Kashf Journal of Multidisciplinary Research
Vol: 02 - Issue 3 (2025)
P-ISSN: 3007-1992 E-ISSN: 3007-200X
https://kjmr.com.pk

SYSTEMATIC REVIEW OF DEEP LEARNING TECHNIQUES IN EGG PLANT DISEASE DETECTION

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DOI : https://doi.org/10.71146/kjmr340

Article Info

Abstract

In recent years, researchers have focused on the automated identification of diseases using hyperspectral images, which is one of the most significant and basic difficulties for sustainable farming. The technology and approaches that have been employed up to this point are narrowly focused and entirely dependent on deep learning models. The most efficient technique for detecting and predicting illnesses from Brinjal pictures is convolutional neural networks. The current study examined several of the neural network processing methods already in use with the goal of identifying Brinjal illnesses. In order to handle the given imaging data, a number of deep learning models and architectures, image processing methods, and data gathering sources were first examined. After presenting the findings of the assessment of a number of currently used deep learning models, the study's conclusion included potential future applications of hyperspectral data processing. In order to identify diseases of the brinjal plant and facilitate further study into the wider possibilities of deep learning, this survey aims to enhance system performance and accuracy. Numerous image sensors and data collection devices were analyzed in order to identify plant illnesses. Lastly, we spoke about how deep learning models can do better than humans when it comes to generalization. In order to create an automated end-to-end plant disease management system, we conclude that realistic plant disease analysis will discover a number of crops, their related diseases early in the season, and correct disease severity assessment.

Keywords:
Deep Learning, Hyper spectral data, Brinjal, Convolutional Neural Network (CNN) models and Image Sensor.

Introduction

According to reports, the most damaging disease in the field is bacterial wilt, which can range in severity from 10% to 90%. Wilt may start to show up shortly after transplanting and persist until fruiting or even the last harvest. Farmers frequently experience significant plant losses before to fruiting, which leads to significant financial losses. In order to colonize the vascular system and prevent the transmission of water and nutrients, Ralstonia solanacearum often enters plant roots from the soil through root damage or any other natural opening. As a result, wilt begins in the higher leaves and, after a few days, the entire plant dies. The primary source of wilt infection is soil, however the pathogen can also be found in seeds and seedlings. As far as we are aware, no IPM-based management strategies have been created or tested in collaboration with farmers to address the coexistence of bacterial wilt and fungal fruit rot in eggplant. In addition to being costly, specific disease management techniques would be challenging for small-holder farmers to apply. Thus, it is important to work with farmers to build a sustainable disease management strategy for eggplants. In fact, farmers' involvement in experimenting enables research to evaluate what is feasible under farmers' circumstances rather than what is technically ideal, which is considerably superior than on-station research [1].

Plant diseases directly affect food production systems both domestically and internationally, resulting in yield reductions that create financial losses. 20% to 40% of the world's food output is lost due to plant diseases and pests, according to the Food and Agriculture Organization (FAO), which is part of the United Nations International Plant Protection Convention. An estimated 13% of the worldwide decrease in agricultural output is attributed to plant diseases. These numbers show how important it is to identify plant diseases in order to minimize output losses. However, understanding the causes of plant diseases is crucial first and foremost. After infection, many plant diseases spread throughout the crop. Therefore, since early disease treatment can help prevent its spread, constant crop monitoring is required. In some circumstances, plant diseases may also manifest later in the growing season following pollination. Plant diseases can take many different forms and impact different parts of the plant. Foliar diseases, or plant diseases that manifest symptoms on the leaves, are the most distinctive characteristics that plant pathologists can see with the naked eye. Specifically, up to 50% of productivity losses are caused by fungal diseases. The majority of current research uses computer vision, machine learning, and deep learning approaches to diagnose illnesses from photographs of plant leaves. Early-season disease detection is essential for accurate plant disease diagnosis. The identification of plant diseases is essential to precision agriculture and plant phenotyping. These two sectors demand a great deal of information, expertise, and technology. Conventional plant disease monitoring and diagnostic methods are expensive, time-consuming, specialized, and unsuitable for precision farming as they need a manual visual inspection. Additionally, these techniques are likely to be impacted by human bias and fatigue, which might result in a decline in accuracy. Studies have examined the use of image processing tools to manipulate photos in attempt to circumvent these inadequate methods for diagnosing illnesses [2].

Worldwide, eggplant is a very popular vegetable. Together, China and India account for almost 85% of global eggplant output. Numerous diseases can affect eggplant, lowering both the crop's yield and quality. Climate change raises the possibility of the creation of new harmful infections and makes these illnesses more severe and unpredictable. In addition to directly influencing the lifetime and spread of infections and insect vectors, environmental conditions, such as meteorological parameters like temperature, relative humidity, and rainfall, can affect the physiological and developmental responses of plants to pathogens. Artificial intelligence (AI) and machine learning have enabled unprecedented automation prospects in agriculture, including the identification and classification of plant diseases. This is one such strategy. Since AI and deep learning-based techniques automatically extract deep features from a series of images and are faster and more accurate than earlier algorithms, image-based disease diagnosis and classification has grown in popularity. Plant disease diagnosis, weed detection, soil mapping, and pest identification are the most popular applications for convolutional neural networks (CNNs), a form of deep learning architecture [3].

A common annual vegetable crop in Asia and many Mediterranean nations is eggplant (Solanum melongena L.). The eggplant, also called "talong" in the Philippines and "brinjal" in India and Bangladesh, is widely regarded as one of the most significant, widely consumed, and fairly priced vegetables in Asia. It is also one of the few inexpensive vegetables in both rural and urban locations. Eggplant is regarded as the fifth most significant crop in the world, with an annual production of 50 million and a value of almost 10 billion US dollars. One of the biggest problems farmers face is serious injury from several insect-pest diseases. Their anticipated revenue is significantly impacted by this issue. Leucin odes orbonalis Guenée, often known as the Eggplant Fruit and Shoot Borer (EFSB), is a common insect infestation that has been the biggest problem for eggplant production in Asia. EFSB causes significant harm to eggplants in their larval stage by making holes, burrowing inside the fruit, and feeding on internal tissues. According to reports, a newborn larvae may bore directly into the fruit of an eggplant, boosting the number of larvae per fruit. Supervised learning is a subset of machine learning that improves itself without explicit programming by adapting to experience. Algorithms for supervised machine learning require external assistance. The training dataset contains an output variable that has to be classified or forecasted. Furthermore, each model uses information that resembles patterns that are extracted from the training dataset to classify or predict the test dataset. Moreover, feature extraction is beneficial since it lowers the resources required to explain massive data sets [4].

One of the most widely planted tropical vegetables in India is brinjal (Solanum melongena L.), which goes by several other names, including aubergine (French), eggplant, baingan (Hindi), and others. Many curries and other foods are made with immature brinjal fruits. Fruits vary in their nutritional content and are modest providers of vitamins and minerals such as calcium, iron, and phosphorus. India produces 12.80 mt of brinjal from a 0.73 mha area, making it the second-largest producer in the world behind China. Brindal is grown in practically every state, however it is most often in Madhya Pradesh, Gujarat, Chhattisgarh, and Bihar. Numerous interrelated elements greatly influence the quality of the fruit, productivity, and development of brinjal. Of these, the INM framework is the most important and vital component. It has been found to have a remarkable impact on brinjal development quality, yield, and organic product quality, as well as on ongoing efficiency achievement. For proper growth and life cycle completion, plants require 17 key mineral elements. The most recent addition to the list of vital nutrients is nickel (Ni) [5].

The infectious sickness known as "Phomopsis curse" is caused by Phomopsis vexans floods. It has a significant impact on brinjal products, leaves, and stems. This infectious disease's contaminated stem can result in blisters and brown or dull sores that are slightly squeezed on the contaminated area's surface. Seedlings divide over time and eventually die. People who spend a lot of time are vulnerable to bacterial assaults. The dark brown, spherical lesions have a smooth surface. The different fruit bodies, known as pycnidia, may be seen as tiny, black specks imbedded in the assembly tissue when the damage is sometimes focused. Influenced leaves may quickly fall off and turn yellow [6].

Figure 1: Segmented images manually of Egg Plant

The Figure 1 shows the diseased leaf and how intricate the image's elements are determines the maximum size of the dataset for these models. As a result, image augmentation techniques were used to artificially enhance the number of photos available in the dataset. It uses picture manipulation techniques that cause distortion in the dataset, such rotation, random translation, and brightness changes. Each pixel was translated randomly by moving it to a predetermined location using a set transformation value of 100 and a factor of a random integer. A random value created within a defined intensity value was added or subtracted to change the image's brightness. In order to maintain the image's characteristics, a fixed value was reached after several attempts. CNN's main hurdles are defining their objectives and training a large number of spectrum image inputs. It has made classifying the variations from the provided input data considerably more difficult for CNN classifier applications. One of the other most difficult parts is utilizing CNN classifiers to analyze the spectrum mixes. Generally speaking, CNN classifiers rely on the integration of ideal factors including texture, color, and object form to categorize a variety of crop illnesses. When the standard pictures are linear, training these parameters is simple. Only when there are hundreds of unbroken spectral bands can such hyper spectral data be trained. Additionally, extracting information from a network's nearby spectral bands in different spectral areas is extremely redundant.

We first gather leaf photos, and then we preprocess the same data's leaf images. A training set and a testing set were created from each pair of leaf photos. On both the test set and validation, we were able to attain an accuracy of over 98.2%. The model serves as the foundation for the web application, which has an intuitive user interface and displays simplified results. The world's food supply is being threatened by plant diseases. This study demonstrates that machine learning using a convolutional neural network approach is technically possible to provide autonomous sickness diagnosis using photo categorization. A publicly accessible dataset of 54,306 images of healthy and ill plant leaves is used to train a convolutional neural network to identify crop species and disease status of 10 different classes. The network achieves 98.2% accuracy using residual network architecture.

Figure 2: The Egg Plant

After resizing the photos to 256 x 256 pixels, we use these downscaled images for both model improvement and prediction. We nearly doubled the amount of the dataset by using data augmentation techniques including shearing, zooming, flipping, and brightness shift. To increase classification accuracy, data augmentation approaches are frequently used with deep learning or conventional machine learning algorithms. The machine learning package in Python was utilized in this work to implement the picture augmentation technique. For typical class photographs, procedures such width and height adjustment, cutting, zooming, horizontal rotation, brightness, and filling were carried out. The picture rotation degree was set up to be generated randomly. Automatic plant disease detection techniques are beneficial because they detect disease symptoms early on, such as when they appear on plant leaves, and reduce the amount of work needed for crop monitoring in big farms. Plant disease and pest diagnosis is one of the most important applications of machine vision research. It is a system that collects images of plants and uses machine vision tools to identify if the images show diseases or petted main objective of optimization strategies is to continually modify the weights until CNN learns as efficiently as possible. Each method performs an updating process. The weights for each instance in the training set are updated with each iteration of the Stochastic Gradient Descent (SGD) method. As a result, it aims to achieve the objective as quickly as possible.

Features of illness

- Fruits get sunken, dark brown areas; leaves get tiny, round brown spots that cause wilting.
- Yellowing and leaf drop are caused by white, powdery fungal growth on leaves and stems.
- Rot at the base of the stem causes seedlings to collapse.
- Brown staining within the stem; yellowing and withering of the leaves.
- Plants suddenly wilt; when cut, the stem discharges a milky white bacterial material.
- Tiny, wet patches on leaves that become brown and have a spotted tint.
- Growth retardation, a greenish- mosaic patterns, and leaf deformation.
- Thick look, small, thin leaves, smaller fruit.
- Rotten fruits and stems due to focused holes.
- They spread viral infections and cause sap chewing, which results in leaf curling and restricted development.

Control Measures

- Manage vectors of bugs such as fly species and insects
- Use bactericides or pesticides as necessary.
- Take out and eliminate contaminated plants.
- Make use of disease-resistant cultivars.
- Rotate your crops.

Material and Methods

This systematic review was conducted in accordance with the Recommended Reporting Items for Systematic Reviews guidelines. The main objective of this study is to identify, differentiate, and evaluate the different methods utilized in eggplant field management using image processing. We have used the concept of transfer learning for the classification. When using transfer learning, the main advantage is that the model learns from previously identified patterns when tackling a problem that is similar to the one being addressed, instead of starting from scratch. By doing this, the model makes use of already-existing data instead of beginning from scratch. Transfer learning is often demonstrated when pre-trained models are used for picture categorization. A model is considered pre-trained if it has been trained on a large benchmark dataset to handle a problem similar to the one we must solve. CNN pre-trained model weights were used for our investigation. The steps taken to find, choose, and obtain the information needed for this systematic literature review are described in this section. The goal of doing a systematic literature review is to locate, evaluate, and examine earlier relevant research that is significant to the goals of the current study.

Search Strategy

An electronic search was carried out using publicly available sites including IEEE Xplore, PubMed, Science Direct, and Google Scholar using keywords relevant to the study's scope. Peer-reviewed conference and journal papers that employed a number of deep learning methods for identifying eggplant field pests were selected and evaluated by us. The search was conducted using the following keywords: "image processing," "eggplant," and "illness detection." These datasets were identified using the Boolean expression "AND."

Criteria for Inclusion

- The original, expert-reviewed research articles that have been presented at seminars and publications.
- The first, expert-reviewed research papers that have been published in journals and conferences.
- .Research papers in the English language. Studies carried out from 2000 to 2022.
- Research that use machine learning measures, such as classifier and accuracy.

Criteria for Exclusion

- Patents, letters, editorials, unpublished studies, case reports, tiny case series, and cross-sectional studies are examples of research publications written in languages other than English..
- Studies that employ machine learning metrics like accuracy and classifier.
- Studies that do not employ a machine language approach to identify pests.
- Research articles that discuss plants or leaves other than banana fields.
- Research published before the year 2000.
- Research done from 2000 to 2022.
- Research publications in English.

Importance of Research

- Enhanced agricultural productivity: By keeping an eye on the environment and spotting pests early on, farmers may take proactive measures to minimize crop damage and boost crop production.
- Investment savings: Using drones equipped with AI and image processing skills may reduce labor costs as well as related expenses for supplies, tools, and materials required for pest control and environmental monitoring.
- Environmental protection: By using drones to control pests, less hazardous chemicals are used, which might be harmful to both the environment and human health.
- Increased efficiency: By integrating drone technology with artificial intelligence and image processing technologies, pesticide detection and environmental monitoring may become much more accurate and efficient.

Figure 3: Shows Diseased Egg Plant

Verticillium dahliae can infect eggplant plants at any point throughout their growth. Symptoms include leaf drooping and yellowing on a few branches or the entire plant. When the leaf edges of affected plants fold inward, it's known as foliar withering. The leaves of severely infected plants become dry and brown. In the Solanaceae family, eggplant (Solanum melongena) is a tropical herbaceous perennial plant that is closely related to tomatoes and is grown for its tasty fruit. It is a long, flat, simple plant with a branching stem. Green leaves with coarsely lobed margins alternately hang from the branches, ranging in length and width from 10 to 20 cm (4–8 in) and 5 to 10 cm (2–4 in), respectively. The shrub produces purple blooms that are 3–5 cm (1.2–2.0 in) in diameter. The fruit is a large, meaty, ovoid berry with many tiny seeds and a glossy, smooth skin that can grow up to 40 cm (15.7 in) in length. Despite being perennials, eggplants are often grown as annuals, but they can reach a height of 1.5 m (4.9 ft). Eggplant comes from the Indian subcontinent and is also known as aubergine or guinea squash. Bacterial canker in pepper can cause fruit and leaf spots as well as, less commonly, systemic wilt. Small blisters or elevated white patches on leaves and stems are the initial signs of localized infections. Later, a white halo forms around the brown, necrotic cores of the leaf spots. Stem lesions frequently extend to produce cankers and take on a crusty look. Fruit symptoms initially manifest as tiny, spherical, slightly elevated patches. Plants with systemic diseases gradually wilt before dying. Infection does not require high relative humidity. Low light levels and warm temperatures typically encourage the development of illness. Golovinomyces cichoracearum: The top and lower leaf surfaces first show tiny, white, powdery, round to irregular patches. Infected regions may spread to include stem tissues, petioles, and leaves. The disease initially affects older leaves before spreading to fresh growth. Eventually, the impacted leaves become necrotic and yellow. Leveillula Taurica: Light-green to bright-yellow spots show up on the top surfaces of leaves during the early stages of infection. Later, these regions become necrotic. The undersides of infected leaves exhibit a powdery, white growth, and the leaves curl upward. When there are several lesions, they frequently combine to cause leaf drop and overall chlorosis. As the illness worsens, younger leaves are affected. Fruits on afflicted plants may become sunburned due to excessive exposure to sunlight.

Table : 1 Research papers for systematic Review

Year	Authors	Techniques	Methodology	Results
2022	Md. Raducanu Haque and Ferdous Sohel [7]	CNN-SVM and CNN-SoftMax pipelines	Researchers suggest using a two-stream deep fusion architecture to categorize eggplant illnesses. Using preprocessed RGB pictures as input, the deep CNN with transfer learning (Inception V3, VGG16, VGG19, ResNet50, Mobile Net, and Nas Net Mobility) may extract features from images in the first stream, which is referred to as feature extraction	The feature maps were shown using the t-SNE method in order to examine the effectiveness of the six feature extraction techniques following the use of transfer feature learning (L, n) and an adjustable learning rate. The findings imply that compared to other models, the features generated using Inception V3, VGG19, and Mobile Net were more discriminative.
2022	Sandika Wahyuni Nasution, Kartika [8]	The YOLOv4 algorithm is used to choose pictures of eggplant plants taken by a camera on a mobile computer device, like a Raspberry Pi 4.	Designing the circuit is the next step. Designing the software for the system that requires the Ras berry Pi comes next. After the software and circuit are finished, compile the Python program and design the tool. The tool will then be tested by using the Raspberry Pi module to test the system. method of system reading.	Every eggplant leaf has a leaf bug. There are more than one or perhaps three insects on a single leaf, so it's no surprise that they land
2019	Naznin Nahar, Md. Rashidul Islam, Mohammad Mahir Uddin, Peter de Jong, Paul C. Struik , Tjeerd-Jan Stomph [9]	T. harzianum with Integrated Pest Management (IPM)	All of the bacteria recovered from soil and seed samples collected from participating farmers, as well as from seedlings cultivated from these, were identified as R. solanacearum by molecular analysis.	Bangladesh's major eggplant-growing region. During the chilly dry season (September–March is the Rabi season), farmers grow egg plants. Two Rabi seasons in a row were used for the study.

2024	**Maria Patrice L. Lajom, Joseph Paul R. Remigio, Edwin R. Arboleda, Rhen John Rey R. Sacala [10]**	**Support Vector Machine (SVM), Arduino Nano as its microcontroller and a near-infrared spectroscopy (NIRS) module**	**The color and intensity of the reflected light from the samples were quantitatively evaluated using an NIRS sensor that has six different wavelengths. These sample reflectance data were used as input to train the SVM classification model.**	**An NIRS sensor with six distinct wavelengths was used to quantitatively assess the color and intensity of the reflected light from the samples. The SVM classification model was trained using these sample reflectance data as input.**
2022	Arya Kaniyassery, Sachin Ashok Thorat, Kodsara Ramachandra Kiran, Thokur Sreepathy Murali & Annamalai Muthusamy [11]	To Develop modern breeding and agronomic tools	Appressoria and the release of toxins, growth regulators, effector proteins, and enzymes that break down cell walls are examples of the general pathogenetic processes of phytopathogenic fungi. Fungal infections that have been widely documented in eggplant have been selected for in-depth examination.	In this paper, we thoroughly examine the prevalent fungal infections of eggplant that have been identified globally, along with the illnesses they produce and their main symptoms.
2022	Izazul Haque Saad, Md. Mazharul Islam, Isa Khan Himel, Md. Jueal Mia [12]	Convolutional Neural Network (CNN)-based transfer learning approach	This section has been broken down into three smaller pieces. Data augmentation and description, system overview, and CNN-based transfer learning come first. Data augmentation techniques such as scaling, shearing, rotation, zooming, fill mode, and flipping were employed.	To begin training our CNN-based transfer learning models, we separated the data into two groups, named train and test, with a predetermined ratio of 80:20. The remaining 80% of the data was used for training, while the remaining 20% was used for testing.
2023	Denis Mamba Kabala , Adel Hafane, Laurent Bobelin & Raphaël Canals [13]	Federated learning for crop disease classifcation using image analysis, convolutional neural network (CNN) , vision transformers (ViT)	We simulated a cooperative group of clients that help to enhance a worldwide model using open source datasets from the "PlantVillage" platform. Initialization, local training, parameter transfer, model aggregation, the global model transfer, and local	We show the outcomes of several model tests for various parameters, including variations in the number of clients taking part in the federated learning process to train the models.

			assessment were its five fundamental stages.	
2024	Yuxi Huang, Hong Zhao, and Jie Wang [14]	YOLOv8-E, based on You Only Look Once version 8 nano (YOLOv8n)	Numerous disciplines have made extensive use of YOLOv8, a significant version of the YOLO series algorithms. This study has chosen YOLOv8n, the lowest model in terms of size, as the baseline model in light of the deployment needs of mobile platforms. We randomly selected eggplant leaves that had necrotic lesions with a light brown center and dark brown outside rings that resembled distinctive target rings. Additionally, in Los Baños, Laguna, Philippines, fruit exhibiting 1306 H. D. AUMENTADO AND M. A. BALENDRES signs of decaying and deeply sunken lesions was randomly gathered. MPEPFR02 from fruit, MBEPLS03, and MBEPLS06 from leaves are three typical isolates of fungi.	This study suggested YOLOv8-E, an improved eggplant illness detection algorithm based on You Only Look Once version 8 nano (YOLOv8n), as a solution to this problem.
2022	Herbert Dustin Aumentado and Mark Angelo Balendres [15]	Using Combined Morphological, Cultural, Pathogenicity and Molecular approaches	The fungal colonies of isolates MBEPFR02, MBEPLS03, and MBEPLS06 were spherical, velvety, brown to black, and had a spreading edge on PDA medium. They were also slightly raised. White mycelium surrounded the gray center of the colony. The isolates were black, grey, and brown in reverse. The cultivation diameter at seven days was 6.70 cm on average (Figure 1). The	On PDA media, the fungal colonies of isolates MBEPFR02, MBEPLS03, and MBEPLS06 were round, slightly elevated, velvety, brown to black, and had a spreading edge. The colony's gray core was encircled by white mycelium. In reverse, the isolates were brown, grey, and black. At seven days, the average size of the culture diameter was 6.70 cm (Figure 1). The smooth, septate, single, or series-connected

			conidia were smooth, septate, solitary or series-connected, and varied in color from dark brown to sub-hyaline.	conidia ranged in color from sub-hyaline to dark brown.
2020	Aravind Krishnaswamy Rangarajan & Raja Purushothaman[16]	Multi-Class Support Vector Machine (MSVM) with Visual Geometry Group 16 (VGG16) architecture that has already been trained	Disease dataset and system configuration. Five primary illnesses caused by pathogens and pests have been identified in this investigation. Under ideal circumstances, these diseases severely damaged the chosen crop. Images of isolated leaf samples taken with various smartphone cameras in a lab setting have been used to develop a dataset for these illnesses.	Eighty percent of the generated dataset was used for training, while twenty percent was used for testing. Since each set's photographs were chosen at random, accuracy varies depending on which images were chosen. Five trials were conducted to confirm its performance because consistency is uncertain. With VGG16, the classification accuracy of the pictures in four different color spaces was examined.
2021	Iftekhar Alam and Md Salimullah [17]	Genetic engineering, Transgenic technology	In the near future, the eggplant would be a viable alternative model plant for studying various facets of plant biology due to its complete genome sequence, effective in vitro regeneration system, and appropriate morphological traits. Suitable morphological characteristics and an efficient in vitro regeneration technique.	The results is In the near future, the eggplant would be a viable alternative model plant for studying various facets of plant biology due to its complete genome sequence, effective in vitro regeneration system, and appropriate morphological traits.
2020	Jake Guabes Maggay [18]	Image Processing Techniques	Image capture comes first, then pre-processing of the obtained pictures (such as cropping, resizing, and augmentation), feature extraction comes next, and image classification comes last. Using Opp, the	The absence of contemporary agricultural inputs, such as varietal selection and the use of recognized and recommended pesticides, was one of the numerous problems the farmers faced when growing eggplant. Fertilizers

			researcher took pictures of the farms' infected eggplant fruits and foliage.	are used by farmers at the transplant, vegetative, mature, or fruiting stages. To stop the insects from spreading, they trim eggplant shoots that have been harmed by shoot borer.
2021	Sk Mahmudul Hassan, Arnab Kumar Maji, Michał Jasinski , Zbigniew Leonowicz and Elzbieta Jasinska [19]	EfficientNetB0, MobileNetV2, InceptionV2, InceptionResNetV2, and Deep Convolutional-Neural-Network (CNN)	Recently, there has been a boom in interest in CNNs, and DL is the most often used architecture because DL models can learn pertinent properties from input pictures at various convolutional levels, which is comparable to how the human brain works.	When compared to InceptionV3, MobileNetV2, and InceptionResNetV2, EfficientNetB0 had the highest accuracy. We employed many measures, such as performance accuracy, F1 score, precision, recall, training loss, and time required per epoch, to assess performance.
2021	Mandwade Vaibhav Ramesh, Balaji Vikram, Abhishek Singh and KR Maurya [20]	Randomized Block Design, Integrated Nutrient Management (INM)	During field preparation, organic manures such as PSB, Azospirillium, farm yard manure, vermicompost, NPK, and neem cake were applied based solely on their nitrogen content. At each picking time, the weight of the fruit from five chosen plants in the plot area was noted, and the average was calculated.	When plants under treatment T2 (100% RDF) reached maturity, their maximum plant height was measured and found to be 95.78 compared to the control. The tallest plant, measuring 93.83 cm Treatment 1 had the lowest value (17.11) at 120 DAT, whereas treatment T2 had the highest plant height, which was substantially different from all other treatments.
2021	M.K. Kalita, P.D. Nath, and D.S. Dutta [21]	Every location that was surveyed had a high prevalence of brinjal small leaf disease.	In seven significant brinjal-growing regions, roving surveys were carried out. Data on disease incidence and variety cultivated in the studied fields were also documented.	Every location that was surveyed had a high prevalence of brinjal small leaf disease. In brinjal crops, several phytoplasma-related illnesses were noted throughout the survey.
2021	Mohammad Monirul Hasan Tipu, Raunak Jahan, Jubaidur Rahman, Mukaddasul Islam Riad, Md. Mashiur Rahman & K. M. Eadun Nabi[22]	To Develop modern breeding and agronomic tools	Jamalpur's coordinates are 89°56′53″ East and 24°55′10″ North. Both nations share a northeastern border with the Indian state of Meghalaya. The districts that surround it are Jamuna River, Bogra, Sirajganj, and Gaibandha in the west;	Based on their prevalence and seriousness, five (5) diseases were determined to be significant in the research regions by the survey. It was shown that the prevalence of brinjal bacterial wilt (60%) and tomato viral disease (41.67%) was higher. The prevalence of brinjal

			Kurigram and Sherpur in the north; Mymensingh and Sherpur in the east; and Tangail in the south.	phomopsis blight (13.33%), tomato wilting (20%), and brinjal viral disease (20%) was medium across different locations.
2024	Drs. Neelam Maurya, Prashant Kumar Singh, and Talapati Aruna Chenna Vydyanad [23]	Phomopsis vexans, Trichoderma spp	The infested leaves and fruit rot samples were gathered from the experimental field at ITM University, Gwalior. Infected fruit rot and leaf blight samples was collected and put in Polythene covers. The samples were brought to the laboratory for observation of microscopic studies. Phomopsis vexans were found in the samples, causing fruit deterioration. Eggplant fruit rot occurs on the fruits as slightly sunken patches that progress to hard sunken lesions.	The symptoms of the disease particularly on the fruits were studied in detail and were found to be more or less identical to those that reported by other investigators (Pawar and Patel, 1957). During tissue isolation, the pathogen was obtained from infected eggplant fruit (Pusa purple round). The fungal culture was obtained from infected plants and designated as Pv
2020	Wei Wang, Yu Zou, Zhipeng Xue, Xiaonan Hu, Yan Guo, Jin Zhang, and Chengxin Yin [24]	Region Proposal Network (RPN), Chan–Vese (CV) algorithm, Deep Learning algorithm	The next three phases make up the majority of the model employed in this article. Finding the sick leaves is the first step. The frame regression neural network and classification neural network are utilized to find and recover the sick leaves in the complicated environment, while the RPN technique is used to train the leagmentation of sick leaves is the second phasef dataset.	The Leaf Localization Outcome: The test picture is fed into the RPN algorithm and the VGG-16 model. The primary blade structure may essentially be framed by the RPN method, which performs better than the original model. The images above show that the RPN method can essentially frame the primary blade structure and be utilized for the subsequent operation, despite the fact that the frame selection range is not precise enough
2022	Preethi S., Dr. Jayanthi M.G., and Dr. Shashikumar D.R.[25]	Binary Crow Search Algorithm (BCSA), PNN Classifier, Optimal Probabilistic Neural Network (OPNN), and Adaptively	Finding the diseased area of the eggplant leaf disease, or brinjal leaf, is the primary goal of the suggested methods. One of the main causes of the dramatic drop in brinjal	This section presents the results and analysis of the classification and extraction of eggplant leaves using an optimal PNN classifier and adaptively regularized multi

		Regularized multi Kernel-Based Fuzzy C-Means (ARMKFCM)	output is the illness on the eggplant leaf.	kernel-based fuzzy C-means. To carry out the accomplished success, we used the ATLAB version.
2022	Md. Tanzim Reza, Md. Humaion Kabir Mehedi, A.K.M. Salman Hosain, Shafi Ahmed, Rabeya Khatun Muna, Samanta Tabassum Promita, and Mehedi Hasan [26]	Three pre-trained models—EfficientNetV2L, MobileNetV2, and ResNet152V2—are used in the Explainable Artificial Intelligence (XAI) strategy, which employs a transfer learning methodology.	In this study, we provided a framework based on pre-trained models (EfficientNetV2L, MobileNetV2, and ResNet152V2) to identify 38 distinct plant illnesses. We then used XAI techniques to forecast the model's prediction with the maximum accuracy.	Our models outperformed the other two models in terms of accuracy on the test set when we assessed them using a quantitative performance assessment criterion. With a score of 99.63%, it performed 0.77% better than MobileNetV2 and 1.19% better than ResNet152V2. However, as compared to ResNet152V2, MobileNetV2's accuracy was marginally higher.
2024	Ali Tufail, Rosyzie Anna Awg Haji Mohd Apong, Chandratilak De Silva Liyanage, and Wasswa Shafk [27]	LR classifier models for plant disease detection (PDDNet) types in conjunction with nine pre-trained Convolutional Neural Networks (CNNs)—DenseNet201, ResNet101, ResNet50, GoogleNet, AlexNet, ResNet18, EfficientNetB7, NASNetMobile, and ConvNeXtSmall—and Lead Voting Ensemble (LVE)	To solve the issue of plant disease detection and classification, we explore feature extraction and fine tuning approaches among the existing TL methods, such as intermediate layers, fine-tuning, and feat feature extractors. The last convolutional layer's output is used as a feature vector for the new task. The task's feature vector is the output of the last convolutional layerure extraction. The selected pre-trained CNNs are used as.	This part mainly displays the results obtained and the discussions that ensued around the proposed models of an integrated ensemble LR model classifier that utilizes deep features and CNN model averages. We evaluated three model approaches—AAE, EA, and LVE—using pretrained networks. The proposed models are based on deep feature extraction. We used the PlantVillage dataset. There are categories for segmentation, color, and grayscale images in this collection.

Results: The majority of research do not employ the conventional datasets to determine CNN model performance. According to this paper, the only way to train and evaluate the current CNN models is to use picture datasets that were collected from the field. discovered that 86% of current models are ineffective in classifying and identifying diseases. According to the current study, in order to get a greater degree of accuracy, the current models even need to be improved in terms of development and application. illustrates how deep convolutional models enhanced their ability to recognize various illness classifications. It is extracted on the models utilized, the providers of data, the prior to processing methods used, and the assessment of the suggested CNN models' overall effectiveness. The results showed the bulk of the CNN models were just partially capable of processing unstructured raw picture input.

Deep learning systems need systematic engineering and design abilities to extract characteristics from the unstructured data into feature vectors, which are then used by the subsystems to often identify and classify certain trends seen in the information intake. This study aims to motivate researchers to employ deep learning techniques for the classification and detection of plant diseases associated with image analysis.

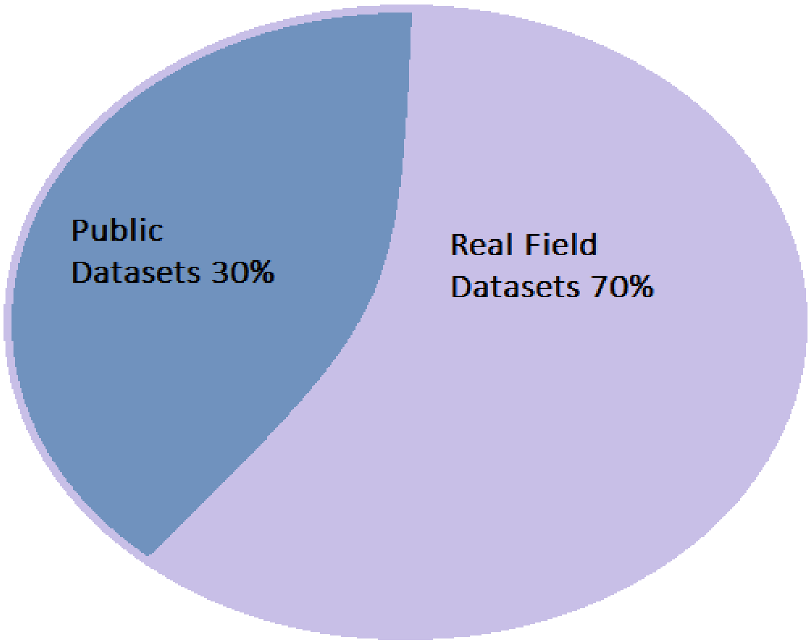

Figure: 4 Pie Chart of used Datasets

Images of both sick plant leaves that were gathered under controlled circumstances are available in a publicly accessible dataset. The pictures show a sick brinjal plant. We utilized the usual open-access Eggplant dataset, which comprises of diseased plant leaves, for both training and testing. The CNN model has to be created and trained so that the same network may be used for different crop classes. shows how well current CNN designs perform when tested on a variety of illness classifications. The image illustrates how the models performed poorly across several illness classifications. It is notified that the models used, the data sources, the pre-processing methods used, and the assessment of the suggested CNN models' overall effectiveness. The results showed that the majority of CNN models were only partially capable of processing unstructured raw picture input.

Challenges in CNN Implementation

Talking about and identifying some of the remaining barriers is the focus of this stage. Improved image preprocessing, classification, and subsequent early crop disease detection may benefit from the findings. Determining their goals and training a vast number of spectrum picture inputs are CNN's biggest challenges. For CNN classifier applications, it has significantly increased the difficulty of classifying the changes from the supplied input data. Analyzing the spectrum mixtures using CNN classifiers is one of the other most challenging aspects. In order to classify a range of agricultural diseases, CNN classifiers often integrate optimal characteristics such texture, color, and object shape. It is easy to train these parameters when the standard images are linear. It is only possible to train such hyperspectral data when there are hundreds of continuous spectral bands. Furthermore, it is very redundant to extract information from adjacent spectral bands in various spectral regions of a network. Using more sophisticated CNN technology still has its challenges. Few situations cannot be addressed using automated techniques like computer vision and image processing because different scholars have diverse opinions on how to apply them. The models that have been proposed so far have a restricted scope and are dependent on the context in which data is collected. It may result in the capture of distinct behaviors that make image analysis more challenging for the categorization and prediction of diseases. Other issues that have been determined to have the greatest influence include:

- Automatic illness diagnosis requires more than just using new computer vision technology.
- The environment in which the input data was collected may also have an effect on how the illness categorization is analyzed.
- It is difficult to distinguish between healthy and sick sections since illness symptoms are not clearly defined.
- The current techniques may be forced to rely on differences in order to differentiate due to visual similarities in the illness signs.
- It was not included in the assessment of illness severity and treatment.
- CNN models that were trained on smaller datasets could be more accurate, but they are unreliable.
- The computational cost of running any CNN on CPUs will be greater than that of GPUs.

Future Scope

In order to increase accuracy, new algorithms with higher performance and additional data sets can be introduced. Additionally, one can experiment with other techniques and create a valid set. creation of a two-headed hybrid strategy. Additionally, dynamic analysis will be performed using a range of dynamic equipment in addition to automated and boring techniques. Transfer Learning is a straightforward yet effective probability-based classifier that takes care of part of the labor-intensive work for you. Additionally, it may be used to determine certain helpful parameters for other machine learning methods. can be used to detect illness by farmers in remote areas. To provide wider use in agricultural disease management, the technology might be modified to identify illnesses in other plants in the Solanaceae family, such as potatoes, tomatoes, and peppers.

Discussion

Because they lower crop quality and productivity, plant infections are a significant issue in agriculture. The absence of diagnostic tools severely limits the advancement and quality of life in developing nations. It is essential to develop low-cost, easily navigable tools for early plant disease diagnosis. suggested a method for identifying and categorizing banana illnesses based on convolution neural networks. The proposed model might be utilized as a decision support tool to help farmers diagnose the disease in the eggplant. The algorithm will then be able to identify the illness if the farmer takes a picture of a leaf showing symptoms. Their primary goal is to distinguish between the two main banana diseases, banana specks and banana sigatoka, under difficult lighting conditions and real-world situations by employing deep learning models to alter the size, quality, attitude, and direction of pictures. In order to make epidemiological predictions about plant health both locally and internationally, an illness triad is an abstract framework that shows how the infectious agent, target crop, and surroundings are related. In light of the complex relationships between the three elements of the disease triangle, breeders of eggplants need to observe new characteristics, such as resistance to pests and diseases, and assess the environmental suitability of the recently created lines. There are currently no thorough evaluations that offer a full grasp of the fungal disease triad of eggplant as a host of interest. This review focuses on the disease triangle, which involves the host, pathogen, and environment, and fungal diseases that impact eggplant worldwide. There includes a thorough discussion of the etiology, pathogenic processes, host defense mechanisms, and genetic foundation of plant disease resistance. Given the dearth of thorough evaluations on this subject, plant breeders, plant pathologists, and eggplant producers can all benefit equally from our analysis [28].

Traditionally, farmers have relied on manual techniques to identify pests, illnesses, and weeds in their agricultural fields; however, this method is sometimes expensive and inaccurate. Deep learning techniques have been created to efficiently categorize different kinds of plant photos in order to address these problems. Several databases of photos of weeds, pests, and plant diseases from various crops were gathered for this purpose. Several deep convolutional neural network (DCNN) designs, such as Mobile Net, DenseNet201, VGG16, Hyperparameter Search, and InceptionV3, were used to augment the data in order to enhance performance. One of the most important aspects of pest treatment is accurate pest identification. Regretfully, conventional methods of pest identification are inaccurate and frequently misclassify pests, which leads to inappropriate pesticide usage. The research introduces Deep-Pest Net, a novel end-to-end deep learning framework for pest classification, in order to address these issues. This cutting-edge model, which consists of eight convolutional and three fully connected learnable layers, combines techniques for picture rotation and augmentation to increase the size and the data set's variety. Using the Deng's crop data set, the Deep-Pest Net architecture was tested and achieved a 100% accuracy rate. The framework was tested on the nine pest species that corresponded to the Kaggle "Pest Dataset" as an additional evaluation, and the results were excellent. This approach has the potential to change how pests are identified and classified, allowing farmers to improve crop security [29].

Climate change has a negative impact on agriculture today, leading to resource problems, particularly water stress and temperature changes. Thus, the production of agricultural commodities should improve steadily while maintaining crop yield and food quality through the use of smart technology and sensor-based artificial intelligence. The future of smart agriculture lies in sensors and artificial intelligence, which will be crucial in lowering labor costs and effort. In the age of contemporary agriculture, smart greenhouses with sensors and microprocessors not only speed up agricultural production technology but also contribute to the creation of high-quality food, which eventually affects the nation's economic growth. This problem could necessitate the application of novel strategies, particularly internet-based and sensor-based smart technologies, to guarantee global food security. By regulating the microclimate for farming throughout the year, greenhouse agriculture ought to be a viable solution to the problems associated with food security. However, the greenhouses' increased inside temperature limits the ability to successfully grow crops and oversee them. For this reason, by managing the greenhouse's internal microclimate, smart technologies such as the Internet of Things (IoT), sensors, artificial intelligence, and smart monitoring systems can overcome the difficulties with traditional greenhouse systems [30].

Collecting thorough data from farmland—including information on plants as well as the environment—is essential to quality agriculture. Environmental factors including temperature, soil moisture, humidity, composition, sun radiation, wind speed, and rainfall, for instance, are thought to indicate changes in the weather and soil pollution and can aid in better managing the use of fertilizer and other inputs. Information on plants, including growth, illness, and insect pests, may be used to forecast output and decide whether to apply pesticides or organic materials. Using machine learning, this disease prediction system will provide a more accurate forecast of potato diseases and suggest appropriate treatments of pesticides and organic materials. Because of its ease of use and robust library, Python is the most extensively used language for machine learning, artificial intelligence, data science, deep learning, and image processing. This system is implemented using the open source Python language and a number of libraries, including OpenCV, Pytesseract, NumPy, SciPy, TensorFlow, and others. Machine learning and clustering algorithms may be used in this disease prediction system to track plant development. Data aggregation in this system aids in transforming unprocessed plant data into precise, understandable information for farmers. Wilting, spots, powdery mildew, galls, and dryness are a few signs that can be seen in the eyes. Various dataset properties are gathered, various methods are applied, and various plots, such as box and bar plots, are created. The forecast is made using an internal dataset with the use of statistical testing. Each sample dataset has a varied accuracy, and several methodologies are compared. A computerized system for diagnosing 10 diseases of four crops (lady finger, lime, hyacinth beans, and eggplant). The wrote work trained and validated the generated dataset using six already trained deep learning models. Convolutional neural networks (CNNs), one of the deep machine learning techniques, are used to extract features from dataset collections. Convolutional neural networks (CNNs), a supervised learning approach, were used to extract features from the aforementioned data set. We use basic, important information for this. CNN can provide a big and accurate number of feature attributes from a vast amount of data. Every data set has been separated into its own distinct data category. Take a data picture, rotate it, and then use CNN to extend the dataset by mirroring each rotated image [31].

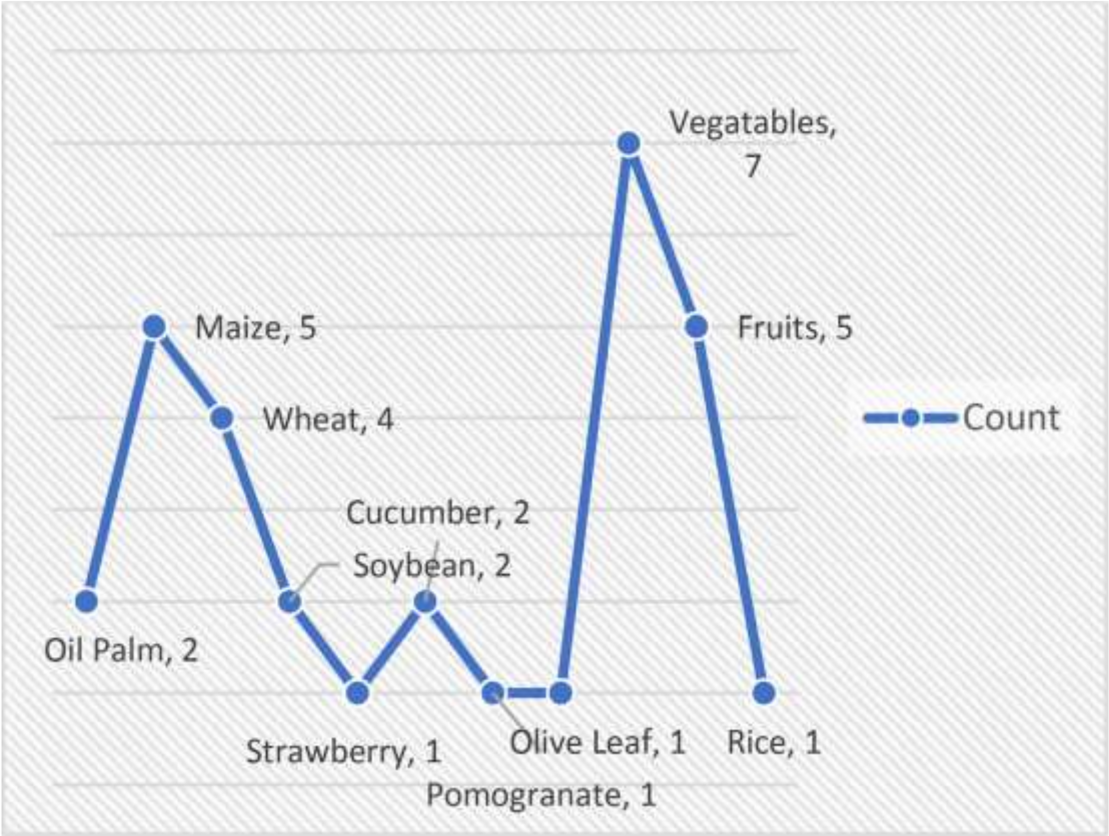

Figure 5: CNN model applications across a range of agricultural fields

Proficiency in cutting-edge research methods would help researchers with more than just using deep learning techniques. In order to identify and forecast different crop diseases at an earlier stage of infection, the study intends to use deep learning techniques to the field of agriculture. It has been noted that DL would identify and classify plant diseases, including those that are healthy and those that are not. It's time to look at DL applications that use complex neural networks, such as the identification and categorization of potential disorders. Accuracy varies depending on the illness class. The accuracy of the model was only 87% for other disease classes, but it was helpful in detecting northern maize leaf blight with 99.9% accuracy. Since distinct models are not being developed for various disease classes, the current study assumes that there should be little variance in detection accuracies when forecasting all crop disease courses. The CNN model has to be created and trained so that the same network may be used for different crop classes.

The performance study of current CNN designs through testing on several illness classes is shown in Figure 8. The image illustrates how the models performed poorly across several illness classifications. The majority of research do not employ the conventional datasets to determine CNN model performance. According to this paper, the only way to train and evaluate the current CNN models is to use picture datasets that were collected in the field during data collection. By using picture augmentation techniques, the dataset's normal sample count was boosted. The quantity of samples for detection was thus equalized. Using all of the data rather than choosing data at random throughout the training phase is made possible by this equal distribution.

Conclusion

In order to convert unstructured data into feature vectors, which allow subsystems to often identify and categorize certain patterns in incoming data, deep learning systems need methodical engineering and design skills. In this study, deep learning methods were surveyed to ascertain their applicability in the field of agriculture. By examining the agricultural industry, 84 pertinent articles were found. We concentrated on the data sources, models used, pre-processing methods used, and assessing the suggested CNN models' overall effectiveness. The goal of this poll was conducted is to encourage the researchers to use deep learning methods for image analysis-related plant disease classification and detection. In order to allow autonomous illness detection through picture categorization, this research shows that machine learning utilizing a convolutional neural network technique is technically feasible. A convolutional neural network is trained to identify crop species and disease status using pictures of both healthy and damaged plant leaves. This article investigated a novel method for automatically classifying and detecting plant diseases from leaf photos using machine learning techniques. Healthy leaves and other disorders that may be visually identified might be distinguished by the created model. From gathering the pictures utilized for training and validation to image augmentation and, ultimately, the process of training the deep CNN and fine-tuning, the entire process was explained.

The integration of image processing CNN classifiers holds significant potential in areas such as plant disease detection, quality control in food production, and pattern recognition across diverse industries. The implications of this research extend eggplant classification, offering potential applications in other crops and plant species. This innovation holds promise for advancing agricultural research and crop classification. When used for eggplant recognition, deep learning—specifically, Convolutional Neural Networks (CNNs)—has shown remarkable efficiency and accuracy in recognizing and categorizing eggplants in a variety of settings. CNNs are resilient against environmental changes like illumination and occlusion because they efficiently extract and learn properties like form, texture, and color. With less human labor, farmers will be able to enhance crop monitoring, quality evaluation, and harvesting procedures because to this breakthrough's enormous potential for agricultural automation. The model may be further improved for real-time detection and deployment in smart agricultural systems by utilizing big datasets and refining CNN architectures. For on-field applications, future research can concentrate on enhancing dataset variety, optimizing hyperparameters, and combining the system with edge computing. Deep learning methods have demonstrated remarkable efficacy in the detection of eggplant illnesses, providing precise and automated diagnosis of a range of plant diseases. Images of eggplants may be analyzed by Convolutional Neural Networks (CNNs) and other deep learning models to accurately identify symptoms including fungal infections, leaf spots, and discoloration. By doing away with the need for human inspection, these models make it possible to detect diseases early and take prompt action, which is essential for increasing crop output and lowering losses. Furthermore, deep learning-based systems are useful instruments for contemporary precision agriculture as they may be linked with mobile and Internet of Things apps for real-time disease monitoring. By integrating a variety of datasets, refining architectures, and creating lightweight models appropriate for deployment on edge devices, future research may concentrate on improving model generalization.

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