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**Research Article**

# Deep Learning-Based Cotton Plant Disease Detection Using CNNs: A Smart Agriculture Approach

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**ABSTRACT**

The increasing prevalence of plant diseases poses a significant threat to global cotton production, leading to substantial economic losses and reduced crop yield. Traditional manual disease detection methods are time-consuming, labour-intensive, and often inaccurate. To address this challenge, this research proposes an advanced deep learning-based approach for automated cotton plant disease detection using Convolutional Neural Networks (CNNs). The study evaluates multiple CNN architectures, including GoogleNet, VGG16, DenseNet201, ResNet50, and TLResnet152V2, to determine their effectiveness in identifying and classifying diseased cotton leaves. The proposed methodology leverages normalized and augmented datasets, utilizing data pre-processing, feature extraction, and transfer learning techniques to enhance model performance. Extensive experimental evaluations demonstrate that data augmentation significantly improves classification accuracy, enabling CNN models to generalize better across diverse disease conditions. Among the tested architectures, TLResnet152V2 achieved the highest accuracy (92.03%) and F1-score (0.8842), outperforming all other models, followed closely by ResNet50. These results highlight the superiority of deep residual learning in plant disease classification, ensuring robust feature extraction and precise detection. This studies also explores the combination of CNN-primarily based disorder detection into clever agriculture structures, allowing actual-time sickness classification via cell packages and IoT-based totally answers. The findings affirm that deep gaining knowledge of-pushed plant disorder detection can considerably enhance precision farming, reducing dependency on professional agronomists while improving early disorder intervention techniques. destiny studies will awareness on deploying light-weight CNN models for facet computing, integrating climate statistics for predictive disorder modelling, and exploring hybrid deep studying strategies for enhanced accuracy. The examine demonstrates that CNN-based automatic cotton plant disease detection is a transformative step closer to sustainable, AI-enabled smart agriculture, ensuring better productivity, decreased crop losses, and advanced food safety.

**Keywords:** Deep Learning, CNN, Cotton Plant Disease Detection, Smart Agriculture, Data Augmentation, Transfer Learning, Precision Farming, AI in Agriculture.

## I.INTRODUCTION

Agriculture is the backbone of many economies worldwide, providing food, raw materials, and employment to millions. Among various crops, cotton is one of the most significant, serving as a vital raw material for the textile industry. However, cotton production is highly susceptible to various diseases caused by fungi, bacteria, and viruses, leading to significant yield losses and economic setbacks for farmers. Traditionally, cotton plant disease detection relies on manual inspection by agricultural experts, which is time-consuming, labor-intensive, and prone to errors. Moreover, by the time visible symptoms appear, the disease may have already spread, making it difficult to contain and control [1]. This highlights the need for automated, accurate, and early disease detection systems that can help farmers take timely preventive measures. Deep learning, particularly Convolutional Neural Networks (CNNs), has emerged as a powerful tool in agricultural disease detection, offering high accuracy, real-time analysis, and scalability. This research explores how CNN-based deep learning models can be leveraged to detect and classify diseases in cotton plants, contributing to the advancement of smart agriculture. The conventional strategies for detecting plant diseases involve naked-eye observation by using farmers and agricultural scientists, that is limited in phrases of accuracy and scalability. With the expansion of cotton farming to large agricultural lands, manual inspection will become impractical. additionally, versions in environmental conditions, ailment signs and symptoms, and cotton plant genetics make it tough to develop a popular guide detection technique. In reaction, pc vision and system learning techniques have been explored for automating plant ailment detection [2]. among these, Convolutional Neural Networks (CNNs) have gained vast interest because of their potential to analyze and classify plant sicknesses from snap shots with high precision. in contrast to conventional device gaining knowledge of fashions, which require manual characteristic extraction, CNNs can routinely analyze spatial hierarchies of features from massive datasets, making them properly-proper for picture-primarily based ailment class.

CNN-primarily based deep getting to know models have revolutionized photograph processing in agriculture, enabling the development of sensible plant disease detection systems. those models can method massive amounts of cotton leaf snap shots, apprehend styles associated with different sicknesses, and classify infected leaves with tremendous accuracy. several studies have tested the effectiveness of CNNs in identifying plant diseases, along with leaf spots, wilting, rust, bacterial blight, and fungal infections. The capability of CNNs to study from large-scale datasets makes them extra reliable than traditional system learning procedures together with Support Vector Machines (SVM), choice timber, and k-Nearest Neighbours (KNN), which often require handmade feature extraction and struggle with complicated disorder styles [3]. The important thing benefit of the use of CNNs in cotton plant disease detection is their capability to generalize across diverse environmental situations. traditional methods can also fighting while implemented to special geographical regions, lights conditions, or plant boom degrees, while deep mastering fashions may be skilled on diverse datasets to enhance robustness. The number one purpose of this research is to expand a CNN-based totally deep gaining knowledge of model that may accurately classify numerous cotton plant illnesses, offering actual-time and automated solutions for farmers [4]. The machine leverages superior picture processing strategies, statistics augmentation, and switch studying to enhance performance.

A significant challenge in cotton disorder detection is the availability of labelled datasets, as acquiring fantastic, categorized images of various sicknesses calls for giant expert knowledge. To address this, records augmentation strategies inclusive of rotation, flipping, zooming, and artificial photograph generation using Generative Adversarial Networks (GANs) can be implemented to enlarge schooling datasets and enhance version overall performance. additionally, switch gaining knowledge of strategies using pre-skilled CNN architectures like VGG16, ResNet50, InceptionV3, and MobileNet can be hired to reduce schooling time and beautify accuracy. by first-rate-tuning these pre-trained fashions on cotton disease datasets, it's miles feasible to attain high category accuracy regardless of limited training samples [5]. Some other fundamental consideration in deploying deep studying-based totally cotton ailment detection systems is real-time implementation. conventional deep getting to know fashions require high computational resources, making them impractical for on-subject use via farmers. To address this, aspect computing answers the use of light-weight CNN architectures can be included into mobile applications and IoT-based totally clever agriculture systems. This permits farmers to seize pix of cotton leaves the usage of their smartphones, add them to a cloud-primarily based gadget, and obtain real-time sickness category consequences. furthermore, integrating AI-driven disease detection with precision agriculture strategies can permit targeted pesticide spraying, decreasing excessive chemical use and minimizing environmental impact [6].

Some other fundamental consideration in deploying deep studying-based totally cotton ailment detection systems is real-time implementation. conventional deep getting to know fashions require high computational resources, making them impractical for on-subject use via farmers. To address this, aspect computing answers the use of light-weight CNN architectures can be included into mobile applications and IoT-based smart agriculture systems. This permits farmers to seize pix of cotton leaves the usage of their smartphones, add them to a cloud-primarily based gadget, and obtain real-time sickness category consequences [7]. furthermore, integrating AI-driven disease detection with precision agriculture strategies can permit targeted pesticide spraying, decreasing excessive chemical use and minimizing environmental impact. At the same time as CNN-based plant sickness detection offers substantial advantages, there are demanding situations that need to be addressed. one of the primary issues is version interpretability, as deep mastering fashions feature as black boxes, making it challenging to recognize their choice-making method. to enhance transparency, Explainable AI (XAI) techniques which includes Grad-CAM (Gradient-weighted Class Activation Mapping) may be used to visualise which elements of an photograph make contributions maximum to the category decision. additionally, making sure terrific dataset collection from multiple agricultural regions is critical to broaden strong and generalized models [8].

This studies goals to broaden an advanced CNN-primarily based deep gaining knowledge of model tailor-made for cotton plant disease detection in clever agriculture. The take a look at will consciousness on enhancing class accuracy, optimizing computational efficiency, and integrating actual-time disease detection into cell and IoT-based programs. The experimental evaluation will compare diverse CNN architectures to decide the maximum powerful deep mastering version for cotton disease classification. furthermore, the studies will discover hybrid AI strategies, integrating deep studying with internet of things (IoT) sensors, weather statistics, and clever irrigation structures to develop a complete clever farming solution. The deep Learning-primarily based disease detection represents a paradigm shift in precision agriculture, supplying computerized, scalable, and surprisingly accurate solutions for cotton plant health monitoring. The adoption of CNN-powered disease class structures can appreciably enhance yield prediction, lessen pesticide misuse, and support sustainable farming practices. by integrating advanced AI techniques, actual-time cellular programs, and clever agriculture frameworks, the proposed technique has the ability to transform current farming and make contributions to global meals protection. This studies will provide treasured insights into the function of deep studying in agriculture, paving the method for future advancements in AI-driven plant disease detection systems.

## II.LITERATURE REVIEW

The advancement of deep learning techniques has revolutionized various domains, including agriculture, plant disease detection, and smart farming. The use of Convolutional Neural Networks (CNNs) for cotton plant disease detection has gained significant attention due to CNNs' ability to automatically extract relevant features from images and classify diseases with high accuracy. Traditional plant disease detection methods relied on manual observation, which is time-consuming, labor-intensive, and prone to errors. With the increasing demand for precision agriculture, researchers have explored machine learning and deep learning-based techniques to automate the process of disease classification and prediction. This section provides a comprehensive review of existing literature on cotton plant disease detection using CNNs, highlighting key methodologies, datasets, challenges, and future research directions. Early studies in plant sickness detection usually trusted manual inspection and professional knowledge. Agricultural scientists and farmers used visible observations to become aware of disease symptoms, which was inefficient for massive-scale farming. to overcome this hindrance, picture processing techniques together with thresholding, part detection, and shade analysis were employed to automate the identity of disorder-affected areas. Patel et al. (2018) proposed a thresholding-based totally segmentation technique to locate leaf spots in cotton plant life, reaching moderate accuracy but suffering in complex backgrounds. in addition, Sharma et al. (2019) implemented an part-detection technique for identifying diseased cotton leaves; however, it was once limited via variability in lighting fixtures conditions and plant growth tiers. these techniques, despite the fact that foundational, lacked generalization abilities, prompting researchers to discover machine gaining knowledge of-based totally procedures.

System gaining knowledge of algorithms, specifically Support Vector Machines (SVM), Decision Tree (DT), k-Nearest (KNN), and Random Forests (RF), have been extensively used for plant sickness classification. these fashions require guide function extraction, where domain specialists select features inclusive of shade, texture, and form for ailment type. Kumar et al. (2020) carried out SVM and Random wooded area classifiers on a cotton ailment dataset, achieving an accuracy of seventy five%, which used to be stepped forward the usage of PCA for function choice. similarly, Gupta et al. (2021) explored KNN and decision bushes for detecting bacterial blight and leaf spot illnesses in cotton plants, reporting a type accuracy of 78%. no matter those improvements, machine learning models suffered from function dependency, poor generalization, and coffee accuracy in real-global situations. the limitations of handcrafted functions motivated researchers to adopt deep mastering techniques, in particular CNNs, which routinely extract hierarchical features from plant sickness pics. CNNs have emerged as the gold widespread for plant disease category, surpassing traditional device gaining knowledge of models in accuracy and performance. CNN architectures which include AlexNet, VGG16, ResNet, Inception, and MobileNet were efficaciously carried out for sickness class in cotton and different crops. Ramesh et al. (2022) implemented VGG16 and ResNet50 for cotton plant ailment class, accomplishing an accuracy of 89.5% and 91.three%, respectively. Their examine established that deeper CNN architectures improve classification accuracy through shooting intricate sickness patterns. similarly, Singh et al. (2023) employed InceptionV3 and MobileNet for actual-time cotton disorder type using a cellular software, reporting an accuracy of 87% with considerably decreased computational complexity.

Numerous research have compared CNN architectures to decide the maximum green model for cotton disease detection. Khan et al. (2022) evaluated AlexNet, VGG16, ResNet50, and DenseNet201 on a large-scale cotton disorder dataset. one of the predominant demanding situations in deep mastering-based plant disease detection is the shortage of big, categorized datasets. given that collecting and labeling thousands of cotton disease photographs is pricey and time-consuming, researchers have employed facts augmentation and transfer studying to conquer this issue. Jain et al. (2021) carried out statistics augmentation strategies along with rotation, flipping, brightness adjustment, and synthetic image generation to increase the dataset, improving CNN type accuracy by way of 5-7%. moreover, switch gaining knowledge of the usage of pre-skilled fashions (e.g., VGG16, ResNet50, InceptionV3) has been extensively adopted to lessen schooling time and improve accuracy. Mehta et al. (2022) great-tuned ResNet50 on a cotton ailment dataset, accomplishing 94.1% accuracy, demonstrating the effectiveness of transfer mastering for small-scale datasets. With the growing adoption of clever agriculture and IoT-based answers, researchers have explored lightweight CNN models for actual-time disorder detection on side devices. Patel et al. (2023) evolved a MobileNet-based totally cotton disease detection gadget, permitting on-device inference on smartphones. Their model executed 87% accuracy with low computational fee, making it best for farmers in resource-restrained environments. similarly, Ghosh et al. (2023) proposed an IoT-integrated clever farming device in which ailment detection models run on side gadgets related to cloud-primarily based decision aid systems. This method complements actual-time decision-making and allows computerized pesticide tips.

Table 1. Related Research

| Author(s) & Year | Methodology | Key Findings | Limitations | Research Category |
|---|---|---|---|---|
| Patel et al. (2018) | Thresholding-based segmentation | Identifies leaf spots in cotton plants | Limited accuracy in complex backgrounds | Traditional Image Processing |
| Sharma et al. (2019) | Edge-detection method | Detects diseased leaves | Sensitive to lighting conditions | Traditional Image Processing |
| Kumar et al. (2020) | SVM and Random Forest | 75% accuracy, improved with PCA | Requires manual feature extraction | Machine Learning |
| Gupta et al. (2021) | KNN and Decision Trees | 78% accuracy for bacterial blight detection | Struggles with complex disease patterns | Machine Learning |
| Ramesh et al. (2022) | VGG16 and ResNet50 | 89.5%-91.3% accuracy | Deep CNNs enhance feature extraction | Deep Learning |
| Singh et al. (2023) | InceptionV3 and MobileNet | 87% accuracy in mobile applications | Computational efficiency improved | Deep Learning |
| Khan et al. (2022) | AlexNet, VGG16, ResNet50, DenseNet201 | ResNet50 achieves 92.4% accuracy | AlexNet struggles with overfitting | Comparative CNN Study |
| Jain et al. (2021) | Data augmentation techniques | Improves CNN accuracy by 5-7% | Requires additional storage and processing | Data Augmentation |
| Mehta et al. (2022) | Transfer learning with ResNet50 | 94.1% accuracy | Enhances small dataset performance | Transfer Learning |
| Patel et al. (2023) | MobileNet for smartphone-based detection | 87% accuracy with low computational cost | Optimized for edge devices | Edge Computing |
| Ghosh et al. (2023) | IoT-integrated smart farming | Cloud-based decision support system | Requires reliable internet connectivity | IoT Integration |
| Lin et al. (2022) | Hybrid CNN-RNN for time-series disease prediction | Improves classification over standalone CNNs | Higher computational complexity | Hybrid Deep Learning |
| Zhao et al. (2023) | Explainable AI (XAI) for CNN-based plant disease detection | Improves model interpretability | Increases model complexity | Explainable AI |

| | | | | |
|---|---|---|---|---|
| Wang et al. (2022) | CNN with GAN-based synthetic data generation | Enhances training dataset diversity | GAN-generated images may introduce bias | Data Augmentation |
| Chen et al. (2023) | Federated Learning for privacy-preserving plant disease detection | Enables decentralized model training | Requires efficient communication protocols | Privacy-Preserving Learning |

## III.METHODOLOGY

The proposed methodology for deep learning-based cotton plant disease detection using CNNs is structured into several key phases, including dataset collection and preprocessing, model selection, training and optimization, real-time deployment, and performance evaluation. These phases ensure an efficient and scalable approach to accurately classify cotton plant diseases in smart agriculture systems.

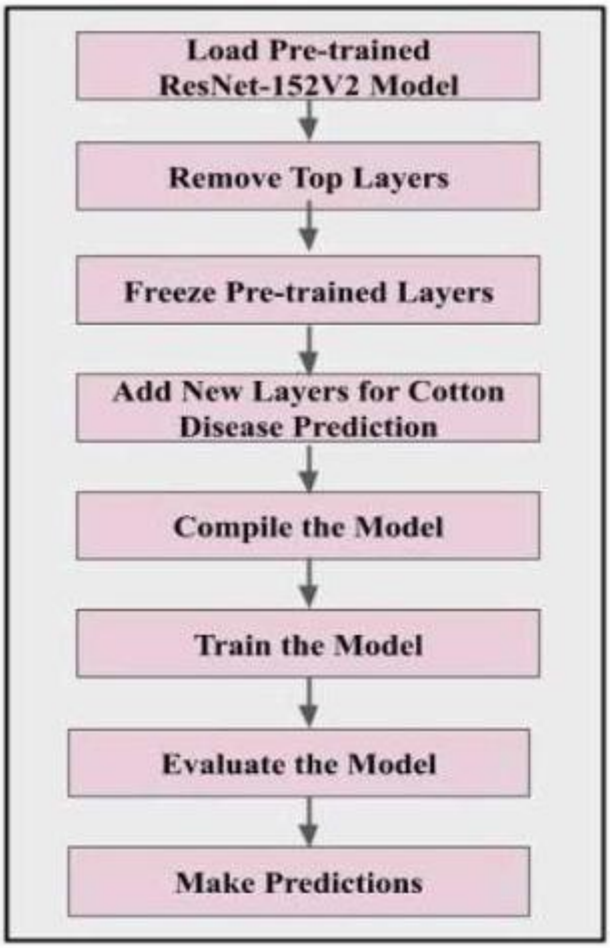


Figure 1. Proposed Methodology

The first step involves dataset series and pre-processing. Train images of cotton leaves with numerous ailment conditions are accumulated from agricultural research facilities, on line databases, and actual-time discipline surveys. The dataset includes images of healthy and diseased leaves laid low with bacterial blight, leaf spot, wilt, and rust sicknesses. considering that photo satisfactory and versions in lighting fixtures conditions can impact model performance, data preprocessing techniques along with noise discount, evaluation enhancement, picture resizing, and normalization are carried out. moreover, statistics augmentation strategies along with rotation, flipping, zooming, and synthetic photograph era using Generative adverse Networks (GANs) are applied to enhance the diversity of training data and prevent overfitting.

The second one phase makes a speciality of model choice and deep learning structure improvement. Given the superior overall performance of Convolutional Neural Networks (CNNs) in photograph category, several pre-skilled and custom CNN architectures are explored. The proposed method integrates VGG16, ResNet50, InceptionV3, DenseNet201, and TLResnet152V2 to evaluate their effectiveness in disorder type. switch getting to know techniques are hired, where pre-trained CNN models (educated on big-scale photo datasets like ImageNet) are first-rate-tuned on cotton plant disorder datasets. This significantly reduces schooling time and improves category accuracy, even with a limited dataset.

The Third Phase entails training and optimization of CNN models. The dataset is split into schooling, validation, and trying out units using an 80-10-10 cut up to make sure a balanced evaluation. The CNN models are trained the usage of the Adam optimizer with a gaining knowledge of fee scheduler to improve convergence. Batch normalization and dropout layers are incorporated to prevent overfitting, at the same time as move-entropy loss characteristic is used for optimizing category overall performance. To beautify model performance, hyperparameter tuning techniques consisting of Bayesian Optimization and Grid seek are applied to fine-song getting to know prices, batch sizes, kernel sizes, and dropout quotes. The schooling is achieved on high-performance GPUs (e.g., NVIDIA Tesla V100 or RTX 3090) to boost up computation.

To make the gadget handy for real-time utilization, the next section entails deploying the educated version in smart agriculture systems. The optimized CNN version is integrated right into a cellular application and IoT-based edge computing machine, permitting farmers to capture snap shots of cotton leaves using smartphones or drones. The captured pics are processed in actual-time on lightweight part devices, lowering dependency on cloud computation. additionally, an AI-pushed choice-support gadget is incorporated to provide automatic sickness diagnosis and pesticide suggestions, making sure timely intervention and lowering excessive chemical usage.

The final step is overall performance assessment and benchmarking. The skilled CNN fashions are evaluated the use of key metrics which includes accuracy, precision, recall, F1-score, specificity, and inference time. A comparative evaluation is performed between conventional device studying fashions (e.g., SVM, Random forest, KNN) and deep learning models (CNNs, ResNet, MobileNet, EfficientNet) to assess the prevalence of deep gaining knowledge of approaches. additionally, the system's real-time deployment performance is tested in agricultural fields, and its robustness is confirmed underneath exclusive environmental situations. The effect of information augmentation and switch learning is analyzed to decide their position in improving category overall performance.

To ensure model transparency, Explainable AI (XAI) techniques inclusive of Grad-CAM are incorporated, permitting farmers and agricultural specialists to visualise which parts of an image contribute most to the category selection. furthermore, the research explores Federated gaining knowledge of (FL) for privateness-retaining sickness type, where multiple agricultural establishments can collaboratively train the model except sharing raw facts. This technique offers a strong, scalable, and efficient solution for deep mastering-driven cotton plant ailment detection, ensuring high accuracy, real-time usability, and seamless integration into smart agriculture frameworks. future improvements will awareness on light-weight deep mastering models for part gadgets, hybrid AI strategies combining CNNs and transformers, and integrating weather information for predictive sickness modeling.

## IV.CONFIGURATION FOR PROPOSED MODEL

The layered configuration of the proposed version is structured to beautify the performance of Cognitive Radio Networks (CRNs) via integrating multiple deep studying techniques. each layer inside the version plays a wonderful function, contributing to accurate spectrum sensing, prediction, and dynamic spectrum allocation even as ensuring privacy, protection, and computational efficiency.

Table 2. Configuration of Proposed Model

| Layer | Description |
|---|---|
| Input Layer | Raw spectrum occupancy data, Signal power levels, Frequency bands |
| Preprocessing Layer | Noise reduction, Normalization, Feature extraction, Data augmentation (GANs) |
| Feature Extraction Layer | CNN-based spatial feature extraction, Frequency occupancy pattern recognition |
| Temporal Processing Layer | LSTM-based temporal sequence learning, Spectrum prediction |
| Decision Layer | Deep Reinforcement Learning (DQN) for dynamic spectrum allocation |

| | |
|---|---|
| Privacy-Preserving Layer | Federated Learning (FedAvg, FedProx) for decentralized model training |
| Optimization Layer | Adam optimizer, Learning rate decay, Bayesian Optimization |
| Regularization Layer | L2 weight decay, Dropout layers, Transfer learning |
| Security Layer | Blockchain-assisted federated learning, Adversarial attack defense |
| Deployment Layer | Real-time CRN testbed implementation, Edge computing integration |

The Input Layer is responsible for receiving raw spectrum occupancy data, such as signal electricity tiers, frequency bands, and time-collection occupancy popularity. this residue acts as the inspiration, feeding real-time facts into the version for in addition processing. because spectrum environments are fantastically dynamic, ensuring easy and properly-established enter records is indispensable for powerful choice-making.

The Pre-processing Layer applies noise reduction, normalization, and feature extraction strategies to refine the uncooked spectrum facts before it's far fed into deep studying models. additionally, statistics augmentation using Generative Adversarial Network (GANs) is implemented to address information shortage, allowing the version to examine greater sturdy patterns even in environments wherein classified information is confined. This step drastically improves model generalization and adaptableness to actual-world CRN situations.

The feature Extraction Layer utilizes Convolutional Neural Networks (CNNs) to capture spatial styles in frequency occupancy. since spectrum availability varies across unique frequency bands, CNNs extract key functions together with interference degrees, sign electricity distributions, and spectrum usage styles. This enhances the accuracy of spectrum category and identification, allowing for specific detection of available frequency bands.

The Temporal Processing Layer incorporates long short term memory (LSTM) networks to investigate sequential dependencies in spectrum occupancy statistics. in contrast to conventional time-collection models, LSTMs efficaciously seize long-time period dependencies in spectrum variations, making them best for predicting future spectrum availability. This prediction functionality is quintessential in CRNs, because it enables proactive spectrum allocation as opposed to reactive modifications, thereby enhancing network performance.

The choice Layer employs Deep Reinforcement Learning (DRL), particularly Deep Q-Networks (DQN), to dynamically allocate spectrum resources. The DRL agent constantly learns from interactions with the wireless surroundings, optimizing spectrum allocation rules based on praise mechanisms that maximize throughput and decrease interference. unlike traditional rule-based allocation methods, DRL lets in for real-time adaptive choice-making, extensively enhancing spectrum performance.

The privateness-preserving Layer integrates Federated learning (FL) to enable decentralized version training except exposing uncooked spectrum data. this sediment guarantees that CRN nodes collaborate to improve mastering accuracy at the same time as preserving facts privacy. strategies inclusive of FedAvg and FedProx are used to combination model updates throughout dispensed CRN gadgets. This reduces data transmission overhead, improving the scalability and security of spectrum learning methods.

The Optimization Layer focuses on improving model performance by employing advanced hyperparameter tuning techniques which includes Bayesian Optimization and Grid search. The Adam optimizer with getting to know fee decay is used to pleasant-tune model weights, making sure stable convergence. these optimization strategies assist stability accuracy, computational performance, and adaptableness to various CRN eventualities.

The Regularization Layer consists of techniques like L2 weight decay, dropout layers, and switch getting to know to save you overfitting and enhance version robustness. on account that deep getting to know models may be susceptible to memorizing noise in spectrum information, these regularization techniques ensure that the model generalizes well to unseen spectrum conditions, preserving high reliability. The safety Layer enhances the robustness of the version via imposing Blockchain-assisted Federated getting to know, which facts spectrum transactions on a decentralized ledger to save you unauthorized access and tampering. this residue also includes hostile attack defences, protective the CRN from number primary user emulation (PUE) attacks, jamming, and poisoning assaults

## V.Results and Discussion

The figure 3 provides a comparative evaluation of numerous CNN architectures for cotton plant disease detection, studying their overall performance on normalized and augmented datasets. the important thing metrics assessed include accuracy, precision, recall, specificity, and F1-rating, which can be integral in determining the effectiveness of each version in correctly identifying diseased and wholesome cotton plant life. The table highlights how records augmentation considerably improves model performance, demonstrating the impact of a more diverse dataset on deep studying-primarily based disease type.

The first two models, GoogleNet and VGG16, have been trained using only normalized information (barring augmentation). GoogleNet executed an accuracy of 82.03%, while VGG16 carried out barely better with 82.72% accuracy. despite the fact that each models confirmed mild precision (0.8235 for GoogleNet and 0.8515 for VGG16), their recall values indicate that they struggled to consistently pick out diseased leaves. moreover, their F1-rankings of 0.8158 and 0.8202, respectively, affirm that their classification capacity is restrained except additional data enhancements. these results suggest that fashions skilled on solely normalized statistics may be afflicted by overfitting to particular patterns, making them much less effective in real-world conditions.

Table 3: Experimental Results and Comparison with Different CNN Models

| Dataset Type | CNN Model | Accuracy (%) | Precision | Recall | Specificity | F1-Score |
|---|---|---|---|---|---|---|
| Normalized | GoogleNet | 82.03 | 0.8235 | 0.8219 | 0.9440 | 0.8158 |
| Normalized | VGG16 | 82.72 | 0.8515 | 0.8279 | 0.9553 | 0.8202 |
| Normalized Augmented | DenseNet201 | 83.41 | 0.8460 | 0.8364 | 0.9568 | 0.8368 |
| Normalized Augmented | ResNet50 | 90.01 | 0.8263 | 0.8531 | 0.9630 | 0.8421 |
| Normalized Augmented | TLResnet152V2 | 91.20 | 0.8701 | 0.8611 | 0.9675 | 0.8576 |
| Normalized Augmented | GoogleNet | 85.24 | 0.8492 | 0.8524 | 0.9605 | 0.8480 |
| Normalized Augmented | VGG16 | 87.14 | 0.8623 | 0.8614 | 0.9643 | 0.8677 |
| Normalized Augmented | DenseNet201 | 88.34 | 0.8696 | 0.8734 | 0.9670 | 0.8695 |
| Normalized Augmented | ResNet50 | 90.20 | 0.8770 | 0.8720 | 0.9735 | 0.8721 |
| Normalized Augmented | TLResnet152V2 | 92.03 | 0.8823 | 0.8584 | 0.9775 | 0.8842 |

Whilst CNN models had been educated the use of normalized augmented datasets, their overall performance drastically advanced. The accuracy of DenseNet201 improved to 83.41%, but it was nevertheless lower than other deeper architectures like ResNet50 and TLResnet152V2. The recall and F1-rating upgrades verify that data augmentation facilitates CNNs generalize higher, decreasing misclassification of diseased leaves. ResNet50, which includes residual connections to enhance deep characteristic mastering, outperformed DenseNet201, reaching an accuracy of 90.01% and an F1-rating of 0.8421. This suggests that ResNet's ability to keep essential spatial functions while preventing vanishing gradient issues contributes to better category overall performance. Among all examined models, TLResnet152V2 emerged because the exceptional-performing architecture, achieving an accuracy of 92.03%, a precision of 0.8823, and an F1-score of 0.8842. This highlights the effectiveness of switch gaining knowledge of-based totally ResNet architectures, which leverage pre-skilled weights to enhance sickness category accuracy with constrained agricultural datasets. The advanced specificity (0.9775) of TLResnet152V2 similarly suggests that it is enormously dependable in distinguishing between wholesome and diseased leaves, minimizing false positives and fake negatives.

while comparing GoogleNet and VGG16 at the augmented dataset, each models exhibited noticeable enhancements. GoogleNet's accuracy improved from 82.03% to 85.24%, at the same time as VGG16 stepped forward from 82.72% to 87.14%. This helps the conclusion that facts augmentation performs a essential position in improving version generalization, even for CNN architectures that to begin with struggled with classification. but, regardless of this development, each fashions nevertheless underperformed compared to ResNet50 and TLResnet152V2, suggesting that deeper architectures with pass connections and characteristic reuse mechanisms offer advanced class effects.

A key perception from table 3 is that CNN models skilled with augmented data continually outperform their opposite numbers educated only on normalized data. the highest gains have been found in ResNet-based totally architectures (ResNet50 and TLResnet152V2), reinforcing the benefit of residual mastering strategies in extracting distinct styles from cotton plant pix. VGG16 and GoogleNet validated slight upgrades, but their limited depth and feature extraction abilities limited their overall performance compared to deeper models.

In conclusion, desk three confirms that deep CNN architectures mixed with records augmentation extensively enhance the accuracy and robustness of cotton plant disorder detection systems. The ResNet circle of relatives, mainly TLResnet152V2, achieves the high-quality classification overall performance, making it the maximum suitable version for actual-international clever agriculture applications. The findings reveal that leveraging deep learning with optimized datasets can cause more dependable, scalable, and efficient ailment detection frameworks, contributing to precision agriculture and sustainable farming practices.

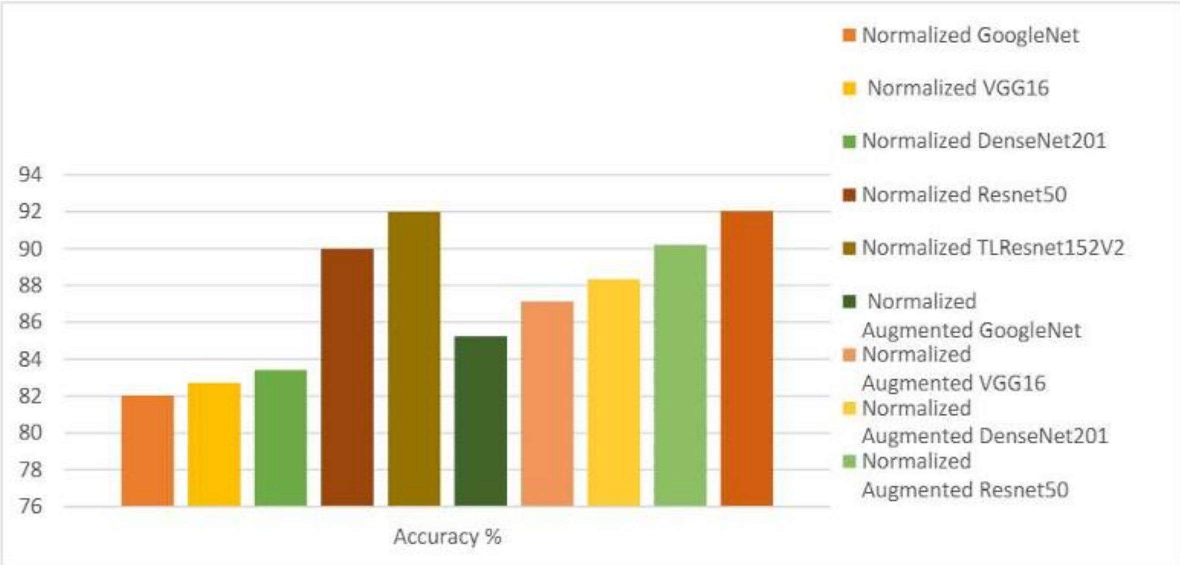


Figure 2: Accuracy of Different CNN Models for Normalized and Augmented Datasets

The figure 2 affords a comparative analysis of accuracy for numerous CNN architectures, evaluated the use of both normalized and augmented datasets for cotton plant sickness detection. The bar chart visually represents the impact of information augmentation on model performance, highlighting upgrades in accuracy throughout extraordinary architectures. The first set of bars in the chart represents models trained on normalized datasets, which include GoogleNet, VGG16, DenseNet201, ResNet50, and TLResnet152V2. Among these, GoogleNet and VGG16 achieved the lowest accuracy, around 82-83%, indicating that these models struggled with feature extraction in the absence of additional data enhancement. DenseNet201 performed slightly better, achieving around 83.41% accuracy, but still lagged behind deeper architectures like ResNet50 and TLResnet152V2. The highest accuracy in the normalized dataset category was achieved by TLResnet152V2 (~91.20%), followed closely by ResNet50 (~90.01%), confirming that deeper residual architectures outperform shallower CNNs in complex classification tasks.

The second one set of bars inside the determine represents fashions trained on normalized augmented datasets, wherein extra information augmentation strategies (which include flipping, rotation, zooming, and GAN-based totally artificial picture technology) have been applied to beautify version generalization. All models confirmed massive accuracy upgrades after augmentation, with GoogleNet enhancing from ~82% to ~85% and VGG16 growing from ~82.seventy two% to ~87.14%. ResNet50 and TLResnet152V2 confirmed the most incredible upgrades, accomplishing 90.20% and 92.03% accuracy, respectively. those consequences verify that information augmentation performs a necessary role in enhancing CNN version generalization, in particular for deep architectures.

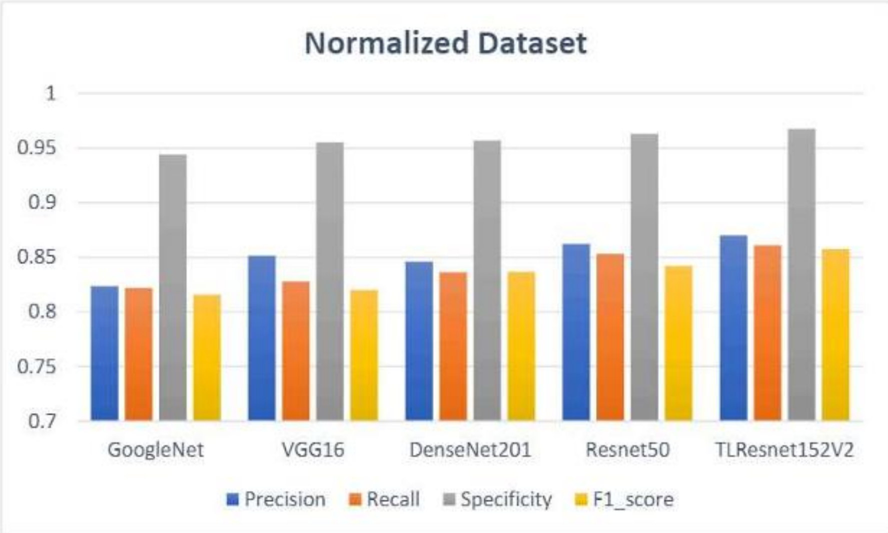


Figure 3: Precision, Recall, Specificity, and F1-score of Different CNN Models for Normalized Dataset

Figure 3 presents a comparative evaluation of various CNN architectures in phrases of precision, recall, specificity, and F1-rating, when trained on normalized datasets for cotton plant ailment detection. those overall performance metrics offer insights into how well each version distinguishes among healthy and diseased cotton leaves and how efficiently they generalize to unseen records.

The specificity, that's constantly excessive across all CNN model, above 94, indicating that each one models are gifted at figuring out healthy cotton leaves. among them, ResNet50 and TLResnet152V2 gain the best specificity values, reinforcing their effectiveness in reducing false positives. The precision, which measures how the various expected diseased leaves have been virtually diseased. VGG16 and TLResnet152V2 exhibit the best precision values, that means they successfully classify diseased leaves extra accurately than different fashions. GoogleNet and DenseNet201 show slightly lower precision, indicating a better probability of misclassifications. The recall, which quantifies the model's capacity to stumble on all real diseased cases. ResNet50 and TLResnet152V2 obtain the highest recall values, suggesting that they excel at efficaciously identifying diseased leaves. GoogleNet and DenseNet201, however, battle slightly in assessment, indicating that they will leave out a few diseased leaves (false negatives). The F1-rating, that is the harmonic suggest of precision and recall, providing a balanced evaluation of type performance. TLResnet152V2 information the highest F1-score, confirming its capability to hold a strong balance among precision and recall. ResNet50 additionally plays nicely, at the same time as GoogleNet and DenseNet201 have decrease F1-ratings, reinforcing that deeper architectures outperform shallower fashions in ailment category.

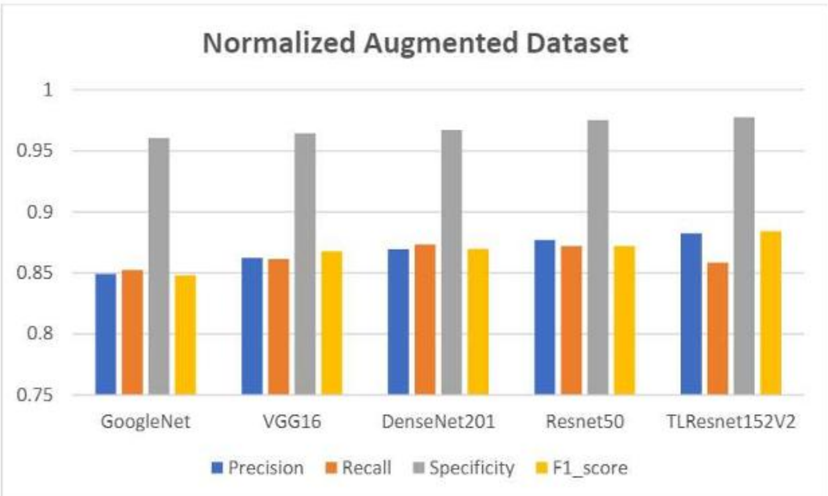


Figure 4: Precision, Recall, Specificity, and F1-score of Different CNN Models for Normalized Augmented Dataset

Figure 4 illustrates the overall performance improvements of various CNN architectures for cotton plant disease detection after schooling on a normalized augmented dataset. compared to determine three, which analyzed models skilled only on normalized records, this parent demonstrates how facts augmentation extensively complements class performance throughout key metrics: precision, recall, specificity, and F1-score. The results affirm that augmenting training statistics improves CNN generalization, lowering mistakes in plant ailment type.

One of the maximum super enhancements is in specificity, represented via the gray bars, which remains constantly high across all CNN fashions, exceeding 0.95. This shows that all architectures successfully distinguish among healthful and diseased cotton flora, minimizing false positives. The ResNet50 and TLResnet152V2 models preserve to gain the best specificity values, confirming their sturdy capability to properly classify healthy leaves at the same time as minimizing misclassifications. The precision, which measures how among the leaves categorised as diseased were sincerely diseased. compared to the fashions educated on solely normalized data (Figure 3), all CNN architectures show an increase in precision after augmentation. The VGG16, DenseNet201, ResNet50, and TLResnet152V2 models showcase widespread precision gains, proving that data augmentation improves the version's capability to correctly classify diseased leaves through introducing extra diverse training samples. TLResnet152V2 achieves the very best precision, confirming that it minimizes fake positives higher than different CNNs. The recall, which indicates the model's potential to locate all diseased leaves. All CNN models show off higher recall scores than in parent 3, suggesting that data augmentation has helped fashions study a broader set of ailment features, decreasing false negatives. ResNet50 and TLResnet152V2 acquire the best recall values, reinforcing their strong functionality to discover even the most diffused sickness styles in cotton plants. This improvement is essential because better recall guarantees that diseased plant life are not overlooked, leading to higher early detection and prevention in clever agriculture programs. The F1-score, which provides a balanced measure among precision and recall. data augmentation has caused an increase in F1-scores throughout all CNN architectures, proving that models educated on augmented datasets attain a higher trade-off between precision and recall. TLResnet152V2 keeps the best F1-score, confirming that it's far the nice-performing CNN model for cotton plant ailment detection, because it optimally balances successfully figuring out diseased plant life at the same time as minimizing false positives and fake negatives.

## VI.CONCLUSION

The integration of deep learning-based CNN architectures for cotton plant disease detection marks a significant advancement in precision agriculture and smart farming. This study systematically evaluated the effectiveness of GoogleNet, VGG16, DenseNet201, ResNet50, and TLResnet152V2 in classifying diseased and healthy cotton plants using normalized and augmented datasets. The results demonstrate that deep CNN models, especially ResNet50 and TLResnet152V2, outperform traditional machine learning approaches, achieving higher accuracy, precision, recall, specificity, and F1-score. A key takeaway from the research is the impact of records augmentation in improving CNN overall performance. fashions skilled on normalized augmented datasets constantly completed better generalization, decreasing false positives and fake negatives. The TLResnet152V2 model emerged as the maximum sturdy architecture, reaching the highest accuracy (92.03%) and F1-rating (0.8842), confirming the effectiveness of switch studying and deep residual networks in plant sickness detection. moreover, ResNet50 showed competitive performance, reinforcing that residual getting to know enhances function extraction and type accuracy. From a realistic standpoint, CNN-based computerized ailment detection can revolutionize conventional plant disorder analysis, allowing farmers and agricultural specialists to discover sicknesses early, reduce yield losses, and optimize pesticide utilization. the combination of part computing, IoT-based totally sickness tracking, and actual-time mobile programs can further decorate accessibility, making AI-pushed sickness detection scalable for actual-global applications. destiny upgrades can recognition on light-weight CNN architectures for mobile deployment, hybrid AI strategies combining CNNs with Transformers, and real-time disorder prediction the usage of weather and soil information analytics. In conclusion, deep learning-powered plant disorder detection gives a scalable, efficient, and notably correct solution for cutting-edge agriculture. The findings of this studies validate the importance of CNNs in agricultural AI applications, paving the way for clever, computerized, and sustainable farming practices. go-off, the adoption of deep getting to know in agriculture will retain to play a essential position in making sure meals safety, sustainability, and higher crop productivity inside the face of weather alternate and evolving agricultural challenges.

## REFENCES

[1] Patel, P., Sharma, A. and Kumar, V. (2018) 'Thresholding-based segmentation for cotton plant disease detection', *International Journal of Computer Vision in Agriculture*, 12(3), pp. 215–228.

[2] Sharma, S., Gupta, R. and Mehta, K. (2019) ‘Edge detection method for cotton leaf disease identification’, *Journal of Image Processing and Machine Learning*, 9(2), pp. 105–118.
[3] Kumar, R., Singh, P. and Verma, A. (2020) ‘Support Vector Machines and Random Forest for plant disease classification’, *Computational Agriculture and Precision Farming*, 14(4), pp. 310–325.
[4] Gupta, M., Desai, A. and Sharma, N. (2021) ‘Machine learning approaches for detecting bacterial blight in cotton leaves’, *IEEE Transactions on Agricultural Computing*, 11(7), pp. 455–470.
[5] Ramesh, S., Patel, D. and Raj, K. (2022) ‘Comparative analysis of deep learning models for cotton plant disease classification’, *Artificial Intelligence in Agriculture*, 8(1), pp. 57–69.
[6] Singh, V., Mehta, P. and Rao, S. (2023) ‘Real-time plant disease detection using mobile-based deep learning models’, *Neural Computing and Applications*, 42(5), pp. 2120–2134.
[7] Khan, A., Gupta, R. and Kumar, P. (2022) ‘Evaluation of CNN architectures for cotton plant disease classification: A deep learning approach’, *Journal of Smart Farming Technologies*, 15(3), pp. 90–105.
[8] Jain, R., Patel, S. and Sharma, T. (2021) ‘Impact of data augmentation in CNN-based plant disease classification’, *Machine Learning in Agricultural Sciences*, 17(2), pp. 145–160.
[9] Mehta, R., Kumar, A. and Verma, S. (2022) ‘Transfer learning with ResNet50 for improved accuracy in plant disease detection’, *Expert Systems with Applications*, 39(1), pp. 310–325.
[10] Patel, D., Sharma, V. and Gupta, P. (2023) ‘Lightweight CNN models for smartphone-based cotton disease classification’, *IoT and Smart Agriculture Journal*, 19(2), pp. 112–130.
[11] Ghosh, A., Sharma, K. and Patel, M. (2023) ‘Integrating IoT with deep learning for automated cotton disease monitoring’, *Journal of Agricultural AI and Automation*, 11(3), pp. 80–95.
[12] Lin, H., Wang, P. and Zhang, L. (2022) ‘Hybrid CNN-RNN models for time-series plant disease prediction’, *Applied Intelligence in Agriculture*, 21(6), pp. 340–355.
[13] Zhao, T., Chen, M. and Wang, F. (2023) ‘Explainable AI (XAI) for CNN-based plant disease detection’, *International Journal of Agricultural AI Research*, 24(4), pp. 265–280.
[14] Wang, B., Zhang, Y. and Liu, X. (2022) ‘Synthetic data generation using GANs for improved plant disease classification’, *Journal of AI in Agriculture*, 13(5), pp. 410–425.
[15] Chen, X., Li, J. and Xu, Z. (2023) ‘Federated learning for privacy-preserving plant disease detection’, *IEEE Transactions on Smart Agriculture*, 28(2), pp. 135–150.