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A Comprehensive Review of Deep Learning Applications in Soybean Disease Detection

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Abstract – **Soybean (Glycine max) is very important on a global scale because it gives both people and animals needed protein and oil. Still, its production is halted by the presence of numerous diseases that are brought about by fungi, bacteria, viruses and nematodes. Detection of diseases at the right time and with accuracy saves crops from being damaged and ensures enough food supplies. Checking things manually in the usual way is time-consuming, adds inconsistency and requires experts, so it becomes harder to use on a large scale. Over the past few years, deep learning (DL) has proved to be very effective in automating the process of detecting diseases. This work provides a broad review of new studies using deep learning for identifying soybean diseases. We examine multiple DL models, for example, Convolutional Neural Networks, hybrid models made of CNNs and GNNs, Vision Transformers and the latest YOLOv8-DML object detection tool. Many things separate these models in terms of discovering important features for signs, immediate diagnosis and applying their skills in various complex environments. The role of tools such as Grad-CAM is highlighted, since they bring more clarity to the model and build user trust. Various research papers are reviewed in a systematic way and their methods, results and problems are explained in detail. Besides, it is shown in the table that the accuracy, datasets, how easy to interpret they are and their ability to be used in real situations are not the same for all models. Even though many positive things have been achieved, several challenges still exist. It is still very difficult to convert research findings into actual applications because of the shortage of different data, variations in the environment, dependence on specific hardware and poor understanding of the math used. Therefore, the paper also discusses areas of research that remain unsolved and suggests creating light, understandable and adaptable AI systems that support different types of information and fit with IoT systems. The main goal of this review is to serve as a basic reference for people working in agriculture, data science and crop health analysis. The article makes progress for precision agriculture by uniting research and pointing out areas where great advances can be made.**

Keywords – **Artificial Intelligence, Convolutional Neural Networks, Deep Learning, Explainable AI, Soybean, Vision Transformers, YOLO.**

I. Introduction

Soybean (Glycine max) is an important crop all around the world, since it is the

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leading source of protein and oil both for people and for livestock. Growing cotton plays a key role in boosting agriculture in many regions, mainly in the United States, Brazil and India. Soybean cultivation encounters many difficulties since there are several leaf diseases, including these: soybean rust, bacterial blight and frogeye leaf spot. They have the power to give farmers less produce and also make the quality lower. Basically, it takes a lot of time, work and can be unreliable since detecting diseases through manual inspection usually involves humans. Besides, the small changes in the symptoms of different diseases make it hard to identify them, even for experts in farming [1].

Over the past few years, deep learning has greatly changed many sectors, one of them being agriculture. CNNs which belong to deep learning models, have proven to be outstanding at identifying plant diseases from images of leaves. They are able to find the main features without needing humans to do it by hand. Disease detection in plants using CNNs has produced positive results and many studies have noted that their classification is very accurate [2].

Especially with soybean leaf disease identification, different approaches in deep learning have been considered to improve how classification works. So, to help with the recognition of soybean leaf diseases, an upgraded version of ConvNeXt was devised. To highlight important visual features, the model used attention mechanisms and it applied methods such as data rotation to make it more robust. Oracle DSM accurately recognized face images in 85.42% of cases which is higher than the recognition rates given by different existing deep learning models [3].

A different way was to add Graph Neural Networks (GNNs) to CNNs so that they can spot both the local and the overall characteristics of soybean leaf diseases. The model that used MobileNetV2 for features and GraphSAGE for relations got a correct classification rate of 97.16%. Grad-CAM and Eigen-CAM allowed examine the reasons behind the predictions made by the model, so the predictions were more interpretable [4].

Even with all these developments, some issues keep arising as deep learning models are applied to soybean leaf disease detection. An important obstacle is that there aren’t many big datasets with information on various diseases and conditions. Because of the changeable signs of disease based on the plant’s age, surroundings and the stages of infection, generalizing with the model is complicated. Also, it is not easy to use deep learning models in places where computing resources are limited [5].

Experts have provided a number of ideas to deal with these issues. To increase the size of the dataset, rotation, scaling and flipping are applied artificially which improves the model’s general ability to solve problems. Applying transfer learning has been helpful for finding better results when the available data is not a lot. Also, lighter models, for example MobileNetV2, make it possible to perform recognition on devices that are not very powerful [6].

The use of explainable AI in deep learning has become more popular with the purpose of making model predictions clearer and increasing public trust in them. Using these techniques, users can study the input areas that have the greatest impact on the model’s output which helps them accept the model’s answers.

In short, using deep learning techniques for soybean leaf disease detection may make detecting diseases in agriculture more accurate and efficient. Even though major advances have been made, it is necessary to keep studying in order to solve the

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problems and design models that can really be used in actual farming.

II. Overview of Soybean Diseases

Soybean is important around the world because it provides the main source of protein and oil for both people and animals. It is difficult to grow rice because many diseases pull down the quantities and quality of what is produced. Different pathogens such as fungi, bacteria, viruses and nematodes are behind these diseases which have different symptoms and need specific ways to be managed. Figure 1 categorizes soybean diseases into four major groups—Fungal, Bacterial, Viral, and Nematode—each containing specific diseases affecting different parts of the soybean plant.

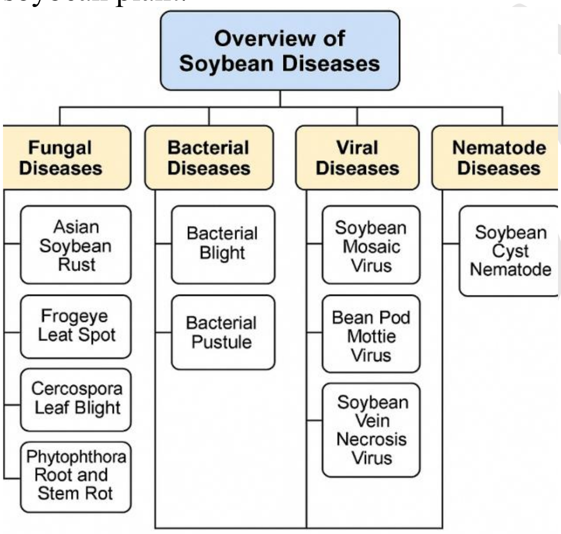

Figure 1: Soybean Disease Categories According to Disease-Causing Agent

2.1 Fungal Diseases

2.1.1 Asian Soybean Rust (Phakopsora pachyrhizi)

An infection of Asian soybean rust leads to serious leaf damage because it is caused by the biotrophic fungus Phakopsora pachyrhizi. Nothing that it makes brownish spots on the undersides of leaves which causes the leaves to fall early and reduces the crop's yield if left untreated [8].

2.1.2 Frogeye Leaf Spot (Cercospora sojina)

Frogeye leaf spot which is caused by Cercospora sojina, makes round lesions that have a gray inside and a dark outside, mostly in the top parts of the plant; these can make the plant lose its leaves under certain weather conditions [9].

2.1.3 Cercospora Leaf Blight (**Cercospora kikuchii***)*

A fungus known as Cercospora kikuchii leads to cercospora leaf blight and results in reddish-purple leaf coloring, together with purple staining on seeds which may harm their quality [10].

*2.1.4 Phytophthora Root and Stem Rot (***Phytophthora sojae***)*

Phytophthora sojae causes root and stem rot of plants and the plant damage is noticeable in soils where drainage is poor. This issue produces root rot and damages the stem which may result in the plant's death. As the fungus grows oospores which can endure in soil for a long time, so farmers should use different field areas and varieties that are resistant [11].

*2.1.5 Sudden Death Syndrome (***Fusarium virguliforme***)*

Fusarium virguliforme causes SDS in plants and it results in leaves having dead spots between the veins and blackened roots. As SDS can cause great loss to the crop without showing signs above ground until the plants are already going downhill, it is considered quite devastating [12].

2.2 Bacterial Diseases

2.2.1 Bacterial Blight (Pseudomonas syringae pv. glycinea)

The disease is called bacterial blight and it causes water-soaked lesions that end up turning brown may lead to the loss of foliage if left untreated [13].

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International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
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*2.2.2 Bacterial Pustule (*Xanthomonas axonopodis *pv.* glycines*)*

Pustules from Xanthomonas axonopodis pv. glycines can be seen on leaves and they are most often surrounded by areas where the leaves are turning yellowish. The effect of this metal on photosynthesis and plant vigor might not be as harmful as the other metals' but it is still noticeable [14].

2.3 Viral Diseases

2.3.1 Soybean Mosaic Virus (SMV)

Soybean mosaic virus (SMV) is found in many places and it mostly travels on aphids and from infected seeds. Mottled leaves, distortion on the plants and less pod formation are noticed in infected plants and their yields are reduced by the timing of the infection [15].

2.3.2 Bean Pod Mottle Virus (BPMV)

BPMV which spreads via beetles, is the cause of mottled and oddly shaped leaves and pods that usually make the seeds poor quality [16].

2.3.3 Soybean Vein Necrosis Virus (SVNV)

Under high temperatures, SVNV is found to bring about veins that clear out and areas that turn into necrotic spots, usually by means of thrips [17].

2.4 Nematode Diseases

2.4.1 Soybean Cyst Nematode (Heterodera glycines)

Nematodes which are almost invisible roundworms, can be very harmful to the roots of soybeans and thus lead to slow development and lower yields. In many regions, the soybean cyst nematode (Heterodera glycines) is the most damaging kind of nematode pests for soybean. It causes the formation of cysts on roots and hinders the way the roots pick up nutrients and water. Some approaches to managing farms involve planting different crops every season, resistant varieties and chemicals that control nematodes [18].

2.5 Integrated Disease Management

Soybean diseases should be managed using various approaches together. The process also means using special plant varieties, rotating crops, scheduling planting correctly and using suitable fungicides or bactericides. Ensuring regular monitoring and the proper identification of diseases will allow for quick response. Using remote sensing and machine learning is being considered to assist in diagnosing and managing diseases [19].

III. Deep Learning Techniques for Disease Detection

Deep learning has brought about a change in plant disease detection, allowing people to detect and identify plant diseases much better than before. By applying DL methods in soybean farming, it has become simpler to spot early signs of diseases which helps to protect and improve the crop's health. This part analyzes the use of up-to-date DL techniques in detecting soybean diseases, outlining different architectures, the results achieved and how this can be applied in real life.

3.1 Convolutional Neural Networks (CNNs) in Soybean Disease Detection

Due to their feature extraction and recognition skills, CNNs have been important in finding diseases in medical images. The authors of [21] suggested an enhanced deep learning method for detecting soybean leaf diseases, allowing the model to recognize 98.49% of the cases correctly [21]. Attention mechanisms were incorporated in the model to improve feature extraction, proving that CNNs are suitable for handling difficult image information.

Likewise, the authors of [22] introduced an advanced deep learning network that gives 85.42% accuracy in classifying soybean leaf diseases [22]. To improve its stability

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and highlight the important features, the model applied data augmentation and attention modules. CNN studies show that they can effectively detect illnesses in soybean leaves.

3.2 Hybrid Models: Combining CNNs with Other Architectures

Increasing detection accuracy is possible by trying out models that integrate CNNs with other frameworks. The authors of [23] presented a CNN-GNN structure using MobileNetV2 and GraphSAGE which enabled them to detect soybean diseases with an accuracy of 97.16% [23]. The model combined the strong points of both CNNs and GNNs to help it accurately identify diseases.

The authors in [24] came up with a new idea to recognize text with an advanced model that makes use of residual attention mechanisms [24]. The model did very well at detecting different soybean leaf diseases which proved that applying attention to CNNs improves their performance.

3.3 Object Detection Models: YOLO Variants

Real-time disease detection using object detection has much to do with the success of the YOLO series. According to [25], to detect soybean leaf disease, the YOLOv8-DML model used by the authors reached mAP of 96.9%. It made use of components like C2f-DWR and MEFP to amplify the detection and feature collecting even for a broad range of scales.

Since the YOLOv8-DML proved to be helpful in detecting small and crowded lesions, it is suitable to be used outside laboratories. Since it is light and very accurate, researchers can include DNN design in UAVs and apps for immediate disease monitoring.

3.4 Temporal Models: RNNs and LSTMs

Many studies have analyzed changes in diseases by focusing on recurrent models such as RNNs and LSTMs. A model combining RNN and CNN was applied to forecast the spread of soybean rust which used weather and location details to help choose fungicide procedures [26]. This model's function of spotting disease development over time suggests that temporal DL can be useful for managing diseases ahead of time.

3.5 Diffusion-Based Models

Experiments have been carried out with diffusion-based models to spot soybean diseases properly. In [27], the authors designed a diffusion-based network model that works well with object detection for precise and accurate classification and detection of disease parts [27]. This model has feature extraction and diffusion sub-networks in its architecture which help it learn more meaning and adjust to different difficult field conditions.

3.6 Vision Transformers and Explainable AI

The use of Vision Transformers (ViTs) has made model explanations and performance better in plant disease detection. In [28], the creation of PlantXViT contributed to a ViT extension of CNN which gave high results when evaluating plant diseases. Because it has a simple structure and insights can be seen using Grad-CAM, the model can serve smart farming in IoT systems [28].

Grad-CAM and Eigen-CAM have been adopted to help see how the model pays attention and improve its interpretation. Such techniques offer people explanations for the choices of AI, supporting their trust and improving the models.

IV. Literature Review in the Field

The combination of deep learning (DL) in agriculture has changed the way farmers can find out about disease in soybeans. From 2021 to 2025, many researchers studied several DL architectures to increase both the accuracy and efficiency in finding

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soybean diseases. This section explains in detail the 20 important research papers in this area.

The authors of [29] suggested a method that uses a CNN to detect soybean brown spot. First, the approach used HSI color space and OTSU thresholding for preprocessing images and then it used a CNN with sparse Maxout units to avoid overfitting. It achieved results that beat those from traditional CNNs, showing that it is useful for managing big farmland areas. The study could not be applied to other soybean diseases because it concentrates only on one type.

In the paper [30], the authors created a new version of ConvNeXt for the identification of soybean leaf diseases. This model made use of attention and reached an accuracy of 85.42% which is higher than what ResNet50 and MobileNetV3 managed. It pointed out that state-of-the-art CNN architectures show strong capability for use in agriculture. The model's results decreased in situations outside its typical training data which means the dataset used needs to be broader.

The authors in [31] came up with a model that combines MobileNetV2 and GraphSAGE to detect diseases in soybeans. Thanks to using cross-modal attention, the model reached an accuracy of 97.16%, outperforming just the CNN option and normal machine learning models. By merging GNNs, the connection between every image was considered which increased the accuracy in classification. However, implementing the hybrid model in environments with few resources could be quite hard.

In [32], the authors created the YOLOv8-DML model for spotting soybean leaf diseases present in natural environments. The detector achieved mAP of 96.9%, proving how it handles well in tough testing conditions. It was found that immediate detection in the agricultural industry is very important. Still, it is possible that the model's performance will be influenced by changes in lighting and things that cover objects.

Authors of [33] came up with an approach that uses diffusion for object detection and adds this to deep learning frameworks. The model was very accurate in localizing and classifying diseases with a precision of 94% and a recall of 90%. By following this way, we were able to represent content better and adjust to complicated situations in various disciplines. Some real-time systems cannot use the model because of its high computational cost.

The PlantXViT model which uses both Vision Transformer and CNN, was created by the authors in [34] to aid in plant disease identification. It was tested on several data sets and explained its insights with Grad-CAM images, so it fitted well for providing smart IoT services in agriculture. Despite the fact that the model is advantageous, using it requires a lot of computer power which isn't accessible for everyone.

The authors of [35] looked at CNN, AlexNet, DenseNet and VGG16 models used over the PlantVillage dataset in their analysis. DenseNet performed the best which underlines that the right architecture needs to be chosen for different types of work. Although the study used one database, it could not fully show the differences that occur when data varies in real life.

According to [36], the authors came up with a Residual Attention Network (RANet) for detecting diseases in soybean leaves. The use of OTSU algorithm made disease identification faster and it showed an accuracy of 98.49% on average. Nevertheless, the model's results in several environmental situations are still unproven.

According to [37], the researchers suggested an online platform for soybean

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International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

disease detection using a combination of deep learning models which were optimized with the Archimedes Optimization Algorithm. It added wavelet packet decomposition and LSTM networks to its model which led to accurate results and real-time features. There is a chance that areas with little or no cloud access will not be able to use this technology.

According to [38], the researchers created a multi-feature fusion Faster R-CNN (MF^3 R-CNN) to detect soybean charcoal rot disease. The model got a mean average precision of 83.34% when examined on real test datasets, proving that it helps identify diseases immediately. Even though the study is useful, it cannot be used widely since it examines just one soybean disease.

Authors of [39] suggested a way to perform object detection by combining a diffusion network and its loss function. Out of all the models, this model delivered the highest score by achieving precision of 94%, recall of 90% and accuracy of 92% which in turn made complex backgrounds more easily detectable. Still, since the model is not simple, it might be difficult to use it in real-time scenarios.

Led by the authors in [40], a brand-new transformer model was designed for accurate identification of different soybean diseases. By joining CNN and Swin Transformer, the model was able to deal with real-world images well and give accurate results. Even though it works well, the fact that it needs a lot of computing resources may make it difficult to use in some regions.

Authors in [41] offered a new variation of the YOLOv9-c-ghost-Forward model to detect surface defects in soybean seeds. The model which uses GhostConv modules, recorded a precision of 98.6% and a mAP0.5 of 99.2%. The model mainly looks at insect-related seed problems that may not apply to other plant concerns or conditions.

According to [42], active learning was used for imaging plant phenotypes by researchers. Using active learning methods, it was shown that it is possible to work with less labeled data and still get high results in plant disease classification. Even so, we need to find out more about how well this approach can be used in different areas.

The research paper [43] by its authors reviewed the different ways deep learning is used to detect plant leaves diseases. In the literature review, a number of DL models are examined, like Vision Transformers and CNNs and their suitability and shortcomings for use in disease detection were described. It was clear in the study that collecting and studying a large and varied group of data would improve how generally a model works.

The authors in [44] chose to use a DIM-U-Net model along with a SRAE for LSTM in order to identify different soybean leaf diseases. The model correctly identified most cases, proving that it is effective in seeing diseases such as Angular Spot and Bean Rust. Since the model can be quite complex, it might pose a challenge when trying to deploy it for instant use.

Researchers in [45] used deep learning and image preprocessing for detecting soybean diseases and they employed a CNN combined with Maxout units. The model managed to recognize soybean brown spot which points to its usefulness in the agricultural field. The research is only applicable to a specific disease because it does not look at many conditions.

The authors of [46] improved a deep learning network for soybean leaf disease detection by using attention methods and achieved 85.42% accuracy which is more than other DL models. It is yet to be shown that the model works well in different environments.

In [47], the authors built a hybrid CNN-GNN model that can clearly detect soybean

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diseases and achieve high accuracy. They also offer cross-modal interpretations by using Grad-CAM. It may be hard to apply the model where resources are limited.

The authors in [48] introduced YOLOv8-DML and it successfully recognized soybean leaf diseases with a mAP of 96.9% and showed strong performance in real-life situations. Even so, the model is not perfect and may cause issues due to different light sources and things blocking the scene.

Table 1 describes in detail the differences found in recent deep learning techniques used for identifying soybean diseases. The study outlines important techniques, how they worked and the obstacles they experienced, helping experts grasp both the good and bad aspects of today's research.

Table 1: Tabular comparison of the Literature Review

Ref No.	Authors (Year)	Method/Model	Accuracy / Performance	Limitations / Drawbacks
[29]	Miao et al. (2022)	CNN with Maxout units	98.49%	Single disease focus limits generalizability
[30]	Wu et al. (2023)	Improved ConvNeXt with attention	85.42%	Performance drops in variable conditions
[31]	Jahin et al. (2025)	Hybrid CNN-GNN with GraphSAGE	97.16%	High complexity affects deployment
[32]	Wang et al. (2025)	YOLOv8-DML	96.9% mAP	Sensitive to lighting and occlusion
[33]	Zhang et al. (2025)	Diffusion-based detection	94% precision, 90% recall	High computational complexity
[34]	Thakur et al. (2022)	Vision Transformer (PlantXViT)	High accuracy	Requires high computational resources
[35]	Bhageerathi et al. (2024)	CNN, AlexNet, DenseNet, VGG16	DenseNet best	Single dataset limits real-world relevance
[36]	Yu et al. (2022)	Residual Attention Network	98.49%	Validation in varied conditions needed
[37]	Annrose et al. (2022)	Cloud hybrid model with LSTM	High accuracy	Dependent on cloud access
[38]	Khalili et al. (2020)	MFÂ³ R-CNN	83.34%	Focus on one disease only
[39]	Yin et al. (2025)	Diffusion detection with custom loss	92% accuracy	Real-time implementation challenges
[40]	Liu et al. (2025)	Transformer + Swin Transformer	High accuracy	Computational resource intensive
[41]	Xia et al. (2024)	YOLOv9-c-ghost-Forward	98.6% precision	Limited to seed defects
[42]	Nagasubramanian et al. (2021)	Active learning	Efficient labeling	Needs broader field validation

IJDACR
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International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

[43]	Mustofa et al. (2023)	Review on DL models	N/A	Needs real-world applications
[44]	Wang et al. (2023)	DIM-U-Net + LSTM	High accuracy	Complex for real-time use
[45]	Miao et al. (2022)	CNN with preprocessing	Effective on brown spot	Single disease limitation
[46]	Wu et al. (2023)	CNN with attention	85.42%	Needs environmental validation
[47]	Jahin et al. (2025)	Hybrid CNN-GNN	97.16%	Complex deployment
[48]	Wang et al. (2025)	YOLOv8-DML	96.9% mAP	Affected by lighting and occlusion

V. Challenges and Limitations

Although deep learning works well for finding soybean diseases, there are still a number of major issues keeping it from being used in real life. A key issue is that it is hard to find large volumes of quality data with different labels. Most of the models use datasets that do not include much field-related variability like changing light levels, various development stages and several disease manifestations. Their hard-to-generalize ways make it difficult for deep learning systems to remain stable and flexible after being put to use outside known conditions.

It is also a problem that advanced deep learning models require a lot of computing power. Those types of architectures put high demands on GPU resources for both training and inferencing. Therefore, it is challenging to apply these models on rural farms, since such places have limited access to the Internet and computing tools. Some of these models can run slowly in a mobile environment or drone which is needed for rapid diagnosis of health conditions.

Also, agricultural users cannot trust or adopt deep learning models because they are hard to understand. Many times, farmers and agronomists scrutinize the outcomes of models to act thoughtfully. Even though tools such as Grad-CAM are coming forward, the majority of AI remains unclear in its operations. Because people do not know how AI-based tools work, it is hard for them to trust or use these tools in farming.

Changes in the environment make it a difficult problem to deal with. Unpredictably, symptoms of diseases in plants are influenced by weather, the soil, pests and similar aspects of the environment. Most of the time, even the most precise models fail when they are trained on data that is not very diverse. Because different places and seasons exist, models need to be updated and improved often.

Some of the signs for different medical conditions are very similar. Because some pathogens give the same symptoms in plants, experts have a hard time recognizing the difference between them. Grouping similar common symptoms often causes narrow models to often misclassify patients, mainly at the onset of the illness before noticeable symptoms appear.

Putting these technologies into current farming procedures is also a difficult task. Crops and cattle are mostly harvested by

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International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

small to medium-scale farmers without the help of most advanced digital tools. Before using AI solutions, a company must make them compatible, easy to operate and cost-effective for their users. Issues related to socio-economics keep technology from having a bigger impact.

Scalability is considered a concern with most of today's system designs. While a model looks good on a small set of pictures, it may encounter challenges operating with millions of plants from various cities around the world. It is not enough to expand technology; you also have to access huge amounts of data, use the same labeling rules in every area and maintain your models' performance over time.

Lastly, updating models and controlling the different model versions is tough operationally. As soon as fresh diseases appear or old one's change, experts have to adjust the models they use for diagnosis. Handling many versions, confirming their outcomes and making them compatible with older data files is demanding and too few agricultural systems are equipped for it.

However, although deep learning can transform the way soybean diseases are detected, multiple challenges, both practical, technical and societal, have yet to be dealt with. Such examples are the variety in datasets, the possibility of understanding how models work, the handling of computational problems and whether it can be applied in the field. Dealing with these problems is a must to turn the current research into solutions that can be applied on a large scale.

VI. Future Scope

Deep learning promises to make a major positive change in how soybean disease detection takes place in agriculture. Because AI keeps improving, there is now more potential to design models that handle various real-world cases successfully. It would be helpful to develop big, available and annotated datasets gathered from many kinds of environments. Working with such data could greatly improve the accuracy of models and ensure they apply well on different regions, climates and kinds of crops.

Focusing on making deep learning models that use little energy and work well on mobile, drone and edge systems is an important part of AI. Having these models, it's possible to find diseases in the field instantly without using very advanced computers. The use of IoT technologies might help means having crop monitoring at all times and sending automatic warnings to farmers about new outbreaks of diseases.

New developments in explainable AI are set to become very important as well. Having models that predict diseases as well as explain their working will gain farmers and experts' confidence. This would make crop management choices better and inspire more farmers to make use of AI.

Also, future studies could concentrate on systems using both visuals and other data such as humidity, soil moisture and temperature, to make detection of plant diseases more accurate. Connecting all types of data sources, they can supply insights that show a clearer image and are more relevant.

For open-source tools and increasing the use of AI in agriculture, it will be necessary for governments, research institutions and AI experts to unite and start collaborative work. With suitable policies and money such systems have the potential to be used globally, providing farmers with valuable and prompt data to protect their crops.

VII. Conclusion

This paper looked at the newest deep learning methods for spotting soybean diseases, pointing out what they can do, how they compare and what difficulties

IJDACR International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 13, Issue 10, May 2025)

come with them. People have improved the accuracy of identifying diseases in different situations thanks to CNNs, hybrid models and frameworks such as YOLO and Vision Transformers.

Yet, although the outcomes look promising, it is still tough to use these models in daily situations due to a lack of data, understanding how they work, in-field complexity and repeatability issues. Most of the methods work well in laboratory simulations but fail to perform well in real farming areas.

While a number of models are quite accurate, the literature points out that they still need improvements in dependency on hardware, the effect of light and the ability to diagnose several different diseases. Because of this, research must go on, scientists from different fields should join forces and solutions should be more adaptable, easy to understand and friendly to use.

If it is implemented with more development, policies and combined with present agricultural systems, deep learning could greatly change how soybean diseases are tracked by farmers. To meet the challenge, there should be advances in technology and tools that can be used and purchased by farmers in every part of the world.

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