AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
Peer Reviewed, Referred & Indexed Journal
E-ISSN:3069-0102
VOL.6, NO. 3(2026)

PLANT DISEASE IDENTIFICATION AND PESTICIDES RECOMMENDATION SYSTEM USING CONVOLUTIONAL NEURAL NETWORK FOR PROTECTION

[1] Kalthi Kavya, [2] Mrs.P.Shraddha
[1] M. Tech Student, [2] Assistant Professor
Department Of Computer Science And Engineering
KLR College Of Engineering And Technology, B.C.M Road, Paloncha, Bhadradri Kothagudem Dist.,Telangana,507115

ABSTRACT

Agriculture is one of the most important sectors contributing to economic development and global food security. However, plant diseases caused by fungi, bacteria, viruses, and other pathogens significantly reduce crop yield and quality, leading to substantial economic losses for farmers. Early and accurate identification of plant diseases is essential for effective crop management and timely application of suitable pesticides. Conventional methods of disease diagnosis rely on manual inspection by agricultural experts, which is time-consuming, labor-intensive, expensive, and often inaccessible to farmers in remote areas. Recent advancements in Artificial Intelligence (AI) and Deep Learning have provided efficient solutions for automating plant disease detection through image analysis.

This project, "Plant Disease Identification and Pesticides Recommendation System Using Convolutional Neural Network (CNN) for Crop Protection," presents an intelligent system that automatically identifies plant diseases from leaf images and recommends appropriate pesticides for effective crop protection. The proposed system utilizes a Convolutional Neural Network (CNN), a deep learning model specifically designed for image classification tasks. The CNN model is trained using a large dataset of healthy and diseased plant leaf images collected from publicly available agricultural datasets. During training, the model learns to recognize disease-specific visual features such as color variations, lesion patterns, texture changes, and leaf deformities. Image preprocessing techniques, including resizing, normalization, and data augmentation, are employed to improve the quality of the input images and enhance the overall performance of the model.

When a farmer uploads an image of a plant leaf through the system, the trained CNN model analyzes the image and accurately classifies it as either healthy or affected by a specific disease. After identifying the disease, the system recommends suitable pesticides, fungicides, insecticides, or biological treatments based on an agricultural knowledge database. It also provides additional information such as recommended dosage, application method, spraying schedule, safety precautions, and preventive measures to ensure responsible pesticide usage and minimize environmental impact.

The proposed system offers several advantages, including rapid disease detection, high classification accuracy, reduced dependence on agricultural experts, optimized pesticide application, lower crop losses, improved productivity, and support for sustainable farming practices. Furthermore, the system can be deployed as a web or mobile application, enabling farmers to access disease diagnosis and treatment recommendations anytime and anywhere using smartphones or other digital devices.

Overall, the proposed CNN-based plant disease identification and pesticide recommendation system provides a reliable, cost-effective, and intelligent solution for modern agriculture. By combining image processing, deep learning, and agricultural expertise, the system supports precision farming, enhances decision-making, reduces unnecessary pesticide usage, and contributes to increased crop productivity, environmental sustainability, and long-term food security.

Keywords

Plant Disease Detection, Crop Protection, Convolutional Neural Network (CNN), Deep Learning, Artificial Intelligence, Image Processing, Pesticide Recommendation, Plant Leaf Classification, Precision Agriculture, Sustainable Farming.

I. INTRODUCTION

Agriculture is essential for human survival. All countries need to increase their agricultural output, but developing countries like India, which have a large population, have an even greater need to do so. Maintaining high food production and quality standards is critical for better public health. One of the reasons that limits each harvest's potential is the development of diseases that may have been stopped if caught sooner. They annihilate crop production since several of those diseases are very infectious. The scattered structure of agricultural areas, together with farmers' lack of expertise, attention, and access to plant pathologists, renders human-aided illness analysis inefficient and unable to satisfy the broad needs. To overcome the limitations of human-assisted disease prediction, it is critical to automate crop disease diagnosis using technology and make affordable, accurate machine-assisted diagnosis accessible to farmers without charging them a fortune. Modern technology, such as computer vision systems and robotics, has helped alleviate some of agriculture's most pressing issues. Some potential applications of image processing in agriculture include precision farming, the creation of weed and pesticides, the monitoring of plant booms, and the regulation of vitamins [1][2]. Although plant pathologists can identify many plant diseases by looking for physical symptoms (such as a significant change in colour, wilting, the appearance of spots and lesions, and many more), soil conditions, and weather patterns, automated plant disease diagnosis is still in its early stages. Businesses still invest a small fraction of their budgets on agricultural technology integration, especially when contrasted with more lucrative sectors like healthcare and education. Promising research attempts have not materialised due to issues with scalability, high implementation costs, and farmers' lack of access to plant pathologists. Modern developments in cell technology, cloud computing, and AI have opened the door to a promising new possibility: a solution to crop diseases that is scalable, inexpensive, and easily deployed. In developing nations like India, internet-enabled mobile phones are quickly becoming the norm. Thanks to the widespread availability of affordable mobile phones equipped with cameras and GPS, anybody may easily share geotagged photos. Through widely available cellular networks, they may link up with more sophisticated cloud-based backend services; these services handle computation-intensive games, centralise databases, and do data analytics. Additionally, AI-based picture assessment has come a long way in the last few years, and it can now accurately realise and classify photos to an extent where it outperforms the human eye. An artificial intelligence algorithm's building blocks are Neural Networks (NN), which are structured like a real brain and consist of many interconnected layers of neurons. Trained on a massive collection of previously classified, "labelled" images, such networks can accurately categorise shimmery, unseen photographs. In 2012, when "AlexNet" emerged victorious in the ImageNet competition, Deep Convolutional Neural Networks (CNNs) became the go-to framework for computer vision and image analysis [3]. Thanks to advancements in NN algorithms, bigger picture datasets, and more powerful processing power, CNNs have reached new levels of overall performance. Not only has AI improved in accuracy, but it has also become more accessible, affordable, and evolutionary because of open source platforms like TensorFlow [4]. Relevant prior work includes image analysis via feature extraction [6], RGB photographs [7], spectral patterns [8], fluorescence imaging spectroscopy [9], and attempts to get healthy and unhealthy crop pictures [5]. Textural function identification was the primary focus of earlier efforts on plant disease detection using Neural Networks. Our method takes use of the expanding capabilities of mobile devices, the cloud, and artificial intelligence to build a complete crop diagnostics device, giving farmers access to the knowledge ("intelligence") of plant

AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
Peer Reviewed, Referred & Indexed Journal
E-ISSN:3069-0102
VOL.6, NO. 3(2026)

pathologists. In addition to facilitating a collaborative strategy for continuously expanding the illness database and seeking expert advice as needed, it improves NN classification accuracy and outbreak monitoring.

Agriculture is the backbone of many developing economies and plays a crucial role in ensuring food security, employment, and economic growth. A significant percentage of the world's population depends directly or indirectly on agriculture for their livelihood. However, agricultural productivity is constantly threatened by numerous factors, among which plant diseases are one of the most serious challenges. Diseases caused by fungi, bacteria, viruses, nematodes, and other pathogens can significantly reduce crop yield and quality, leading to substantial economic losses for farmers and affecting the global food supply chain.

Traditional methods of plant disease diagnosis primarily rely on manual observation by agricultural experts or experienced farmers. These conventional approaches are often time-consuming, expensive, and prone to human error, especially in remote rural areas where agricultural experts are not readily available. Furthermore, many plant diseases exhibit similar visual symptoms during their early stages, making accurate diagnosis difficult without specialized knowledge. Delayed identification of diseases frequently results in severe crop damage, excessive pesticide usage, environmental pollution, and reduced agricultural productivity.

Recent advancements in Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) have revolutionized various sectors, including agriculture. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated exceptional performance in image recognition and classification tasks. CNN models automatically extract relevant features from images without requiring manual feature engineering, making them highly suitable for identifying diseases from plant leaf images. By analyzing color variations, texture changes, lesion patterns, and other visual characteristics, CNN-based systems can accurately classify healthy and diseased plants.

The proposed **Plant Disease Identification and Pesticides Recommendation System Using Convolutional Neural Network** is designed to automate the process of disease diagnosis using leaf images captured through smartphones, cameras, or agricultural drones. Once the disease is identified, the system provides suitable pesticide recommendations, dosage guidelines, application methods, and preventive measures. This integrated solution assists farmers in making timely and informed decisions regarding disease management while minimizing crop loss and optimizing pesticide usage.

The system leverages a large dataset of plant leaf images containing both healthy and diseased samples. The CNN model undergoes training using thousands of labeled images representing different crop species and disease categories. During training, the neural network learns hierarchical image features such as edges, textures, disease spots, discoloration patterns, and complex leaf structures. After successful training, the model can accurately classify new unseen images into their respective disease categories.

In addition to disease identification, the recommendation module plays a vital role in supporting farmers. Based on the detected disease, the system suggests scientifically approved pesticides, fungicides, insecticides, or bio-control methods. It also provides information regarding pesticide dosage, spraying intervals, safety precautions, waiting periods before harvesting, and integrated disease management practices. Such recommendations promote responsible pesticide use and reduce unnecessary chemical application, thereby protecting both crops and the environment.

The integration of Artificial Intelligence with precision agriculture contributes significantly toward sustainable farming practices. Farmers can detect diseases during the early stages before severe damage occurs, allowing immediate intervention. Early diagnosis improves crop health, reduces treatment costs, minimizes pesticide misuse, and enhances overall agricultural productivity. Furthermore, mobile and web-based implementations of the proposed system increase accessibility for farmers in rural regions, enabling real-time disease diagnosis using smartphones.

1.2 Background of the Study

Plant diseases remain one of the leading causes of reduced agricultural productivity worldwide. According to agricultural research, nearly 20–40% of annual crop production is lost due to various plant diseases and pest infestations. Traditional disease diagnosis methods require agricultural experts, laboratory testing, or visual inspection, which are often inaccessible to farmers in remote regions. With the rapid development of Artificial Intelligence and Deep Learning, image-based disease diagnosis has become an efficient and cost-effective alternative. CNN models have consistently achieved high accuracy in plant disease classification, making them one of the most promising technologies for smart agriculture.

1.3 Problem Statement

Farmers often face significant challenges in accurately identifying plant diseases during the early stages of infection. Limited access to agricultural experts, incorrect disease diagnosis, delayed treatment, and excessive pesticide application result in reduced crop yield, increased production costs, environmental pollution, and financial losses. Therefore, there is a need for an automated, intelligent, and accurate system capable of identifying plant diseases from leaf images and recommending suitable pesticides for effective crop protection.

1.4 Aim of the Project

To develop an intelligent deep learning-based system using Convolutional Neural Networks for automatic plant disease identification from leaf images and to recommend appropriate pesticides for effective disease management and crop protection.

1.5 Objectives of the Study

- To collect a comprehensive dataset of healthy and diseased plant leaf images.
- To preprocess plant images for improved model performance.
- To develop a CNN model for accurate disease classification.
- To identify multiple plant diseases across different crop species.
- To recommend suitable pesticides based on the identified disease.
- To provide dosage instructions and safety precautions for pesticide application.
- To reduce crop losses through early disease detection.
- To minimize unnecessary pesticide usage.
- To improve agricultural productivity and crop quality.
- To support sustainable and precision farming practices.

1.6 Scope of the Project

The scope of this project includes the automatic identification of plant diseases using deep learning techniques and the recommendation of appropriate pesticides based on disease prediction. The system can be implemented as a web application or mobile application, allowing farmers to upload leaf images for instant diagnosis. Future enhancements may include IoT integration, drone-based monitoring, multilingual support, weather-based disease forecasting, and real-time farm surveillance.

1.7 Significance of the Study

The proposed system offers numerous benefits to farmers, agricultural researchers, policymakers, and agribusiness organizations.

- Enables early detection of plant diseases.
- Improves disease diagnosis accuracy.
- Reduces dependence on agricultural experts.
- Minimizes crop losses.
- Promotes responsible pesticide usage.
- Supports precision agriculture.
- Enhances food security.

- Protects environmental health.
- Increases farmers' profitability.
- Encourages sustainable farming practices.

EXISTING SYSTEM

Nearly one-third of India's harvest goes to waste due to pests and diseases. Careless use of pesticides, many of which are toxic and biomagnified, poses an additional serious threat to human health. Possible solutions to these problems include early disease detection, crop monitoring, and individualised therapies. In most cases, experts in agriculture can identify a disease only by observing its symptoms. However, farmers have a hard time getting in touch with professionals.

Issues with the Existing System (3.1.1): Misusing pesticides, because of their strong toxicity and ability to biomagnify, is a major risk to human health.

Items Being Sought After:

The project's author is training a library of plant disease pictures using artificial intelligence, especially a convolution neural network (CNN). As soon as new photos are added, CNN can identify which plant illnesses exist in the photos. The author is storing CNN train models and images on cloud services. So, using data saved in the cloud, the author uses Al to predict plant illnesses.

We used a smartphone instead of investing the time and money into developing an Android app, therefore we created it as a web app using the Python programming language.This web-based service allows users to train a CNN model, which then uses the user-uploaded images to forecast the onset of disease. When deployed to a live web server, this app will get the user's location from the request object and display it on a map.

Advantages of the Proposed System:

Take images of the affected regions to accurately identify plant diseases and get treatments using a mobile app.

Proposed System:

The proposed blockchain-based online voting application presents a transformative approach to addressing the shortcomings of traditional voting systems. At its core, the system leverages blockchain technology to create a decentralized and immutable ledger that ensures the integrity and security of the voting process. By decentralizing the infrastructure and removing the reliance on a central authority, the proposed system mitigates the risk of manipulation, fraud, and coercion that often plague traditional voting systems.

One of the key features of the proposed system is transparency. Through the use of blockchain technology, the entire voting process becomes transparent and auditable in real-time. Each vote is recorded as a transaction on the blockchain, providing an immutable and tamper-resistant record of the election results. This transparency fosters trust among voters, election authorities, and other stakeholders, as anyone can verify the integrity of the electoral process and independently audit the results.

Moreover, the proposed system prioritizes security by leveraging the cryptographic features of blockchain technology. Each vote is encrypted and securely stored on the blockchain, safeguarding it against unauthorized access or tampering. The decentralized nature of the blockchain network further enhances security by eliminating single points of failure and reducing the risk of cyber attacks or data breaches. Additionally, the use of smart contracts ensures that the voting process is executed according to predefined rules and protocols, minimizing the potential for human error or manipulation.

In terms of accessibility, the proposed system offers a convenient and user-friendly voting experience. Through the use of an online platform, voters can securely cast their ballots from any location with an internet connection, eliminating the need to physically visit polling stations. This accessibility is particularly beneficial for individuals with mobility or transportation constraints, as well as those living in remote areas. Moreover, the system incorporates measures to ensure inclusivity, such as support for multiple languages and accommodations for voters with disabilities.

Privacy is another critical aspect of the proposed system. While maintaining transparency and integrity, the system also prioritizes voter privacy by employing cryptographic techniques and zero-knowledge proofs. These techniques allow voters to anonymously cast their ballots without revealing their identities or voting preferences, ensuring the confidentiality of their choices while still enabling the verification of the overall election outcome

PROPOSED SYSTEM ADVANTAGES:

The proposed system, **Plant Disease Identification and Pesticides Recommendation System Using Convolutional Neural Network (CNN) for Crop Protection**, is an intelligent agricultural decision-support system designed to automatically identify plant diseases from leaf images and recommend suitable pesticides for effective disease management. Unlike traditional methods that rely on manual inspection by agricultural experts, the proposed system employs deep learning techniques to provide fast, accurate, and reliable disease diagnosis.

The system uses a Convolutional Neural Network (CNN), a state-of-the-art deep learning model specifically designed for image classification tasks. Farmers or agricultural personnel can capture images of infected plant leaves using a smartphone, digital camera, or other imaging devices and upload them to the system. Before classification, the images undergo preprocessing operations such as resizing, normalization, noise removal, and image enhancement to improve quality and consistency.

The CNN model extracts hierarchical features from the leaf images, including color changes, lesion patterns, texture variations, and disease-specific characteristics. Based on these extracted features, the model accurately classifies the plant as healthy or identifies the specific disease affecting the crop. Once the disease is detected, the recommendation module retrieves suitable pesticides, fungicides, insecticides, or biological treatments from a predefined knowledge base.

The proposed system also provides comprehensive information such as the recommended pesticide name, dosage, spraying schedule, application method, safety precautions, and preventive measures. This helps farmers apply pesticides responsibly while minimizing excessive chemical usage and reducing environmental pollution. Additionally, the system can be implemented as a web or mobile application, making it easily accessible even in remote agricultural regions.

The solution supports early disease detection, minimizes crop losses, improves agricultural productivity, reduces dependence on agricultural experts, and promotes sustainable farming practices. Furthermore, the CNN model can be continuously trained with additional datasets to recognize new diseases, improve classification accuracy, and adapt to different crop varieties and environmental conditions.

Overall, the proposed system integrates Artificial Intelligence, Deep Learning, Image Processing, and Agricultural Knowledge to provide a smart, scalable, and cost-effective solution for modern precision agriculture.

Advantages of the Proposed System

1. **High Disease Detection Accuracy**
   - Utilizes Convolutional Neural Networks (CNNs), which provide high accuracy in classifying plant diseases from leaf images.
2. **Early Disease Identification**
   - Detects diseases at an early stage, enabling timely treatment and preventing severe crop damage.
3. **Automatic Disease Diagnosis**
   - Eliminates the need for manual inspection by agricultural experts, reducing human error.
4. **Instant Pesticide Recommendations**
   - Suggests suitable pesticides, fungicides, insecticides, or bio-control methods immediately after disease detection.
5. **Reduced Crop Losses**

   - Early diagnosis and appropriate treatment help minimize crop damage and improve overall yield.
6. **User-Friendly Interface**
   - Farmers can simply upload a leaf image through a mobile or web application without requiring technical expertise.
7. **Time-Saving**
   - Provides disease diagnosis within seconds, significantly reducing the time required for traditional laboratory testing.
8. **Cost-Effective Solution**
   - Reduces expenses associated with expert consultations, laboratory analysis, and unnecessary pesticide usage.
9. **Environmentally Friendly**
   - Encourages precise pesticide application, reducing excessive chemical spraying and protecting soil, water, and ecosystems.
10. **Supports Precision Agriculture**
    - Integrates Artificial Intelligence and Deep Learning technologies to enable data-driven farming decisions.
11. **Scalable System**
    - Can be expanded to support additional crops, diseases, regional datasets, and multilingual interfaces.
12. **Real-Time Monitoring**
    - Can be integrated with smartphones, IoT devices, drones, or cloud platforms for continuous crop monitoring.
13. **Improved Agricultural Productivity**
    - Healthy crops and timely disease management contribute to increased productivity and better-quality produce.
14. **Reduced Human Errors**
    - CNN-based automated classification ensures consistent and reliable disease identification.
15. **Accessible in Remote Areas**
    - Mobile-based implementation allows farmers in rural locations to access expert-level disease diagnosis.
16. **Decision Support for Farmers**
    - Provides treatment guidelines, dosage recommendations, spraying intervals, and preventive measures to assist in effective crop management.
17. **Supports Sustainable Farming**
    - Promotes responsible pesticide usage and environmentally sustainable agricultural practices.
18. **Continuous Learning Capability**
    - The CNN model can be retrained with new datasets, enabling the system to recognize additional plant diseases and improve prediction accuracy over time.
19. **Better Resource Management**
    - Optimizes the use of pesticides, labor, and farming resources, leading to reduced operational costs.
20. **Enhanced Food Security**
    - By reducing crop losses and improving yield, the system contributes to stable food production and long-term agricultural sustainability.

II. LITERATURE SURVEY

2.1 Evaluated image processing algorithms in the context of farms

The writers behind it are Lalit P. Saxena and Leisa J. Armstrong.

An overview: It has been suggested in a number of studies that agricultural productivity may be enhanced by using computer technology. One technique that is about to become an invaluable asset is image processing. This study provides a cursory overview of how academics and farmers might use image processing techniques to enhance agricultural operations. Image processing has been useful in many fields, including precision agriculture, weed and pesticide technologies, plant nutrition management, and growth monitoring. This study delves into several image processing applications in the agricultural industry.

2.2.2 Imagenet classification with deep convolutional neural networks

Hinton, G. E., Krizhevsky, A., and Sutskever, I. (2004)

We trained a large, deep convolutional neural network to categorise the 1.2 million high-resolution images submitted to the ImageNet LSVRC-2010 competition into a thousand separate groups. Our top-1 error rate on the test data was 37.5% and our top-5 error rate was 17.0%, in comparison to the previous state-of-the-art. A 1000-way softmax, three fully-connected layers, and five convolutional layers make up the neural network. Six hundred fifty thousand neurons and sixty million parameters make it up. One or more max-pooling layers follow the convolutional layers. Training was accelerated by using a very efficient GPU implementation of the convolution process in conjunction with non-saturating neurons. A recently-developed regularisation method called "dropout" was used to drastically reduce overrides in the fully-connected layers. We also entered our model in the ILSVRC-2012 competition, where it achieved an impressive top-5 test error rate of 15.3%, significantly outperforming the second-best entry.

2.3 Assisting a Bayesian classifier with soms to identify diseased plants in their natural habitats

The writers are D. L. Hernández-Rabadán, F. Ramos-Quintana, and J. Guerrero. When Juk was

An overview: This work presents a methodology that integrates a supervised learning approach (a Bayesian classifier) with a nonsupervised learning method (a self-organizing map, or SOM) to segment sick plants grown in uncontrolled environments like greenhouses. Factors such as background and lack of control over lighting pose significant challenges in these settings. Two support vector machines (SVMs) are used during the training process. The first SOM uses K-means to categorise images into two groups: those with vegetation and those without. The images are then grouped by colour. Should the first SOM make a mistake in its categorization, the second SOM will intervene and rectify the situation. Using two-color histograms created from the two colour classes, the conditional probabilities of the Bayesian classifier are computed. During testing, the Bayesian classifier takes an input picture and employs image segmentation and binary transformation to retrieve the incorrectly classified non vegetation zones by contour extraction and analysis. In the trials, the proposed approach achieved better results than two of the most widely used colour index techniques.

Utilising visible-near infrared spectroscopy for the identification of Huanglongbing in citrus plantations

S. Sankaran, J. M. Maja, R. Ehsani, and A. Mishra wrote it.

An overview: This study evaluates the feasibility of using visible-near infrared spectroscopy for the detection of Huanglongbing (HLB) in citrus plantations. Spectral reluctance data was collected from 93 plants infected with HLB and 100 healthy citrus trees using a visible-near infrared spectrometer. There were 989 spectral features included in the data, which spanned 350-2500 nm. Standardisation and averaging per 25 nm of the spectral data was done during data processing to reduce the spectral characteristics from 989 to 86. First and second derivatives, as well as a composite dataset formed by combining the first two and second derivatives with the pre-processed raw data, were created from the pre-processed raw data. Using principle component analysis (PCA), we looked at the pre-processed datasets to further reduce the number of features supplied to the classification technique. One half of the major components dataset was used to train the classification algorithms, while the other half was used to test them. This was followed by a randomization procedure. There was a 75% to 25% split between training and testing. There were 145 samples in the training dataset and 48 samples in the testing dataset. We tested k-nearest neighbour, linear discriminant analysis (LDA),

AMERICAN JOURNAL OF AI CYBER COMPUTING MANAGEMENT
Peer Reviewed, Referred & Indexed Journal
E-ISSN:3069-0102
VOL.6, NO. 3(2026)

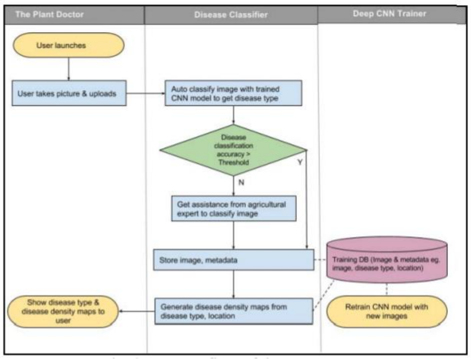
and soft independent modelling of classification analogies (SIMCA), three distinct classification methods. The reporting of the algorithms' classification accuracy's is based on an average of three runs. On the second derivatives dataset, the QDA-based classification system outperformed the others, with an average overall accuracy of 95% and HLB-class accuracy of almost 98%. In sum, the combined dataset demonstrated excellent performance from the SIMCA-based algorithms, with a 92% classification accuracy and a false negative rate below 3%.

For Computer Vision 2.5, The Inception Architecture Reexamined

Vincent Vanhoucke, Christian Szegedy, Sergey Ioffe, Zbigniew Wojna, and Jonathon Shlens—

An overview: Convolutional networks are the backbone of modern computer vision systems, allowing them to execute a wide variety of tasks. Since 2014, extremely deep convolutional networks have grown in popularity because to their remarkable performance on several benchmarks. Larger models with greater processing costs provide immediate improvements in most tasks (given sufficient labelled data for training), but computational efficiency and a limited number of parameters continue to play a determining role in some applications, such as mobile vision and big data. We explore scaling strategies for networks that aim to maximise the use of the extra processing power by using correctly factorised convolutions and aggressive regularisation. When we compare our methods on the validation set from the ILSVRC 2012 classification challenge, we find that they significantly outperform the competition: The top-1 error for single frame assessment is 21.2% and the top-5 error is 5.6% using a network with less than 25 million parameters and a computational cost of 5 billion multiply-adds per inference. Utilising an ensemble of four models with multi-crop assessment, our findings reveal a top-1 error of 17.3%, a test set error of 3.6%, and a top-5 error of 3.5% in the validation set.

SYSTEM ARCHITECTURE



III. MODULES

1. **User Management Module**

This module handles user registration, login, and logout functionalities for both regular users and admin. It ensures authentication, profile creation (including details like phone, DOB, state), and session management to protect resources and maintain personalized user experiences.

- **Register:** Allows new users to create accounts with validation for passwords, usernames, and emails.
- **User Login:** Supports login by username or email with profile validation.
- **Admin Login:** A separate login for admins with hardcoded credentials for administrative access.
- **Logout:** Clears user sessions to securely log out users.

2. **Dataset Upload and Model Training Module**

This component enables users to upload engine health datasets, which are validated and saved on the server. It automatically preprocesses the data (feature scaling), trains multiple machine learning models (Random Forest, SVM, KNN, Gradient Boosting, Decision Tree), evaluates their accuracy, and saves the trained models and scalers for future prediction.

- Checks dataset integrity (must have at least two classes).
- Performs train-test split and data standardization.
- Trains ensemble models and persists them in the filesystem.
- Displays model accuracies to users.

3. **Engine Health Prediction Module**

Users can input real-time engine sensor data (10 features), which is preprocessed and fed into the saved models. Using majority voting across the ensemble of classifiers, the system predicts engine status as "Good" or "Faulty."

- Loads saved scaler to normalize inputs consistently.
- Runs predictions on all models and combines results via voting.
- Stores prediction results in the user's session.
- Provides condition status and detailed repair recommendations when faults are detected.

4. **Recommendation Viewing Module**

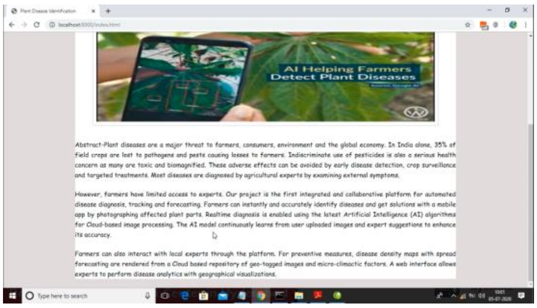
Based on the latest prediction stored in the user's session, this module displays a summary of engine health and maintenance advice tailored to the predicted condition.

5. **User and Admin Dashboards**

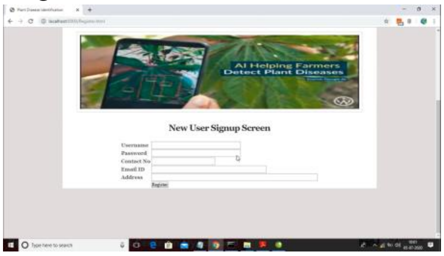
- **User Dashboard:** Personalized interface for users after login, possibly to upload data, predict engine health, or view profile.
- **Admin Dashboard:** Secure admin panel for managing registered users and monitoring system operations.
- Includes views to list all users for admin oversight

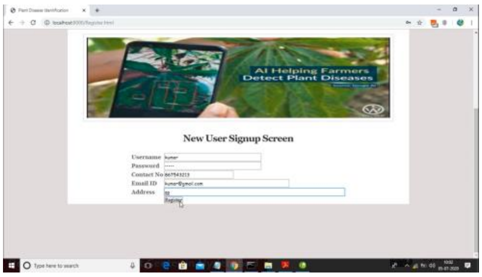
IV. SCREEN SHOTS

Index.html

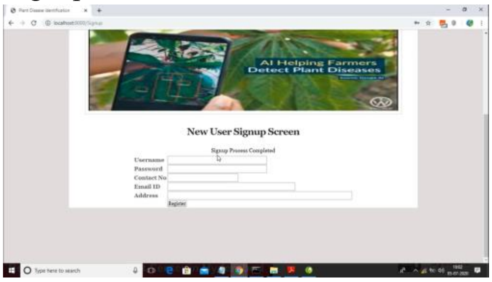


Register.html

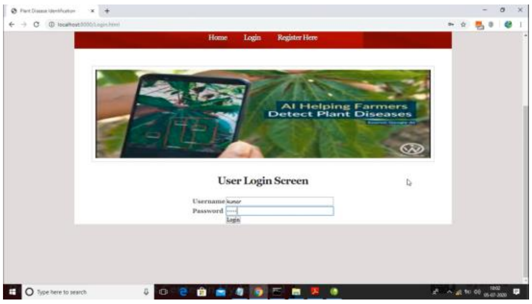




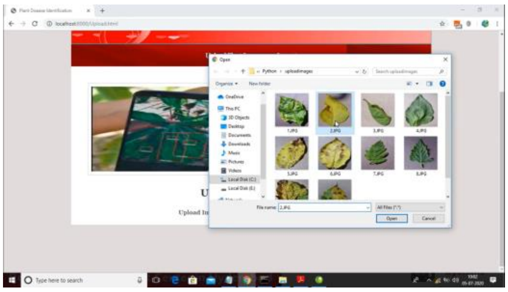
Signup

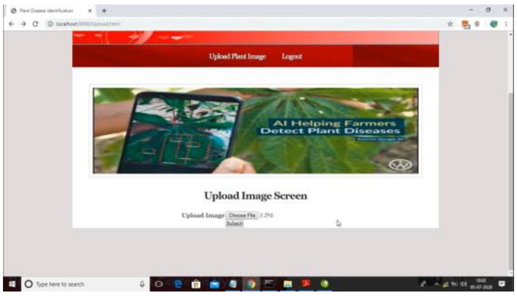


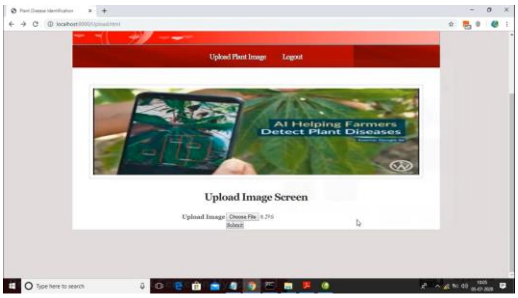
Login.html

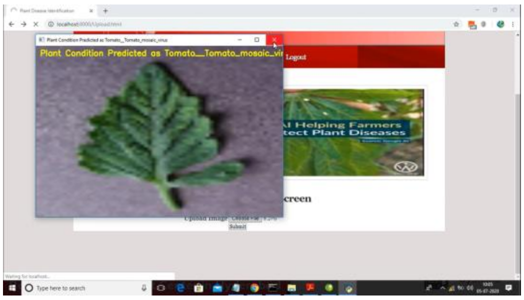


Upload.html









V. CONCLUSION

A major issue in the agricultural arena is the need for early, accurate crop disease prognoses and information on disease outbreaks. In order to help farmers make quick judgements on what disorder management measures to use, this research suggests an automated, low-value, and person-friendly quit-to-stop solution to this problem. This concept introduces a social collaborative platform to gradually increase accuracy, uses geocoded pictures for sickness density maps, applies deep Convolutional Neural Networks (CNNs) to disease classification, and imparts a professional interface for analytics, among other ways it improves upon present work. "Inception" is a high-quality deep CNN model that enables the cloud-based, user-facing mobile app to provide real-time illness classification. The collaborative approach allows for the continuous enhancement of infection type accuracy by retraining the CNN version by automatically adding user-submitted images to the cloud-based education dataset. It is also possible to generate infection density maps using publicly accessible geolocation data within user-brought images stored in the cloud, in conjunction with existing data on collective illness classifications. In conclusion, our experimental results show that the proposal is practically deployable in a number of ways: it can detect early symptoms of diseases, differentiate between illnesses within the same family, perform better with high fidelity real-life training records, become more accurate as the training dataset grows, and run well on a cloud-based entirely infrastructure that could handle a huge variety of disease classes.

CUISINE STATIONS AND FUTURE WORK

In order to strengthen the connection to the pollution, future research should expand the model to include more variables. We may supplement the picture collection with farmer inputs about soil, previous applications of fertiliser and pesticides, and publicly available environmental factors like temperature, humidity, and rainfall to improve our model's accuracy and enable disease predictions. We also want to decrease the frequency of expert engagement and broaden the spectrum of agricultural disorders that may be managed, excluding newly discovered diseases. Finding the advantage is as simple as averaging the ranks for each category. More accurate class predictions with less human intervention will result from the ability to automatically normalise user-uploaded photos into the Training Database. This method may also be used to automate the monitoring and alerting of infection development utilising time-dependent disease density maps. With the use of predictive analytics, users may be alerted when disease outbreaks are possible in their own area.

FUTURE SCOPE OF THE PROJECT

The **Plant Disease Identification and Pesticides Recommendation System Using Convolutional Neural Network (CNN) for Crop Protection** has significant potential for future enhancements. With continuous advancements in Artificial Intelligence (AI), Deep Learning (DL), Internet of Things (IoT), cloud computing, and precision agriculture, the system can be expanded to provide more intelligent, accurate, and comprehensive agricultural support. The following are the major future enhancements that can be incorporated into the proposed system.

1. Multi-Crop Disease Detection

The current system can be extended to support a wider variety of crops such as rice, wheat, maize, cotton, sugarcane, tomato, potato, banana, mango, grapes, and other horticultural crops. Training the CNN model with larger and more diverse datasets will enable it to recognize diseases across multiple crop species with higher accuracy.

2. Detection of Additional Plant Diseases

Future versions of the system can include hundreds of plant diseases caused by fungi, bacteria, viruses, nutrient deficiencies, and pests. Expanding the disease database will improve the usefulness of the system for farmers cultivating different crops under varying climatic conditions.

3. Mobile Application Development

A dedicated Android and iOS mobile application can be developed to allow farmers to capture leaf images directly using their smartphones. The mobile application can provide instant disease diagnosis, pesticide recommendations, and preventive measures even in remote agricultural areas.

4. Real-Time Disease Monitoring Using IoT

The system can be integrated with Internet of Things (IoT) devices such as smart cameras, environmental sensors, and automated field monitoring systems. These devices can continuously collect crop images and environmental data, enabling real-time disease surveillance and early warning alerts.

5. Drone-Based Crop Inspection

Unmanned Aerial Vehicles (UAVs) or agricultural drones equipped with high-resolution cameras can be used to monitor large agricultural fields. The captured images can be analyzed using the CNN model to identify disease-affected regions quickly and accurately, reducing manual inspection efforts.

6. Cloud-Based Disease Diagnosis

Cloud computing can be integrated to process large volumes of crop images efficiently. Farmers can upload images from any location, while cloud servers perform disease classification and deliver instant recommendations. This approach supports large-scale deployment without requiring high-end devices.

7. Weather-Based Disease Prediction

Future versions can incorporate weather forecasting data such as temperature, humidity, rainfall, wind speed, and soil moisture to predict the likelihood of disease outbreaks before symptoms become visible. This will help farmers take preventive actions and reduce crop losses.

8. Personalized Pesticide Recommendation

The recommendation module can be enhanced to provide personalized pesticide suggestions based on crop type, disease severity, geographic location, climatic conditions, government regulations, and pesticide availability in local markets. It may also recommend eco-friendly and biological alternatives whenever appropriate.

9. Integration with Precision Agriculture

The proposed system can become part of a precision agriculture platform by combining GPS, Geographic Information Systems (GIS), satellite imagery, and sensor data. This integration will enable site-specific disease management and optimized resource utilization.

10. Multilingual Support

Future implementations can support multiple regional and international languages, enabling farmers from diverse linguistic backgrounds to interact with the application comfortably. Voice-based interaction can also be incorporated for users with limited literacy.

REFERENCES

1. Babburi, S. Privacy-Preserving Collaborative Framework with Auditable Federated Learning.
2. Maturi, S. Y. (2022). Vulnerabilities in the 802.11 wireless client selection mechanism. International Journal on Recent and Innovation Trends in Computing and Communication, 10(1), 106–117
3. Shashank, A. (2025). Self-Healing Data Pipelines for Enhanced Reliability: A Paradigm Shift in Enterprise Data Management. Journal of Computer Science and Technology Studies, 7(8), 1097-1104.
4. Gaddam, S. Integrating Analytics into the Development Process: Bridging the Gap between Data Insights and Design Execution.
5. Bajarang Bhagwat, V. (2023). Optimizing Payroll to General Ledger Reconciliation: Identifying Discrepancies and Enhancing Financial Accuracy. JOURNAL OF ADVANCE AND FUTURE RESEARCH, 1(4). https://doi.org/10.56975/jaafr.v1i4.501636
6. Poojari, R. INTELLIGENT SYSTEMS+B108 AND APPLICATIONS IN ENGINEERING.
7. Maturi, S. Y. (2022). Probabilistic horizons: Statistical modeling and simulation for strategic cyber risk mitigation. Journal of Information Systems Engineering and Management, 7(2).
8. Adabala, P. K. (2024). Utilizing predictive analytics to improve efficiency and decision-making in ERP-connected supply chains. International Journal of Intelligent Systems and Applications in Engineering, 12(22s), 2465
9. Kavuri, S. (Ed.). (2024). Shift-left and shift-right testing approaches: A practical roadmap for continuous quality in agile and DevOps. Journal of Information Systems Engineering and Management, 9(4). https://doi.org/10.52783/jisem.v9i4.127
10. Venkata Pavan Kumar Gummadi. (2023). MuleSoft Batch Processing: High-Volume Streaming Architecture. Computer Fraud and Security, 50–57. https://doi.org/10.52710/cfs.886
11. Shashank, A. (2025). AI-Enhanced ETL Processes: Leveraging Artificial Intelligence for Optimized Data Integration Systems. Journal Of Multidisciplinary, 5(8), 219-225.
12. Harshitha, G. K., Nandigama, C., & Thiripalu, P. (2026). An exploration into identification of opportunities and challenges of establishing and running an enterprise in the area of biofuels. Minnesota Journal of Business Law and Entrepreneurship, 2026(1), 1159–1168.
13. Kandula, S. T. R., Boyapati, P. K., & Susarla, R. S. (2025, April). Optimized Cloud Resource Management Using Deep Dendritic Artificial Neural Networks Integrated with Kubernetes and Terraform. In International Conference on Computer Vision and Robotics (pp. 454-465). Cham: Springer Nature Switzerland.
14. Boyapati, P. K. Building a centralized data operations hub for healthcare enterprise integration. IJSAT-Int. J. Sci. Technol. 16 (2). https://doi.org/10.71097/IJSAT.v16.i2.3219