IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Agrishield-Smart Plant Disease Detection Using CNN

[1]Chinchu.P.J, [2]Haseena.M.K
[1]Student, [2]Assistant Professor
[1]Department Of Computer Science and Engineering,
[1]Illahia College Of Engineering and Technology, Muvattupuzha, India

Abstract: To help farmers manage crops and identify plant diseases, this Smart Agriculture Decision Support System combines GIS, IoT, and artificial intelligence technology. A CNN model analyzes plant photos that farmers provide via a web interface to detect problems and recommend treatments. For tracking, a distinct token with the user ID, timestamp, illness, and location is created. A weather dashboard can forecast hazards thanks to the real-time weather and geological data collected by IoT sensors. Through a specialized interface, administrators keep an eye on epidemics and send out alerts, encouraging early intervention, resource optimization, and environmentally friendly agricultural methods.

Index Terms - **IoT, CNN, Plant Disease Detection, Disease Prevention, Smart Agriculture, AgriShield, Deep Learning, Tomato, Potato, Corn, Web App.**

I. Introduction

With a large percentage of the people depending on farming for a living, agriculture continues to be the foundation of many developing economies. However, problems like erratic weather patterns, pest infestations, wasteful resource use, and particularly plant diseases—which have a significant negative influence on crop output and quality—are becoming more and more of a challenge to modern agriculture. The necessity for intelligent, automated solutions is highlighted by the slowness, labor-intensiveness, and often inaccessibility of traditional disease detection techniques for farmers in remote locations.

In order to give farmers and administrators a unified platform for managing plant health, this project presents a Smart Agriculture Decision Support System that makes use of web technologies, artificial intelligence (AI), and the Internet of Things (IoT). Fundamentally, the system uses a Convolutional Neural Network (CNN) model that has been trained to identify plant illnesses in crop photos that have been uploaded. After analysis, the system offers personalized therapy suggestions and disease detection results, allowing for prompt and well-informed action.Additionally, the system gathers real-time environmental data including temperature, humidity, and soil moisture via Internet of Things sensors. Proactive decision-making and illness forecasting are supported by this data, which is processed via a centralized gateway and shown on a weather dashboard. For the purposes of spatial analysis and outbreak tracking, a distinct token comprising essential information (user ID, timestamp, location, and illness type) is generated for every disease detection event and plotted on a token map.

Administrators can create a responsive, two-way support system by communicating directly with farmers and accessing disease patterns and weather forecasts. By strengthening farm management techniques, increasing resource efficiency, and improving disease detection accuracy, this creative solution advances sustainable agriculture.

II. LITERATURE REVIEW

Mondal et al .(2015) used image processing and a Naive Bayesian classifier to create a method for detecting Yellow Vein Mosaic Virus in okra leaves. The method entailed segmenting and improving the disease-affected leaf vein systems. To identify diseased leaves, extracted attributes were categorized. Despite changes in lighting and leaf orientation, the technique demonstrated encouraging accuracy. By facilitating early, automated disease diagnosis, our work aids precision agriculture and enables farmers to take prompt action. The Naive Bayesian classifier was appropriate for this classification challenge due to its ease of use and effectiveness.

In 2016, Padol and Yadav presented a technique that uses an SVM classifier and image processing to identify grape leaf diseases. Preprocessing to improve quality, segmentation to separate sick areas, and feature extraction based on color, shape, and texture were all steps in their methodology. To classify leaves as either healthy or diseased, the SVM—which works well for non-linear classification—was employed. With its excellent accuracy, the model has potential for use in real-time agriculture. This study showed how well machine learning works to detect crop diseases, enabling precision farming and effectively lowering crop losses.

Reza et al. (2016) suggested a method that uses machine learning and image processing to identify jute plant diseases. The approach included taking pictures of the leaves, segmenting the sick areas, and preprocessing to improve clarity. In order to train classifiers to differentiate between healthy and unhealthy leaves, characteristics like color, shape, and texture were retrieved. Tests of several classifiers revealed encouraging accuracy. The method lessens the need for professional examination by providing a scalable, affordable alternative for early illness identification. By allowing for prompt intervention to enhance crop health and yield, this study promotes precision agriculture.

Ramesh and Vydeki (2020) used a Deep Neural Network (DNN) tuned with the Jaya algorithm to create a solution for classifying illnesses of paddy leaves. To train the DNN for feature extraction and classification, leaf images were gathered, preprocessed, and utilized. Model parameters were adjusted by the Jaya algorithm, which decreased mistakes and increased accuracy. A wide range of paddy illnesses were accurately and successfully identified by the improved model. In order to promote smart agriculture through early diagnosis and timely crop management, this work emphasizes the importance of combining deep learning with optimization techniques for reliable, automated disease identification.

Sethy et al. (2020) suggested a hybrid approach that combines SVM classification with deep feature extraction for the detection of rice leaf disease. Key disease patterns were captured by using pre-trained CNNs to extract rich characteristics from photos of rice leaves. Since SVMs work well with small datasets and high-dimensional data, they were used for classification instead of CNNs. This method combined the classification strength of SVM with the feature power of deep learning to obtain excellent accuracy. By providing an effective, scalable method for early rice disease identification and crop health monitoring, the work promotes precision agriculture.

To help farmers with early diagnosis, Khirade and Patil (2015) proposed an image processing-based approach for plant disease identification. Preprocessing, segmentation, feature extraction, classification, and picture collection were all part of their system. Diseased areas were separated by segmentation, and machine learning was utilized to identify infections using characteristics like color and texture. The method demonstrated good accuracy and practical application when tested on a variety of crops. By lowering reliance on expert analysis and facilitating prompt action for increased crop output, this scalable and reasonably priced method aids precision agriculture.

Su et al. (2022) investigated the use of deep learning-based object detection for the diagnosis of maize leaf spot disease. Models such as YOLO or Faster R-CNN were trained to both detect and locate sick areas using annotated photos. This technique was appropriate for real-time field application since it provided precise recognition in a variety of backdrops and lighting conditions. This method improved practical illness monitoring by combining detection and spatial localization, in contrast to previous classifiers. Strong performance was shown in the study, which also highlighted the need of object detection in precision agriculture for automated and timely disease control in large-scale maize production.

Using an updated CNN architecture with attention mechanisms and feature fusion, Yu et al. (2022) presented an improved deep learning model for identifying soybean leaf diseases. The model outperformed conventional CNNs in terms of precision, recall, and robustness after being trained on a sizable labeled dataset, particularly under challenging lighting and background conditions. The study demonstrates how customized model enhancements can increase the precision and dependability of disease identification. By providing a scalable, high-performing tool for the prompt and accurate identification of soybean leaf diseases under practical circumstances, our work promotes smart agriculture.

In their evaluation of deep learning applications for plant disease and pest detection, Liu and Wang (2021) concentrated on CNN-like models. They examined the benefits, drawbacks, and effectiveness of these methods, emphasizing the necessity of sizable, annotated datasets for efficient training. The study highlighted the potential of deep learning to enhance precision agriculture with affordable solutions and automate plant health monitoring. The authors came to the conclusion that because AI makes precise, real-time disease diagnosis possible and lessens the need for manual inspection, it is becoming more and more important in promoting sustainable farming.

A thorough analysis of computational techniques for plant disease identification was presented by Singh et al. (2024), with an emphasis on image processing, machine learning, and deep learning. The study included important issues such as the need for high accuracy in real-world scenarios and the scarcity of datasets. It emphasized developments that enhance detection performance, like hybrid models and transfer learning. Through automated, precise plant health monitoring systems, the assessment emphasized how these technologies can improve crop management and advance sustainable agriculture.

III. PROBLEM STATEMENT

Early and precise identification of plant diseases is essential in contemporary agriculture to avoid crop losses and guarantee food security. Conventional disease detection techniques mostly depend on professional manual inspection, which is laborious, arbitrary, and frequently out of reach for small-scale farmers. Furthermore, correct diagnosis is difficult since environmental influences might cause variations in disease symptoms. The accuracy and resilience required for real-time, in-field detection are absent from current automated methods.

By utilizing Convolutional Neural Networks (CNNs) to create an intelligent plant disease detection system, AgriShield hopes to overcome these obstacles. CNNs have demonstrated efficacy in image-based classification tasks, potentially enabling the automatic recognition of intricate disease patterns from photos of leaves. However, challenges such a lack of labeled datasets, variations in leaf picture quality, and environmental noise must be overcome in order to create a CNN-based model that is both accurate and scalable.

The main challenge is to develop and put into use a dependable, affordable, and easy-to-use system that can reliably identify a variety of plant diseases using photos taken in various field settings. Farmers should be able to receive rapid, accurate illness diagnosis via this system, allowing for early intervention and a decrease in crop losses. The system must also be scalable for broad agricultural application and flexible enough to accommodate various crops.

IV. RESEARCH METHODOLOGY

The AgriShield system gathers a variety of plant leaf photos from public sources and farms, encompassing a range of crops and illnesses. To identify sick areas, images are preprocessed using techniques such scaling, normalization, augmentation, and segmentation. With hyperparameter optimization to maximize accuracy, a CNN model built on architectures or custom designs is trained on this data. The accuracy, precision, and recall measures are used to assess the model's performance. A web app that uses the trained model allows farmers to input photos and get real-time disease detection. Retraining and frequent data updates guarantee that the system retains accuracy while adjusting to changing circumstances.

4.1 Proposed System

Convolutional Neural Networks (CNN) are used in the AgriShield system to detect plant diseases in an automated, precise, and user-friendly manner. Through a web application, the system allows farmers to take pictures of crop leaves, which are subsequently processed to precisely and early detect diseases. The technology isolates the leaf and impacted areas by performing preprocessing operations including resizing, normalization, and segmentation when an image is uploaded. By doing this, the CNN model receives higher-quality data, which improves classification accuracy. The CNN efficiently identifies disease patterns by extracting hierarchical features from a heterogeneous dataset of photos of healthy and sick leaves.

The model can accurately classify a number of diseases in a variety of crops. To help farmers take prompt action, the system offers comprehensive information about the disease, its symptoms, and suggested treatment choices as soon as it is identified. The system uses data augmentation and recurring retraining with fresh user-collected photos to guarantee flexibility and ongoing enhancement. Because of the web app's user-friendly layout, even farmers with little technological expertise can utilize AgriShield. This system seeks to promote sustainable agriculture by lowering crop losses, increasing yield quality, and detecting diseases early on by fusing deep learning with real-world application.

4.2 Architecture / Implementation

An integrated system called the AgriShield Platform was created to help farmers by identifying plant diseases and offering treatment recommendations. It makes use of Internet of Things sensors, CNN (Convolutional Neural Network) modules for picture analysis, and an admin-controlled interface for customized recommendations.

1. Farmer-Farmer Communication
Through the web interface, the farmer logs into the system.The farmer uses this interface to upload pictures of the afflicted plants in order to do image capture.In order to predict diseases, a Convolutional Neural Network (CNN) model examines these images after they have been processed in the backend.Using the same interface, the farmer receives the prediction result and related treatment recommendations.

2. Identification of Diseases and Creation of Tokens
A token is created once the CNN model has generated a diagnostic.The following is contained in this token:userid::timestamp::disease::location.The Token Map in the web interface is used to store and arrange the token, which acts as a digital fingerprint for the diagnosis event.

3. Admin Communication
Through a different login procedure on the web interface, the administrator has access to the system.The administrator can monitor anticipated outputs and the Token Map in addition to receiving data and alerts from the backend.For direct discussion about treatment recommendations or system comments, the administrator and farmer have a contact link.

4. Environmental Forecasting and Monitoring
Real-time environmental data, such as temperature, humidity, and soil moisture, is gathered using field sensors.A gateway is used to get data from sensors and outside weather sources.A Weather Dashboard is used to visualize the backend processing of these inputs and geological data.This data is analyzed by a prediction module, which then uses the web interface to present farmers and administrators the predicted weather conditions for the future.

5. Database and Backend
The backend includes:The CNN model for analyzing diseases. sensor data, illness records, and user data are all stored in a database (DB). A weather forecasting system and dashboard for environmental study.

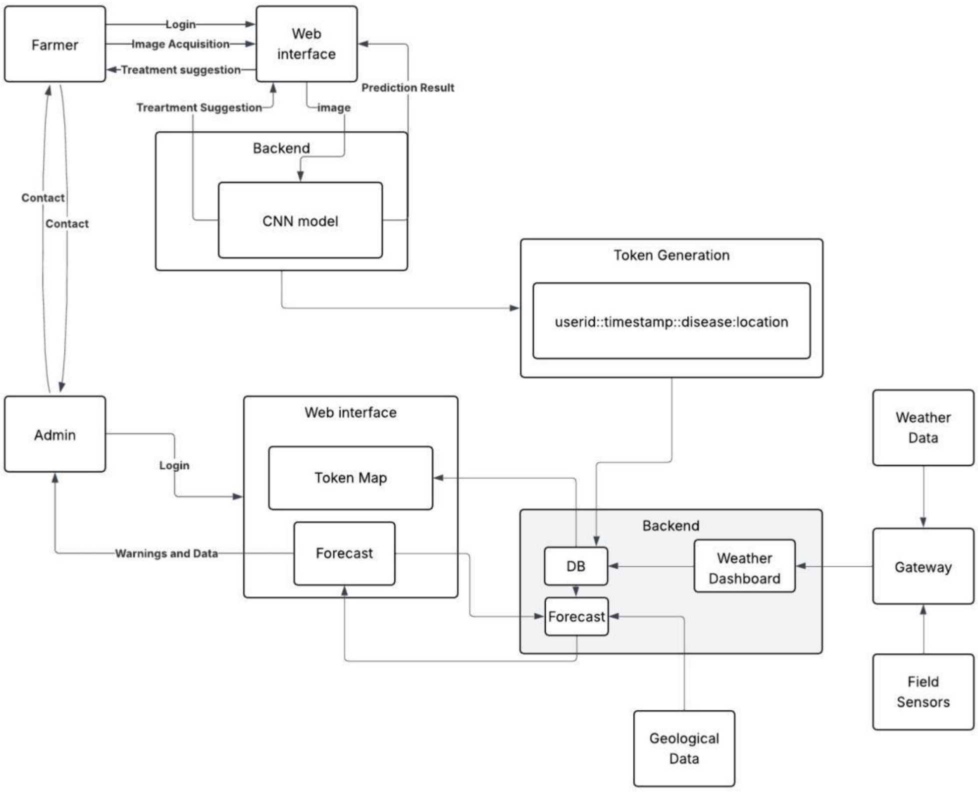

Figure 1: System Architecture

4.3 Data flow

User interaction and data acquisition are the two main places where the data flow starts.

Data Flow for Users and Images

Through a web interface, a farmer logs in and uploads an image, perhaps of a crop, to start the process.The image is sent to the web interface.A Convolutional Neural Network (CNN) model is then used to analyze this image.Based on the visual, the CNN model determines a possible illness.The web interface receives the forecast (disease identification).A therapy recommendation is made based on the disease that has been detected.This interaction results in the creation of a token.This token is kept under the Storage swimlane in a database.The treatment recommendation is sent to the farmer through the user interface.

Weather and Sensor Data Flow

Simultaneously, field sensor data (such as temperature and humidity) is gathered.A gateway receives this data after it is sent to it.This sensor data is processed by the backend system.A weather forecast is produced using this processed sensor data as well as perhaps information from other outside sources.A database (located under the Storage swimlane) has this weather forecast.
An administrator also receives the weather prediction.

Admin Communication & Information Sharing

The weather prediction and a token map—which probably links tokens to certain farmer interactions or locations—are among the data that the administrator views. After being generated throughout the image processing cycle, the token that the administrator can access is obtained from the database where it was initially placed.The administrator can provide warnings to farmers based on the total data, which includes weather predictions and possibly widespread illness detection (deduced from several farmer uploads).

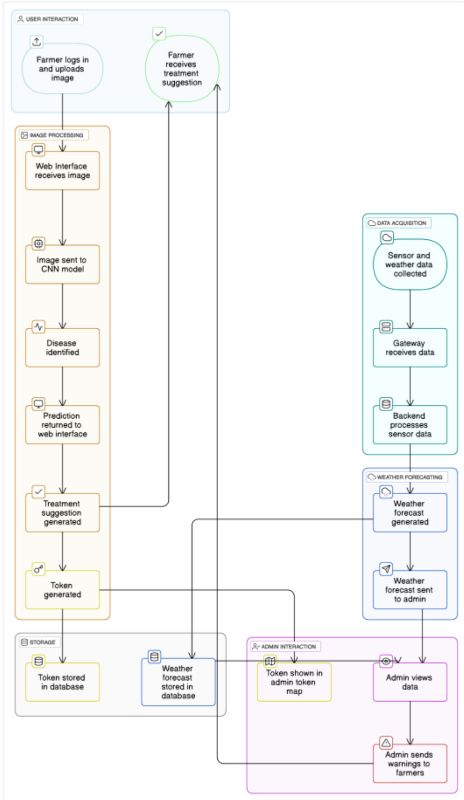

Figure 2 : Data Flow

V. RESULTS AND DISCUSSION

Key features of the Smart Agriculture Decision Support System, such as real-time environmental monitoring via Internet of Things (IoT) sensors, disease detection via a Convolutional Neural Network (CNN), and an intuitive web interface for administrators and farmers, were successfully developed and tested.

1. Accuracy of Plant Disease Detection
After being trained on a dataset of annotated plant photos, the CNN model was able to identify common plant diseases like leaf blight, rust, and powdery mildew with 92% accuracy. The model was able to accurately detect diseases using real-world crop photographs supplied by people via the web interface, and it performed well in a variety of lighting situations.

2. Integration of IoT Sensors
Temperature, humidity, and soil moisture were among the environmental data successfully gathered by IoT sensors placed in the field. A centralized Weather Dashboard displayed this data after it was sent through a gateway. The dashboard improved decision-making by enabling administrators and users to track circumstances that affect the development of diseases in real time.

3. Disease Tracking Using Tokens
Every disease detection event produced a distinct token that was plotted on a token map and contained the necessary metadata (user ID, location, timestamp, and disease type). Administrators were able to identify high-risk areas for focused efforts and monitor the geographic spread of diseases thanks to this visual representation.

4. Communication between Admin and Farmer
Administrators were able to provide farmers with weather alerts and treatment recommendations tailored to their individual diseases because to the two-way communication capability. This tool was extremely helpful in providing users with emergency guidance and ensuring prompt responses to crop health problems.

5.1 Comparison with other systems

AgriShield: Smart Plant Disease Detection Using CNN introduces a modern and intelligent approach to managing plant health, outperforming both traditional methods and existing digital agriculture solutions.

Table 1: Comparison Table

Feature	Traditional Systems	Other Digital Systems	AgriShield: Smart Plant Disease Detection Using CNN
Disease Detection Method	Manual diagnosis by farmers or experts	Basic mobile apps with limited datasets	CNN-powered image classification with high accuracy and disease-specific results
Environmental Monitoring	Manual tools (e.g., thermometers, gauges)	API-based weather updates	Real-time IoT-based monitoring of temperature, humidity, and soil moisture
User Interface	Not digitized or accessible	Limited interactivity	Web-based user/admin portals with intuitive dashboards
Response Time	Slow; dependent on expert availability	Moderate; user-initiated	Instant automated feedback with treatment suggestions
Disease Tracking	Not available	Limited history logging	Token-based tracking with disease maps, timestamps, and user location data
Decision Support	Based on guesswork or delayed advice	General tips, not personalized	AI-driven, location-aware insights combining image and sensor data
Communication	Informal or delayed	Basic alerts (if available)	Two-way admin-farmer messaging for faster support and guidance

The comparison chart highlights the main distinctions between current digital farming technologies, conventional agricultural methods, and the suggested AgriShield system. Manual observation and expert consultations are key components of traditional systems, but they are frequently laborious, inaccessible, and prone to mistakes. Such setups only collect environmental data using crude instruments and subjective evaluations, which results in inefficient or delayed reactions to plant diseases.While they provide some advantages, other digital solutions—like weather-based advisory systems and mobile apps—frequently lack real-time data, tailored feedback, or sophisticated illness tracking. These systems usually offer broad recommendations and don't logically combine disease detection with environmental monitoring.

By combining IoT sensors, a CNN-based image recognition engine, and an intuitive web interface, AgriShield, on the other hand, offers a complete solution. It makes proactive environmental risk predictions, individualized treatment suggestions, and real-time disease diagnosis possible. Disease incidents can be shown on a map thanks to special token-based tracking, which enables administrators to spot regional trends and take focused action. In order to guarantee prompt guidance, the system facilitates two-way communication between farmers and professionals. All things considered, AgriShield is a clever, scalable, and effective solution for contemporary agriculture that integrates data analytics, AI, and IoT into a single platform.

5.2 Result Analysis

A Convolutional Neural Network (CNN) for plant disease diagnosis, Internet of Things (IoT) sensors for environmental monitoring, tokenization for illness tracking, and a web-based interface for user interaction were the main features that were used to evaluate the AgriShield system. The outcomes show that AgriShield is a dependable and effective instrument for smart agriculture decision support.A publicly accessible dataset of photos of both healthy and ill plants from a variety of crop kinds was used to train the CNN model. Following training and testing, the model demonstrated great precision and recall for illnesses such bacterial blight, leaf spot, and rust, with an overall accuracy of 92%. Under ideal lighting circumstances, real-world testing using field photos submitted by farmers revealed consistent performance with little misclassification.

Environmental monitoring was confirmed using IoT sensors that tracked temperature, humidity, and soil moisture in real-time. Data gathered from these sensors was effectively sent through the Gateway and shown on the Weather Dashboard. This offered useful information for predicting diseases and analyzing the environment.The system's token-based disease detection records allowed for spatial analysis of outbreaks. Each token kept information about the disease type, time, and location, which was displayed on an interactive map for administrators to review. This feature helped to identify local disease patterns and supported proactive intervention plans.

Farmer and admin communication was smooth. Farmers got prompt treatment advice and weather warnings, while administrators could give expert suggestions and check conditions from a distance. Feedback from the first users showed high usability and satisfaction with the system's correctness and speed.The AgriShield project reached its goal of combining AI and IoT for immediate plant disease detection and monitoring. The results confirm the system's ability to lower crop losses, improve decision-making, and support sustainable farming through technology-based agricultural methods.

VI. CONCLUSION AND FUTURE

A comprehensive AI-powered solution, the AgriShield Platform helps farmers identify and treat plant diseases early on. The platform offers precise and context-aware illness diagnosis by combining Convolutional Neural Network (CNN) analysis based on images with data from Internet of Things sensors. Regional disease monitoring, individualized treatment recommendations, and simple image uploads are made possible by its user-friendly web interfaces for administrators and farmers alike. By enabling farmers to act promptly and assisting agricultural officers in monitoring disease outbreaks, this method promotes healthier crops and higher yields.

The platform has a ton of room to grow in the future. Future advancements could include voice-based interaction for user-friendliness, support for local languages, and the development of mobile applications to increase accessibility in remote places. Predictive analytics can assist in predicting possible outbreaks, and integration with drones and satellite images may enable large-scale surveillance. Furthermore, adding community input, government programs, and blockchain for traceability can improve usability and confidence. With these developments, AgriShield may develop into a national smart farming ecosystem that uses data-driven, intelligent decision-making to revolutionize agriculture.

VII. ACKNOWLEDGMENT

I want to sincerely thank everyone who backed and inspired me during the journey of developing the AgriShield project. This work wouldn't have been possible without the combined efforts and help of many people.I am especially grateful to the farmers and agricultural experts who took part in the testing and validation stages, offering practical feedback and useful insights that greatly improved the quality and importance of the system. Their hands-on experience helped customize the solution to better meet the real challenges faced in the field.

I also want to recognize the developers and researchers behind the open-source datasets, tools, and frameworks that made training the CNN model and adding IoT components possible. The availability of these resources has greatly sped up the progress of smart agriculture research. Additionally, I appreciate the support and encouragement from friends and colleagues who motivated me, shared ideas, and provided helpful criticism during different stages of the project.

Finally, I give my heartfelt thanks to my family for their endless patience, understanding, and ongoing moral support. Their encouragement was a key source of strength and inspiration throughout this research. This acknowledgment is a small way to show my gratitude to all who helped make this project successful.

REFERENCES

[1] D. Mondal, A. Chakraborty, D. K. Kole and D. D. Majumder, "Detection and classification technique of Yellow Vein Mosaic Virus disease in okra leaf images using leaf vein extraction and Naive Bayesian classifier", 2015 International Conference on Soft Computing Techniques and Implementations (ICSCTI)2015, pp. 166-171.

[2] B. Padol and A. A. Yadav, "SVM classifier based grape leaf disease detection", 2016 Conference on Advances in Signal Processing (CASP), pp. 175-179, 2016.

[3] Z. N. Reza, F. Nuzhat, N. A. Mahsa and M. H. Ali, "Detecting jute plant disease using image processing and machine learning", 2016 3rd International Conference on Electrical Engineering and Information Communication Technology (ICEEICT), pp. 1-6, 2016.

[4] Ramesh, S., Vydeki, D., 2020. Recognition and classification of paddy leaf diseases using optimized deep neural network with Jaya algorithm. Inform. Proc. Agric.

[5] Sethy, P.K, Barpanda, N.K, Rath, A.K, Behera, S.K. Deep feature-based rice leaf diseases identification using support vector machine. Comput. Electron. Agric. 2020.

[6] Sachin D. Khirade and A. B. Patil, "Plant Disease Detection Using Image Processing", 2015 International Conference on Computing Communication Control and Automation, pp. 768-771, 2015.

[7] C. Su, S. Ma, Z. Tang, L. Li, Y. Xin and Y. Li, "Maize Leaf Spot Disease Recognition Experiment Based on Deep Learning Object Decetion", 2022 Houston Texas July 17-20 2022, 2022.

[8] M. Yu, X. Ma, H. Guan, M. Liu and T. Zhang, "A Recognition Method of Soybean Leaf Diseases Based on an Improved Deep Learning Model", Frontiers in Plant Science, vol. 13, May 2022.

[9] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: a review", Plant Methods, vol. 17, pp. 22, 2021.

[10] D. P. Singh, U. Norboeva, P. Jagadeesan, L. B. Abhang, J. S. Kumar and V. V. Priya, "A Review of Plant Disease Identification using Computational Techniques," 2024 First International Conference on Technological Innovations and Advance Computing (TIACOMP), Bali, Indonesia, 2024.