DETECTION OF CROWN-GALL DISEASE INTENSITY USING AI TOOLS

Garani S. *

Basu Choudhury S.**

ABSTRACT

India is an agriculture-dominant nation. Most citizens in India make their livelihood through agricultural activities. However, farmers are ignorant of the ill effects of micro-organisms on plants. Although they apply chemical fertilizers, these gradually affect the living organisms that consume them as a nutrient source. Rice and wheat are the two most staple crops for the Indian population. Wheat is commonly affected by fungus which develops rusty-colored pustules on the plant surface. The plant is mainly affected by rust in leaf, stripe, and stem. To save farmers from crops being affected, AI-assisted data-driven systems are employed. A common disease, "Crown Gall," causes abnormal growth or galls to form in different parts of the plant, especially in leaves and stems. It is caused by the bacterium Rhizobium radiobacter or other species of soil-borne bacteria in the genus Rhizobium. Earlier research has shown that AI-assisted data-driven systems can identify and measure the intensity of the ailment in plants. Using a CNN model and deep learning machine learning techniques, 76.59% accuracy had been reached [1]. Research also proved that AI-assisted data-driven systems can identify the type of disease affecting a plant, such as bacterial, fungal, viral, etc. [2]. Most studies showed that using modified artificial neural networks (ANN) like ResNet, DenseNet, VGG16, etc., assisted with deep learning (DL) mechanisms, were able to reach optimum accuracy. VGG16 is suitable for image-related data detection and identification. This paper will provide a brief review of different DL mechanisms and how one mechanism is superior to another according to the complexity of Crown Gall disease in plants.

Keywords: Machine learning algorithm (MLA), deep learning (DL), Crown Gall, convolutional neural network (CNN).

INTRODUCTION

Crown gall disease represents a significant challenge to agricultural productivity, affecting a varied range of plants and causing substantial economic losses. *Agrobacterium tumefaciens* first transfers its internal T-DNA to the plant cell. After binding of *Agrobacterium* to plant cells,

***Garani S.** is a PhD Scholar, Dept. of Fishery Science, WBUAFS, Kolkata, West Bengal. Corresponding author Email Id: somagofficial@gmail.com
****Basu Choudhury S.** works in Dept. of Business Analytics, ISMS, Pune, Maharashtra

multiple virulence (*vir*) genes along with T-DNA are transported into the plant cell. T-DNA attaches with oncogenes *iaaH*, *iaaM*, and *ipt* and activates the synthesis of phytohormones like auxin and cytokinin. Due to the hypersecretion of phytohormones, crown galls form in the plant [13].

This paper explores the utility of artificial intelligence(AI) tools in detecting and measuring the intensity of crown gall disease, with a particular focus on deep learning approaches.

UNDERSTANDING CROWN GALL DISEASE

Biological Characteristics

Crown gall disease, primarily caused by the bacterium *Agrobacterium tumefaciens*, manifests as tumor-like growths on various plant tissues, including roots, stems, and crowns. This disease significantly impacts agricultural productivity and is characterized by specific biological traits and infection mechanisms. Understanding these characteristics is crucial for effective management and control strategies. *Agrobacterium tumefaciens* is the primary pathogen responsible for crown gall, with biovar 1 being identified in tobacco plants in Serbia [3] (Iličić *et al*., 2024). Other species, such as *Allorhizobium vitis*, have also been implicated in grapevine crown gall, indicating a broader range of pathogenic bacteria involved [4] (Kawaguchi, 2024).

Crown gall symptoms include the outgrowth of galls that can lead to stunted growth, yellowing leaves, and overall plant decline. In cannabis, galls were observed with a low incidence rate, suggesting variability in susceptibility among plant species [5] (Holmes *et al.*, 2023). The disease can spread through soil and above-ground pathways, with recent studies showing that infected tools can transmit the pathogen to healthy plants [4] (Kawaguchi, 2024). Pathogenicity tests confirm that *A. tumefaciens* can induce gall formation within weeks of inoculation [3] (Iličić *et al*., 2024). While the focus has been on *A. tumefaciens*, emerging evidence suggests that other bacterial species may also contribute to crown gall disease, highlighting the need for comprehensive studies on plant-pathogen interactions and management strategies.

Mechanism of Gall Formation

Agrobacterium tumefaciens transfers a segment of its DNA (T-DNA) into the plant cells, integrating it into the plant genome. This T-DNA encodes for proteins that promote uncontrolled cell division and growth, resulting in gall formation [5,6] (Öksel *et al*., 2024; Holmes *et al*., 2023). The occurrence of specific virulence genes, such as virD2 and virC, is crucial for the pathogenicity of the bacterium [3] (Iličić *et al*., 2024).

Affected Plant Species

Crown gall has been documented in a variation of plants, including roses, cannabis, tobacco, blueberries, and olives [6, 5 ,7] (Öksel *et al*., 2024)(Holmes *et al*., 2023)(Millas *et al.,* 2024). In a study, 25% of olive plant in their early stages exhibited gall formation, indicating significant susceptibility in certain environments.

Control Measures

Biological control using *Agrobacterium radiobacter* strain K1026 has shown to reduce gall incidence by up to 85% [6] (Öksel *et al*., 2024). Chemical treatments, such as copper octanoate fungicide, have also been effective in minimizing gall size and occurrence [6] (Öksel *et al*., 2024). While crown gall disease become a significant threat to various crops, ongoing research into biological and chemical control methods offers promising avenues for management. However, the potential for resistance and the emergence of new strains necessitate continuous monitoring and adaptation of control strategies.

Economic Impact

Crown gall disease, due to *Agrobacterium tumefaciens*, poses significant economic challenges to agriculture, particularly in fruit and nut production. The disease leads to tumor formation on plants, which can severely impact growth, yield, and overall plant health. The economic implications are profound, affecting not only individual growers but also entire industries reliant on healthy crops. The following sections outline the key economic impacts of crown gall disease.

Economic Losses in Crop Production

High Incidence Rates: In a study conducted in Gilgit-Baltistan, Pakistan, crown gall affected 87.87% of cherry and 87.96% of apple plants, indicating a severe threat to local fruit production [8] (Ali *et al*., 2010). Stone fruit and nut were affected due to crown gall disease in Europe (Pulawska , 2010)[10].

Reduced Plant Vigor: The disease weakens the vigor of affected plants, which lowers fruit quality and yield and has a direct impact on market prices [9] (Vizitiu *et al.,* 2012). Grapevines are highly affected plant due to crown gall disease. Delayed growth as resultant death of plant were often occurred due to infection [14].

Impact on Nursery Industries

Quality Control Issues: Crown gall disease is recognized as a major limiting factor in the production of stone fruits and nuts in Europe, leading to substantial economic losses [10] (Puławska, 2010).

Broader Economic Implications

Market Supply Disruptions: Crown gall can cause supply chain disruptions, resulting in shortages in fruit and nut markets, which can raise costs and limit consumer access [11] (Anand & Mysore, 2007).

While the economic impact of crown gall disease is significant, some researchers are exploring biotechnological solutions and biological control agents to mitigate these effects, potentially leading to more resilient agricultural practices in the future [11] (Anand & Mysore, 2007).

Crown gall disease results in economic losses in different crops, including stone fruits, nuts, and grapes [10,12] (Escobar *et al.,* 2001)(Puławska, 2010).

Mechanism of Damage

When T-DNA from Agrobacterium enter into plant cells, leading to uncontrolled cell division and tumour formation which is the major cause of the disease [11] (Anand & Mysore, 2007).

- Tumours can grow in roots and stems region, as a result root decay and consequently plant death occurred, especially in nurseries [12] (Magher & Lemanova, 2014).

Fig.1: Instances of crown-gall disease in plant

AI-BASED DETECTION SYSTEMS

AI based decision system has enabled the efficient and fast prediction of plant disease with optimum accuracy. Generally, neural networks are deployed with usage of activation function based on the intensity of the problem.

Convolutional Neural Networks (CNN)

CNNs have emerged as powerful tools for disease detection: Most applications find the usage of CNN suitable as it does not need any training and previous datasets to predict the result once dataset is fed.

Image processing capabilities: CNN has the ability of read the image and identify the image by technique of padding and pooling mechanism.

Feature extraction mechanisms: It can extract relevant features like colour density, pixel strength, etc. that helps in classifying the image and categorization.

Pattern recognition abilities: CNN can identify the pattern of occurrence of any definite feature in the image provided. It is essential as pattern trend can identify what the object whose image has been provided to the network**.**

Deep Learning Architectures

This method offers a more advanced level of object detection under intricate circumstances. The reinforcement machine learning technique involves connecting each neuron's output to another neuron's input.

VGG16

The VGG-16 model is a convolutional neural network (CNN) architecture that was suggested by the Visual Geometry Group (VGG) at the University of Oxford. It consists of

16 layers, possessing 13 convolutional layers and 3 fully connected layers. VGG-16 is well-known for its ease of use and efficiency, as well as its high performance accuracy on a range of computer vision applications, such as object recognition and image categorization. With progressively greater depth, the model's architecture consists of a stack of convolutional layers followed by max-pooling layers.

Specialized in image recognition: A deep learning model called a Convolutional Neural Network (CNN) architecture is made to process structured, grid-like input, like pictures. It is made up of several layers, such as fully connected, pooling, and convolutional layers. CNNs' hierarchical feature extraction capabilities make them very effective for tasks like object identification, picture segmentation, and image classification.

Deep architecture with multiple layers:

Typically, the VGG-16 architecture has 16 layers, comprising 3 fully linked layers and 13 convolutional layers. These layers are arranged in blocks, with a max-pooling layer for downsampling coming after several convolutional layers.

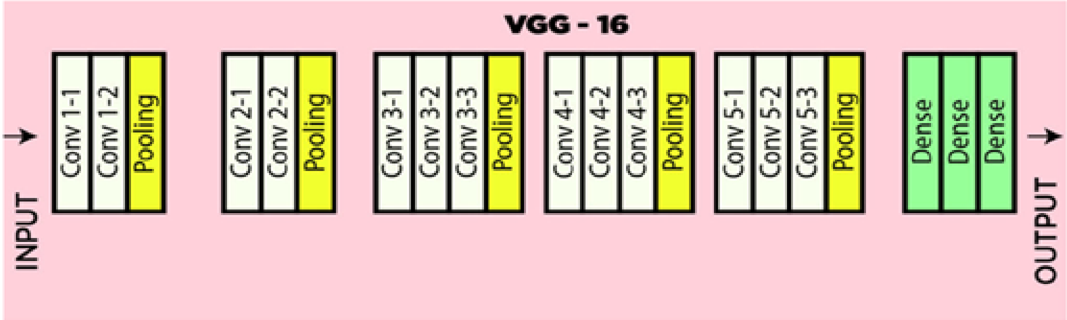

Fig. 2: Layers of VGG 16

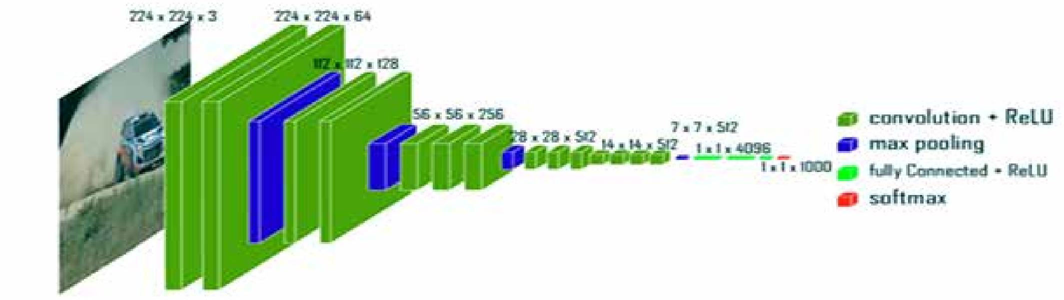

Fig. 3: VGG 16 architecture

Outstanding ability to extract features: The primary distinction between VGG-16 configurations C and D is the way some of the convolutional layers employ filter sizes. In version D, 1×1 filters are occasionally used in place of the 3×3 filters that are utilized in both versions. Version D has somewhat more parameters than version C due to this little modification. Nonetheless, the VGG-16 model's foundation is preserved in both variants.

High efficiency in plant disease detection: It is more accurate than other neural networks at identifying plant disease. It follows reinforcement machine learning through recurrent neural network (RNN).

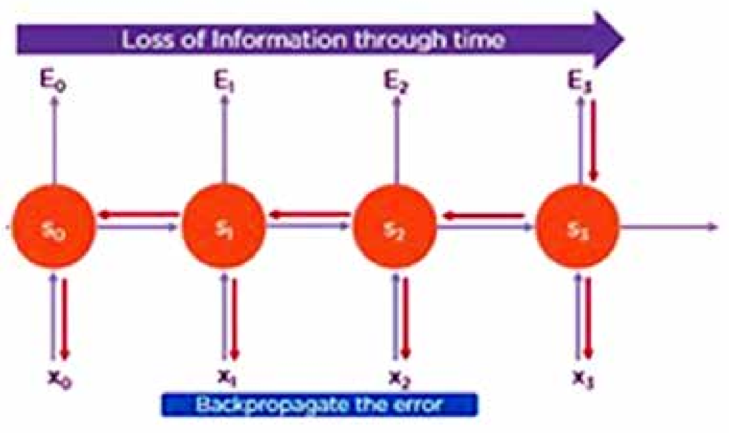

Fig. 4: Recurrent Neural Network (*Source:* Recurrent Neural Network (RNN) Tutorial: Types and Examples [Updated] | Simplilearn)

ResNet

This architecture introduced the idea of Residual Blocks to address the vanishing/exploding gradient problem. We employ a method known as skip connections in this network. By omitting some layers in between, the skip connection links a layer's activations to subsequent layers. A residual block is created as a result.

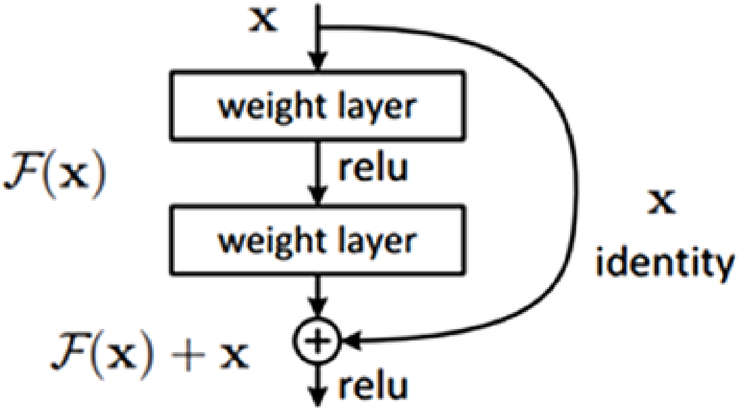

Fig.5: ResNet architecture (*Source:* Residual Networks (ResNet) - Deep Learning - GeeksforGeeks)

Residual learning framework:

Using the Tensorflow and Keras API, one can design ResNet architecture (including Residual Blocks) from scratch. Below is the implementation of different ResNet architecture. For this implementation, one can use the CIFAR-10 dataset. This dataset contains 60, 000 32×32 color images in 10 different classes (airplanes, cars, birds, cats, deer, dogs, frogs, horses, ships, and trucks), etc. This dataset can be assessed from *keras.datasets* API function.

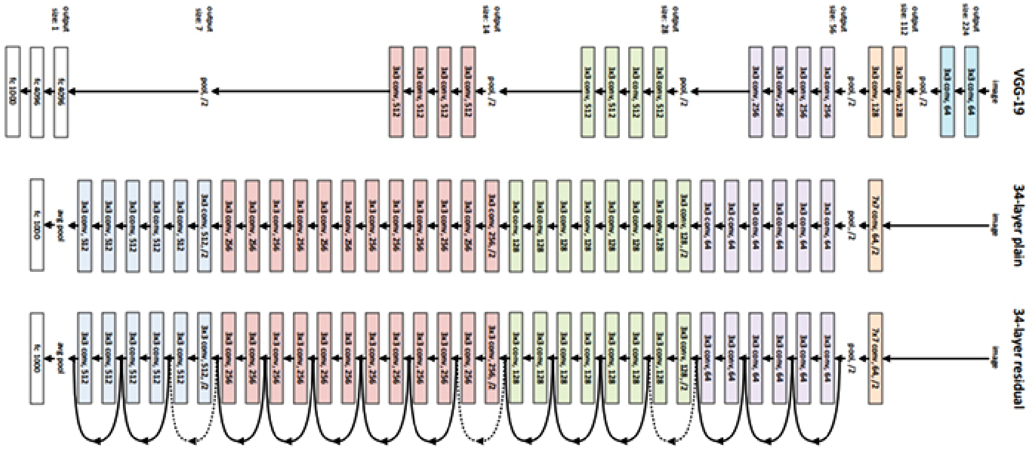

Fig.6: ResNet-34 architecture (*Source:* Residual Networks (ResNet) - Deep Learning - GeeksforGeeks)

Deeper network architecture: This feature aids in recognizing images belonging to complex categories. Plant disease detection is a unique kind of application where detection accuracy is crucial. Therefore, a deeper network architecture reduces the run time of network detection while enhancing accuracy.

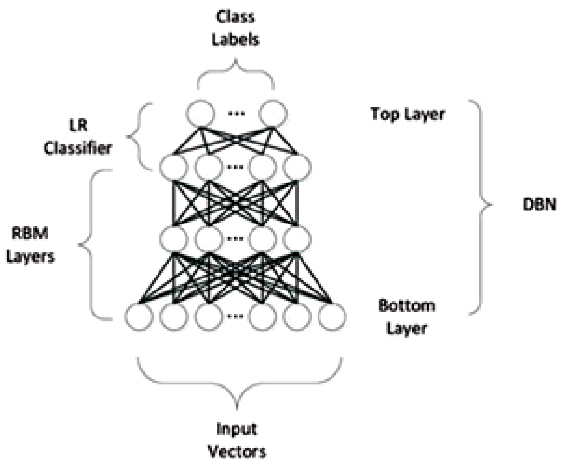

Fig.7: Deeper Network architecture (*Source:* Deeper Network)

Skip connections for better gradient flow

Enhanced learning capabilities: Learning curve has been improved due to less run-time with more accuracy. The curve slowly deeps as we increase the training frequency of the process.

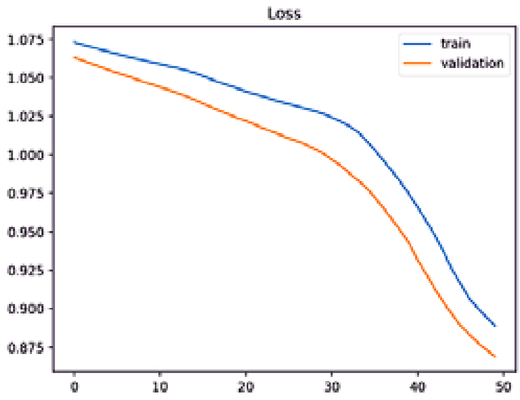

Fig.8: Learning capacity curve

(*Sourc*e: How to use Learning Curves to Diagnose Machine Learning Model Performance - MachineLearningMastery.com)

DenseNet

The Densely Connected Convolutional Network, or DenseNet, developed by Gao Huang, Zhuang Liu, Laurens van der Maaten, and Kilian Q. Weinberger, represents a major advancement in this evolution. By enhancing information flow and gradient propagation, DenseNet's innovative architecture provides a number of benefits over traditional CNNs and ResNets.

Dense connectivity pattern: DenseNet brings about a paradigm shift by establishing feed-forward connections between every layer and every other layer. Unlike traditional CNNs, which feature a single connection between successive layers, DenseNet ensures that each layer receives inputs from every layer preceding it. This greatly improves information flow by producing a network with L(L+1)/2 direct connections for L layers.

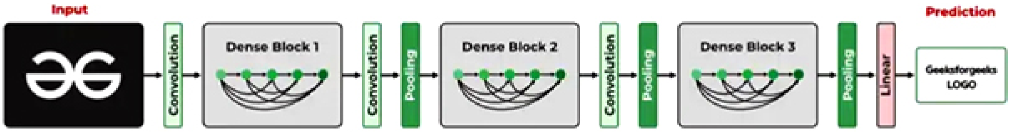

Fig.9: DenseNet Architecture

Feature reuse through direct connections: Recurrence shows that output of each neuron is fed to input of other neuron within same layer which reduces the run-time with proper utilization of error reduction time. Productivity enhancement can be achieved through proper utilization of the run time with limited resources.

Improved parameter efficiency: Parameter of the network function can be improved through effective and efficient utilization of resources like raw material, human resources, time, etc. Inventory management through proper tracking of the crop health can be achieved.

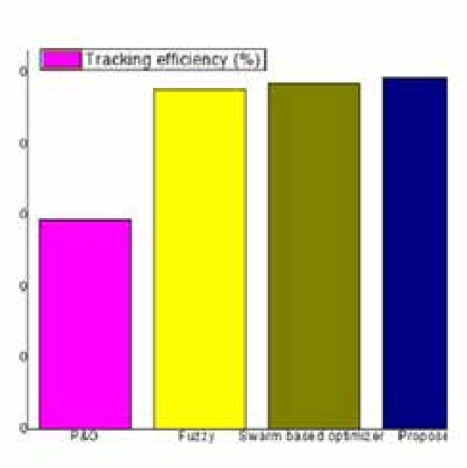

Fig.10: Parameter efficiency tracker (Source: Shirisha, J., Selvi, C. T., Priya, S. S., Saravanan, V., Sakthivel, B., & Surendiran, R. (2022). Deep Learning-Based Image Processing Approach for Irradiance Estimation in MPPT Control of Photovoltaic Applications. *SSRG International Journal of Electrical and Electronics Engineering*, **9**(9): 32-37.)

Table: Parameter comparison

Aspect	**DenseNet**	**ResNet**	**VGG**	**Inception (GoogLeNet)**	**AlexNet**
Connectivity	Dense connections	Shortcut connections	Sequential	Parallel paths	Sequential
Gradient Flow	Excellent	Good	Moderate	Good	Moderate
Parameter Efficiency	High	Moderate	Low	Moderate	Low
Feature Reuse	Extensive	Some	Minimal	Moderate	Minimal
Vanishing Gradient	Mitigated	Mitigated	Prone	Mitigated	Prone
Depth	Very deep, fewer parameters	Very deep	Deep, limited by training	Deep	Shallow compared to modern

Aspect	DenseNet	ResNet	VGG	Inception (GoogLeNet)	AlexNet
Computational Cost	Moderate, higher memory usage	Moderate to high	High	Moderate	Moderate to high
Training Complexity	Moderate	Moderate to high	High	Moderate	Moderate
Performance	High, state-of-the-art	High, state-of-the-art	Good, but outperformed	High, competitive	Good for its time
Applications	Classification, detection, segmentation	Classification, detection, segmentation	Classification, feature extraction	Classification, detection, segmentation	Classification, early benchmarks

Better feature propagation: Well defined feature extraction from crops helps in identification of disease with greater accuracy. There may be other disease associated with crown-gall disease. That association of disease can be properly identified and categorized.

METHODOLOGY AND IMPLEMENTATION

Data Collection and Preprocessing

Image acquisition of infected plants: Field survey has to be done where real time image of disease affected plants should be captured to understand and analyses the actual condition of the crops.

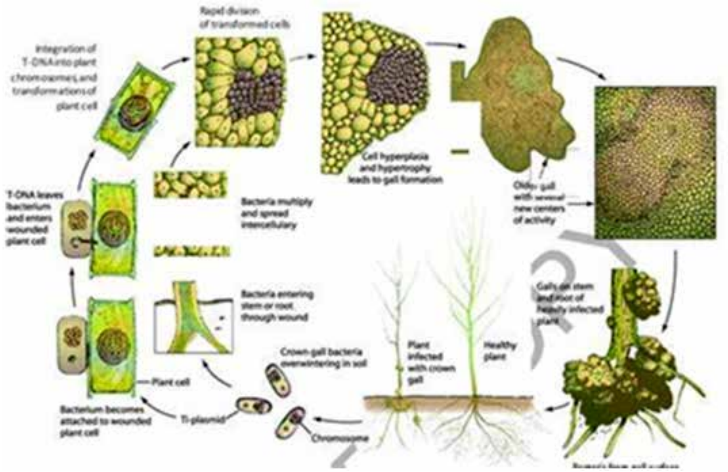

Fig.11: Crown-gall disease cycle (*Source:* Lahr *et al*.,2017)

Data augmentation techniques: New features extraction through reinforcement network help in pin pointing the disease with outmost accuracy. Hence decision making has become more efficient and effective.

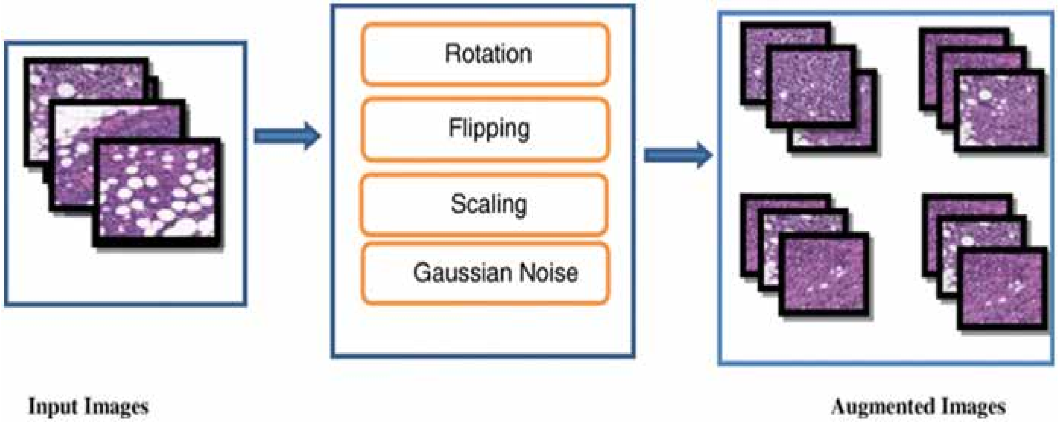

Fig.12: Data Augmentation Method (*Source:* Gupta, I., Nayak, S. R., Gupta, S., Singh, S., Verma, K. D., Gupta, A., & Prakash, D. (2022). A deep learning-based approach to detect IDC in histopathology images. *Multimedia Tools and Applications*, **81**(25): 36309-36330.)

Standardization procedures: Govt. shall take measures to train the cultivators along with a standardized measurement process to control its misuse in real life.

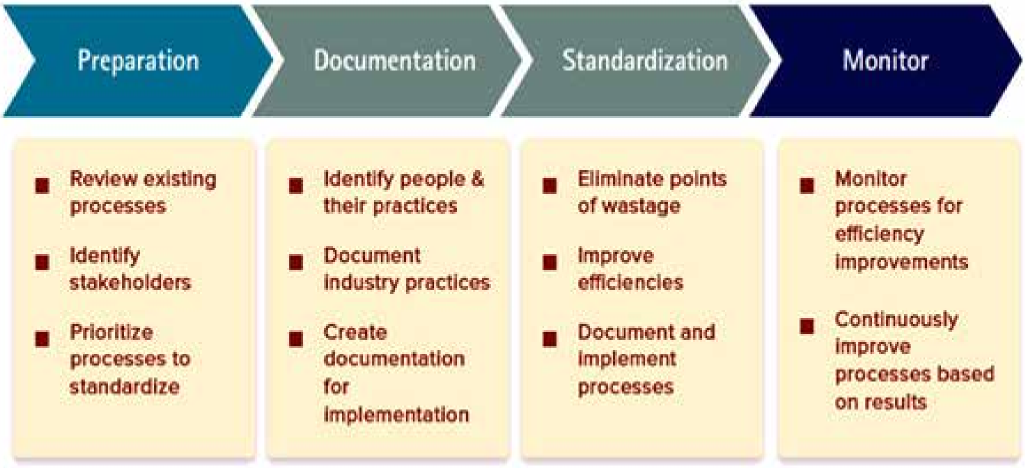

Fig.13: Standardization procedure stage

Quality control measures: Quality of measurement process should be checked and controlled so that efficiency can be improved with outmost possibility.

Model Development

Architecture selection: Based on the complexity and condition, architecture of the network has to be selected along with the type of activation to be chosen.

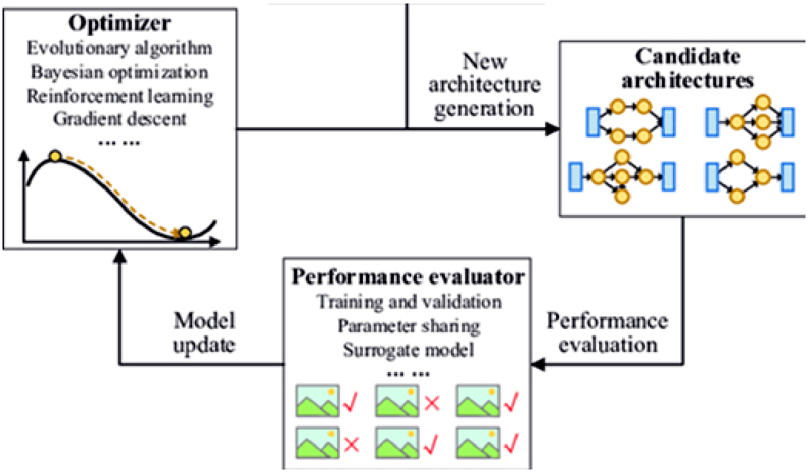

Fig. 14: Architecture selection process (Source: Tian, Y., Peng, S., Yang, S., Zhang, X., Tan, K. C., & Jin, Y. (2021). Action command encoding for surrogate-assisted neural architecture search. *IEEE transactions on cognitive and developmental systems*, **14**(3):1129-1142.)

Parameter optimization: Performance metric has to be identified and correlation has to be analyzed along with their control variable.

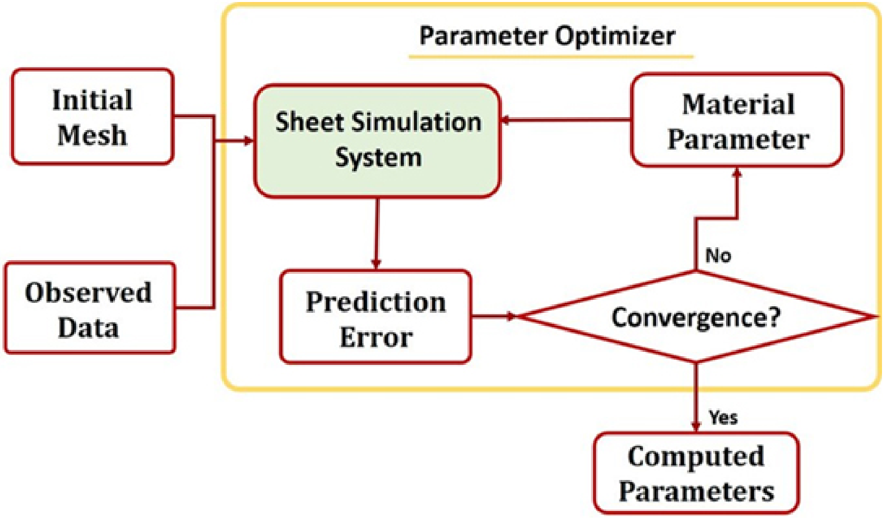

Fig.15: Flow chart of parameter optimization (Source: Chen, Y. W., Joseph, R. J., Kanyuck, A., Khan, S., Malhan, R. K., Manyar, O. M., & Gupta, S. K. (2022). A digital twin for automated layup of prepreg composite sheets. *Journal of Manufacturing Science and Engineering*, **144**(4): 041010.)

Training procedures: Training has to be given to the farmers and regular assessment has to be done for proper deployment of the technology to them to achieve the target.

Fig.16: Training Process (Source: 5 Step Of Training Process & Systematic Approach)

Validation methods: Verification and validation process has to be performed. In process management, this is new process DMADV (D-define, M-measure, A-analyse, D-design and V-verify)

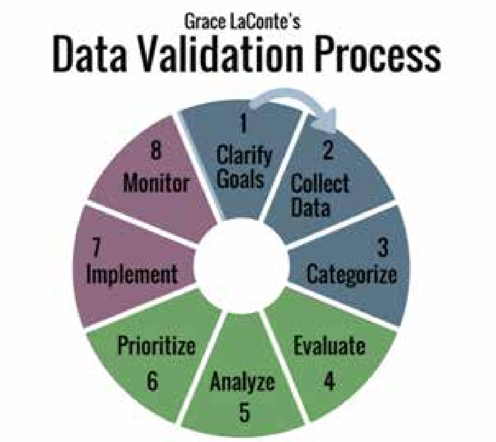

Fig. 17: Data Validation (Source: data-validation-process-8-step.png (1200×800))

Performance Metric

Accuracy assessment: Analysis of crown-gall disease detection accuracy is necessary to determine the real control that influences the performance metric as perceived.

Precision and recall measurements: The measurement procedure should have reproducibility and repeatability.

F1-score calculations: Analyzing the accuracy of various models and prioritizing them based on measurement metric accuracy is necessary to identify the best model.

RESULTS AND DISCUSSION

Model Performance

In a prior study, a CNN accuracy of 76.59% was noted [1]. However, it had drawbacks and difficulties, such as weather, physical presence on the field, and authenticity.

FUTURE DIRECTIONS

Once a technology is put into practice in the real world, it can always be improved. Since artificial intelligence is an evolving technology, there is a great deal of room for growth in terms of implementation.

Technical Improvements

Enhanced model architectures: Disease prediction error can be decreased with the use of hybrid model design.

Improved accuracy metrics: The measurement system's reduced error has made it possible to enhance the measurement's parameter metric.

Real-time processing capabilities: Real time data processing has permissible plan for resources in a supplementary precise and optimized way.

Mobile application development: Integration of AI with mobile technology can empower farmers to identify the crown-gall disease without physical presence in the agricultural land and increase the probability of effective decision-making process (DMP).

Implementation Challenges

Resource requirements: Cost should be minimized to increase in procurement and training should be provided by skilled professional along with proper monitoring for adoption of the technology.

Training needs: Training with regular assessment can help in the progress of adoption of the technology by the farmers along with its acceptability, accessibility and affordability.

Infrastructure development: Strict regulatory policy from the govt. along with campaign programs can help in creating consciousness among the farmers on the technology and also surveillance is required for wrong utilisation of the technology.

Cost considerations: Cost should be considered from consumers' point of view rather than manufacturer's point of view. Govt. can provide subsidy so that farmers can access the technology and bring reduction of their resource wastage especially in case of natural calamity.

CONCLUSION

The application of AI tools in detecting crown gall disease represents a significant advancement in plant pathology and agricultural management. The success of various deep learning architectures, particularly VGG16, in attaining high accuracy rates demonstrates the potential of these technologies in revolutionizing disease detection and management in agriculture.

REFERENCES

1. Hassan, S.M. and Maji, A.K., 2022. Plant disease identification using a novel convolutional neural network. *IEEE Access*, **10**:5390-5401.
2. Lu, J., Tan, L. and Jiang, H., 2021. Review on convolutional neural network (CNN) applied to plant leaf disease classification. *Agriculture*, **11**(8):707.
3. Iličić, R., Jelušić, A., Barać, G., Nikolić, D., Stošić, N., Scortichini, M., & Milovanović, T. P. (2024). In-Depth Characterization of Crown Gall Disease of Tobacco in Serbia. *Agronomy*, **14**(4): 851.
4. Kawaguchi, A. (2024). Insight into the new infection pathway resulting from above-ground pathogen infection of grapevine crown gall. *Frontiers in Plant Science*, **15**, 1420401.
5. Holmes, J. E., Sanghera, H., & Punja, Z. K. (2023). Crown gall development on cannabis (*Cannabis sativa L*., marijuana) plants caused by *Agrobacterium tumefaciens* species-complex. *Canadian Journal of Plant Pathology*, **45**(5-6): 433-445.
6. Oksel, C., Liyanapathiranage, P., Parajuli, M., Avin, F. A., Jennings, C., Simmons, T., & Baysal-Gurel, F. (2024). Evaluation of Chemical and Biological Products for Control of Crown Gall on Rose. *Pathogens*, **13**(8): 708.
7. Millas, P., Sandoval; Espinoza, B., Carrasco; Fernández, J., Fuentes, C., Correa, F., & Sagredo, B. (2024). First report of Rhizobium rhizogenes causing crown gall on blueberry and cherry in Chile. *New Disease Reports*, **49(**1):e12253.
8. Hussain Ali, H. A., Khalil Ahmed, K. A., Azhar Hussain, A. H., & Imran, I. (2010). Incidence and severity of crown gall disease of cherry, apple and apricot plants caused by *Agrobacterium tumefaciens* in Nagar Valley of Gilgit-Baltistan, Pakistan.
9. Vizitiu, D. E., Dejeu, L. C., Rădulescu, I., & Popescu, C. F. (2012). Preventing and limiting the spread of crown gall in vineyards.
10. Pulawska, J. (2010). Crown gall of stone fruits and nuts, economic significance and diversity of its causal agents: tumorigenic *Agrobacterium spp. Journal of Plant Pathology*, S87-S98.
11. Anand, A., & Mysore, K. (2006). Agrobacterium biology and crown gall disease. In *Plant-associated bacteria* (pp. 359-384).
12. Magher, M., Lemanova, N., & Magher, M. (2014). Biological control of crown gall in horticulture.
13. Gohlke, J., & Deeken, R. (2014). Plant responses to Agrobacterium tumefaciens and crown gall development. *Frontiers in Plant Science*, **5**, 155.
14. Kawaguchi, A. (2022). Risk assessment of inferior growth and death of grapevines due to crown gall. *European Journal of Plant Pathology*, **164**.