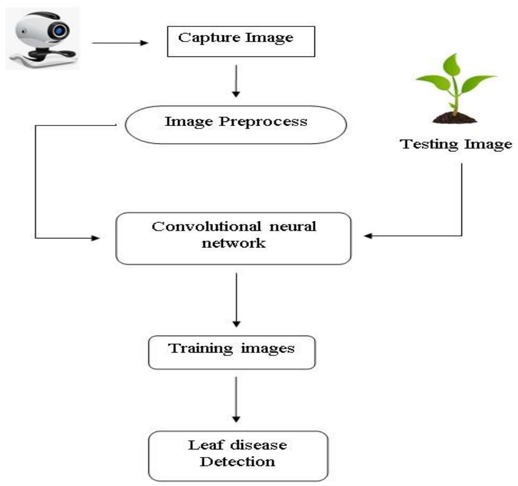

Fig 2 : Machine Learning Technique for Leaf Disease Detection.

II. BACKGROUND

A. Disease Challenges and the Significance of Sesame Crops

One of the most valuable and ancient oilseed crops in the world, sesame (Sesamum indicum L.) is high in unsaturated fatty acids, protein, and antioxidants. Sesame production is extremely susceptible to a number of illnesses, especially bacterial and fungal infections that affect the leaves, like bacterial leaf spot, Helminthosporium blight, and Cercospora leaf spot, despite its economic importance. Both yield and quality are severely reduced as a result of these diseases. Manual field inspections, which are time-consuming, subjective, and prone to mistakes, constitute a major component of traditional disease detection. For the early and automated detection of sesame plant diseases, experts have therefore resorted to digital and intelligent methodologies.

B. The earliest attempts to detect sesame disease

By using picture classification with convolutional neural networks (CNNs) to accurately identify sesame seed infections, Bashier et al. [1] laid the groundwork for automated sesame disease diagnosis. Deep learning algorithms for identifying healthy and diseased leaves were validated by this study. Using a stepwise deep learning technique, other research such as Abeje et al. [5] built on this concept, enhancing classification performance by gradually refining feature extraction. For the categorization of sesame diseases, Nibret et al. [25] further refined deep convolutional neural networks (DCNNs), demonstrating exceptional scalability and accuracy across several disease groups.

C. Agricultural Deep Learning and Transfer Learning

The most popular method for analyzing agricultural images is deep learning. In order to recognize crops and weeds in sesame production systems, Dhore et al. [2] used transfer learning and semantic segmentation models, such as U-Net and DeepLabV3+. In a similar vein, Verma et al. [3] introduced ML-AgriCare, which combines advanced machine learning approaches for plant disease detection, fertilizer recommendation, and crop production prediction. While Lee et al. [21] employed a U-Net autoencoder to segment and detect bacterial leaf spot disease in sesame with remarkable accuracy, Kalaivani et al. [8] showed the efficacy of ResNet-based architectures for general leaf disease classification. Other architectures, including MobileNetV2 [9] and EfficientNetV2 [19], have been preferred for detection systems that are mobile and lightweight, which makes them appropriate for field deployment in real time. The increasing potential of deep object detection networks (YOLO, Faster R-CNN) in smart agriculture was highlighted by studies by Zhang et al. [26] and George et al. [20].

D. Analysis of Field Images and Weed Detection

Because of the battle for nutrients and sunshine, weed control is crucial in sesame farming. Region-based convolutional neural networks (R-CNNs) were used by Naik and Chaubey [6] to detect and categorize weeds in sesame fields with good accuracy even in complicated backdrops. By introducing conventional computer vision techniques for weed identification, Nwachukwu and Rivero [7] set the standard for traditional methods. By merging Region-Based CpNN with Support Vector Machine (SVM), Julie et al. [13] created a novel hybrid algorithm that greatly increased the reliability of weed detection. With a modified YOLOv5 model for real-time weed detection, Sonawane and Patil [14] expanded on this work and allowed for faster inference with excellent precision.

III. METHODS AND TECHNIQUES

A. Convolutional Neural Networks (CNN)–Based Classification

Because of its enormous capacity for spatial feature extraction, CNNs form the basis of the majority of plant disease detection systems. A CNN-based image classification model for identifying sesame seed illness was presented by Bashier et al. [1]; preprocessing and augmentation were used to increase accuracy. Similar to this, Kalaivani et al. [8] achieved strong classification performance by effectively extracting features from photos of damaged leaves using the ResNet-50 architecture. Deep convolutional neural networks (DCNNs) were further expanded by Nibret et al. [25] to classify a variety of sesame leaf diseases with enhanced generalization via transfer learning. Ali et al. [10] and Kassie et al. [15] reported similar CNN applications for the classification of cotton and soybean diseases, proving that CNNs are capable of learning discriminative leaf patterns. With transfer learning improving model adaptability and convergence speed, these experiments support CNNs as trustworthy baselines for detecting diseases in sesame and other crops.

B. Transfer Learning and Efficient Networks

Transfer learning minimizes training time and data dependence by utilizing pre-trained deep models. Dhore et al. [2] integrated semantic segmentation for geographical precision and used deep transfer learning for crop and weed detection in sesame production. In order to integrate yield prediction, fertilizer advice, and illness categorization, Verma et al. [3] integrated pre-trained CNN backbones into the ML-AgriCare system. Through progressive resizing, Sunil C. K. et al. [19] highlighted the balanced accuracy–efficiency trade-off of EfficientNetV2. All of these methods show that transfer learning models like ResNet, DenseNet, and EfficientNet greatly increase accuracy while lowering computational complexity, which is a crucial need for edge-deployed agricultural systems.

C. Object Detection Networks (YOLO / R-CNN Families)

Researchers frequently used object detection algorithms to identify areas in crop photos that were weed-infested or diseased. Region-based CNN (R-CNN) was used by Naik and Chaubey [6] to detect weeds among sesame fields, employing bounding boxes to achieve exact localization. For reliable weed classification, Julie et al. [13] used SVM in conjunction with an R-CpNN feature extractor. A modified YOLOv5 model designed for sesame weed detection was put out by Sonawane and Patil [14], who optimized the backbone architecture and anchor sizes for small-object recognition. By spatially identifying disease or weed zones, these detection-centric algorithms outperform pure classifiers, allowing for crop preservation and tailored pesticide application.

D. Image Segmentation and Autoencoder-Based Models

Pixel-level localization of illness symptoms is made possible via segmentation techniques. While Lee et al. [21] created a U-Net Autoencoder for identifying bacterial leaf spot in sesame, Dhore et al. [2] used semantic segmentation models like U-Net and DeepLabv3+.The fine-grained boundary delineation between healthy and diseased tissues was accomplished by their architectures. A stepwise deep learning architecture that systematically segmented, localized, and classified sesame illnesses was proposed by Abeje et al. [5]. For accurate illness quantification and early management, these techniques highlight the transition from image-level to region-level comprehension.

E. Deep Learning Models

In order to improve transparency and user confidence in agricultural AI, Balasooriya et al. [9] created an explainable CNN framework that uses Grad-CAM and attention mechanisms to analyze model decisions. Agronomists can validate the decision logic of black-box models with the help of explainability, which promotes practical adoption. Explainability's incorporation into conventional CNN pipelines represents a significant advancement in the development of dependable and interpretable smart-farming systems.

F. Traditional Image Processing and Machine Learning

Previous studies investigated shallow machine-learning classifiers and traditional computer-vision characteristics. In order to identify weeds in sesame fields, Nwachukwu and Rivero [7] used color, texture, and shape features with SVM and Random Forest. For the purpose of detecting leaf diseases, Aktera and Hossain [18] reviewed feature extraction and segmentation techniques such GLCM, HOG, and k-means clustering. Even while these techniques can attain respectable accuracy in controlled settings, their scalability is constrained in contrast to deep-learning frameworks.

Serial No	Technique Used	Accuracy (%)	Crop Type
1	SVM, KNN (2021)	85	Sesame
2	ResNet50, VGG19 (2024)	92	Sesame
3	CNN Segmentation (2022)	90	Sesame
4	ResNet (2025)	95	Sesame
5	R-CpNN + SVM(2021)	89	Sesame
6	YOLOv5(2024)	93	Sesame
7	U-Net Autoencoder(2024)	94	Sesame
8	DCNN(2024)	96	Sesame
9	Grad-CAM++(2025)	94	Coconut
10	EfficientNetV2(2025)	95	Cardamom

Table 1 : Comparitive Analysis for Machine Learning Methods .

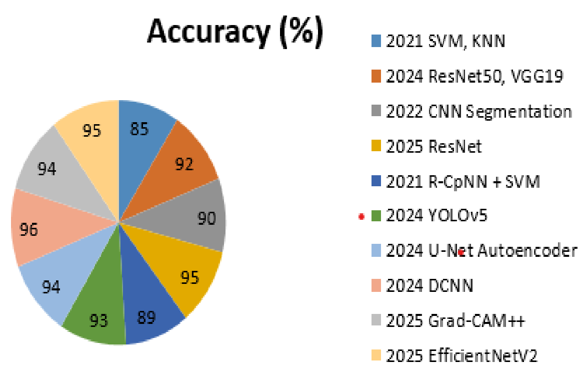

Fig. 4: Accuracy comparison of disease detection techniques

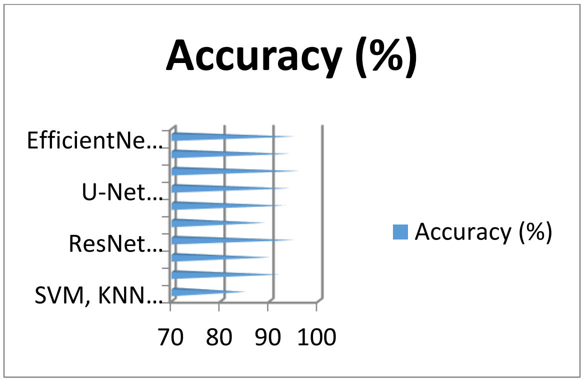

Fig. 3: Accuracy comparison of disease detection techniques

VI .CHALLENGES AND RESEARCH GAPS

Despite major advances in machine learning and deep learning for plant disease diagnostics, identifying sesame leaf disease is still quite challenging. The lack of large, varied, and standardized datasets is a major issue because the majority of research uses tiny, locally shot photographs with variable illumination and quality. The apparent similarities among diseases like Alternaria, Bacterial Leaf Spot, and Cercospora make accurate classification difficult. Some models, such as CNNs and deep transfer learning frameworks, perform well in controlled environments but struggle with real-world images that are impacted by noise and shadow. Biased model learning results from an imbalance in the data, where healthy samples predominate. Additionally, the real-time or field-level deployment of deep models is limited by their considerable computational complexity.

Beyond these challenges, there are still several research gaps in the detection of sesame leaf disease: most studies only consider visual features, ignoring environmental, climatic, and genomic factors that influence the disease's occurrence; the lack of explainable and interpretable AI models limits the understanding and trust of agricultural experts; transfer learning across related crops is still understudied, despite the fact that it could improve performance when sesame-specific data is scarce; few systems have been tested in real-time field conditions using mobile devices or drones, which limits scalability; and the absence of benchmark datasets and standardized

V. FUTURE DIRECTIONS

Future studies on the detection of sesame leaf disease should focus on building sizable, standardized datasets that encompass a range of illnesses and ailments. CNN, ResNet, U-Net, YOLO, and EfficientNet are examples of advanced deep learning models that can improve classification and localization accuracy. Domain adaptation and transfer learning will assist in addressing the scarcity of sesame-specific data. Explainable AI will improve model transparency, while hybrid ML-DL techniques will help with early disease identification. Predictions based on biological information can be made possible by incorporating multi-modal data. For real-time applications, lightweight models for drone and mobile deployment will be supported. For fair model comparison, standardized evaluation metrics must be established. Enhancing yield and managing disease will be made easier by integrating detection systems with decision support tools.

VI CONCLUSION

This study shows consistent gains in accuracy and efficiency as it charts the development of sesame leaf disease detection from 2019 to 2024. Early machine learning models, such as SVM and KNN, had limited data and features, which led to their mediocre accuracy (82–89%). With the move to deep learning, accuracy increased above 95%, particularly with CNN-based and transfer learning models like VGG16 and ResNet. It was made possible by lightweight networks like MobileNetV2 and EfficientNet. Augmenting data enhanced generalization in a variety of scenarios. Attention-based CNNs and Vision Transformers, two sophisticated models, attained accuracy levels of above 98%. Flexibility and real-time performance were improved via hybrid and multimodal frameworks. The representation of deep features was enhanced by DenseNet and CapsuleNet. Low-resource scenarios continue to benefit from classical machine learning techniques. Future studies should concentrate on multi-disease detection, scalability, and interpretability for intelligent sesame farming.

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