Crop Diseases Detection Using Image Classificationwith Deep Learning

Bappaditya Das[1]
Computer Science & Engineering
Rama University
Kanpur, INDIA
mail2bappadityadas@gmail.com

C S Raghuvanshi [2]
Computer Science & Engineering
Rama University
Kanpur, INDIA
*drcsraghuvanshi@gmail.com

***Abstract*— Early identification and recognition of crop diseases help to protect national and global food security by minimizing yield losses. Deep learning technology has recently made strides in plant disease diagnosis, giving us a robust system with high accuracy. The development of a knowledge base can help to improve the system qualitatively and fulfil the requirements of farmers by identifying the challenges they face in the real world. In addition, deep learning has developed into a hub for research in the area of agricultural plant protection, including identifying plant diseases and evaluating pest ranges. The research on plant diseases still needs to fill a few gaps, despite the wide range of applications, to help disease control on farms. This paper details the development of deep learning technologies in recent years to diagnose crop leaf diseases. This study focuses on ongoing trends and difficulties in identifying plant leaf disease using deep learning and cutting-edge imaging techniques. We hope that this work will be useful to researchers interested in the identification of crop diseases.**

***Index Terms*—deep learning, disease detection, crop, image classification**

I. Introduction

India is fundamentally an agricultural country because half of the Indian population depends upon agriculture and allied activities. The agricultural sector has contributed steadily around 15% to 20% of the Indian Gross Domestic Product (GDP) for the past few years. Unfortunately, Indian agricultural production increased by only 11% in the last 14 years, which is a very dismal growth performance compared to other developed countries. Both centrally and state-level schemes, reforms, and policies are taken to boost this sector's growth. Recently, many technologies, particularly IoT-based farming, are advancing worldwide with more precision, making this farming smarter. But transforming those so-called precision farming and smart agriculture in India is still not encouraging. An IoT-based sustainable smart agriculture system for India using machine learning by a collection of practices for cultivating and producing food by integrating a healthy ecosystem, economic profitability, and socio-economic equality is still a challenging task in India.

Agriculture and its allied sectors are the primary sources of livelihood for many households in rural India. Agricultural activity is the highest contributor to India's GDP, but a NSS report released by the Ministry of Statistics & Program Implementation in September 2021 disclosed the most pathetic figure regarding the monthly income level of Indian farmers.The report 'Situation Assessment of Agricultural Households and Land and Holdings of Households in Rural India 2019' also revealed that in India, there are 50% indebted agricultural households, and the average outstanding loan per agricultural household is Rs.74,121. In India, 34.2% of agricultural households possess, on average 0.01 - 0.40(ha.) whereas 35.6% holds 0.40 - 1.00 (ha.) land. Instead of having so many small (1.00-2.00 ha.) and marginal (¡ 1.00 ha) farmers crops, productivity is not so low but is very good in selected crops. From this report, it may be inferred that most agricultural households still farm crops using traditional techniques and are far away from modern smart agriculture or precision farming technology because of illiteracy or poor financial conditions. As per the report, considering both the paid out expenses and imputed expenses, the average monthly income per agricultural household in India from July 2018 to June 2019 is Rs 8337, i.e. daily income of farm households becomes Rs 278, which is nearly the same as the minimum daily revised wage rate of unskilled manual workers paid in Chandigarh under the Mahatma Gandhi NREG Act, 2005 published on 31 st March 2018 by Government of India, Ministry of Rural Development, Department of Rural Development.

Till we are proud for our farmers but the problems they are facing become a national concern. Lots of farmer's suicide is an warning message to the Indian agricultural system. Several expert committee had been formed by the Government of India for probing the agrarian crisis. 'Indian agriculture is currently passing through a period of severe crisis' was asserted by one of the expert committee under the chairmanship of R.Radhakrishan. According to National Crime Records Bureau (NCRB),2015 data more than 3 lac Indian farmers committed suicide in 20 years i.e from 1995 to 2015. Fig 1. shows that number of suicide is decreasing gradually but not yet stopped.

Focusing on this alarming numbers, research scholars started to figuring out the actual reasons behind this terrible condition of Indian farmers. The outcomes of various research classified the cause of farmer's suicide region wise.Scarcity of irrigation infrastructure, nonavailability of traditional credit system, crop price fluctuation and indebtedness among farmers are identified as the major causes for committing suicide among the farmers in Maharashtra. In Karnataka, crop produc-

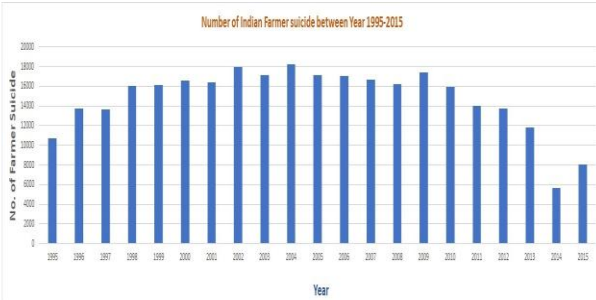

Fig. 1: Number of Indian farmers committed suicide from Year 1995 - 2015

tivity well below the expected level, increasing cultivation cost, crop failure, market disturbances and indebtedness leads to farmer's suicide. Whereas in Punjab, surging non-agricultural expenditure, excessive input of fertilizers and pesticides were found responsible for such a pathetic situation [2]. NCRB,2015 also identified that 98% of suicided farmers hold not more than 4 ha. farm land. Out of this 98%, 72% hold less than 2ha. farm land. So, it is clear from the above data that the small(1-2 ha.), marginal(less than 1 ha.) and medium farmers(2-4 ha.) are the worst affected.

Major Issues in Agriculture Sectors in Present Scenario:

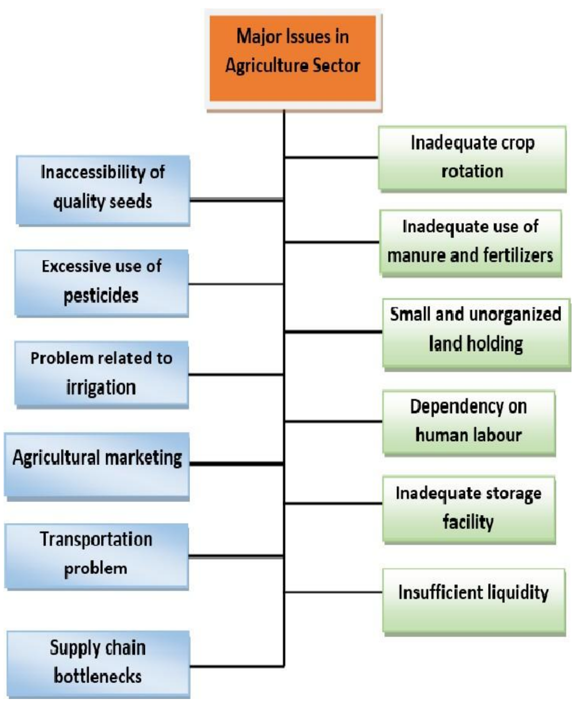

Fig. 2: Major issues and challenges in agriculture sector

Inadequate crop rotation: Soil deterioration, upsurge pest infestation and nutrients imbalance are the adverse effects of conventional long term practice of cultivating cereal(rice)-cereal(wheat) in a same land [1]. To maximize crop output by preserving soil fertility, rotation of pulse-cereal must be implanted [2].

Inaccessibility of quality seeds: Good quality seeds are crucial and fundamental requirement to achieve the good yield of crop. But unfortunately due to sky-high price of excellent quality seeds the accessibility of those seeds are limited to only large scale Indian farmers. As a result small and marginal farmers need to compromise with comparatively lower quality seeds. Several governmental initiatives had been taken to resolve the problem but till now the problem is not uprooted completely.

Inadequate use of manure and fertilizers: Indian farmers are cultivating crops for years without much care for replenishment due to which soils have turned into depleted and exhausted. As a result, farmers are getting average yield that's among the lowest in global perspective. Periodic use of quality manure and fertilizers can solve this significant problem. Efficient nutrient management plays the vital role for better productivity, long-term sustainability with minimum environmental damage. Cow dung are widely used as manure by the poor farmers due to affordable price of chemical fertilizers.

Excessive use of pesticides: pesticides is often important to protect and conserve the crops. But excessive use of pesticides is not only harmful for society but it also degrades the nutrients in the food. Governmental data shows the differences between the assessed requirements and sales of NPK in India for last few years. It also clearly indicates that our farmers are using much more fertilizers than estimation.

Small and unorganised land holdings: Holding small and scattered piece of land is the major threat of to Indian agriculture. This problem of low productivity due to fragmented land is more unrestrained in the state of Bihar, Kerala, Uttar Pradesh and in West Bengal. The process of moving manure, fertilizers, seeds and cattle from one slice of land to another become more time consuming. Irrigation in small fields becomes an issue and huge portion of fertile land gets wasted in this process. Merging these small land and common crop cultivation may be one the solution of this problem which lead to decrease the input cost of farming.

Problems related to irrigation: China, largest irrigated country followed by India. Irrigation is the determining parameter for agriculture. Disordered nature of monsoon Indian farmers cannot rely entirely on rain. But conventional method of irrigating the land lead to misuse the water. Modern IoT based technological mechanism should be adopted by the farmers for optimum use of harvesting rainwater and groundwater.

Dependency on human labour: Activities like tilling of the soil, sowing of seeds, fertilizer spreading, irrigating, weeding and harvesting all are till now mostly dependent on human labour. But in agricultural developed country like Israel all the above activities are technology based.

Agricultural marketing: Marketing of agricultural products is still a major challenge in rural India. Due to the absence of viable marketing infrastructure poor farmers are compelled to depend on local merchants and traders to unload their agricultural products negotiating with the price. This distressed selling of their cultivated crops at low price small farmers are exploited financially day by day.

Inadequate storage facilities: Inadequate storage facility in rural India forced poor farmers to sell their harvested products at the prevailing prices. Sufficient storage facility with proper monitoring will be helpful for farmers by reducing crop losses.

Transportation problem : Smoother road connectivity of rural villages with cities will be beneficial for farmers to sell their products with good price by avoiding local merchants and traders.

Insufficient liquidity: Without sufficient liquid cash it is quite difficult to run a successful setup. But it is very unfortunate that poor farmers have inadequate cash which lead them to borrow money form lenders and commission agents at excessively high rates and interest.

Supply chain bottlenecks: Nearly about 30% of the global agricultural output is estimated to be lost during the process of distribution. Due to unprofessional logistics India loses 20% of its agricultural production. Inclusion and involvement of so many people sometimes degrades the efficiency of a system.

Food security becomes a global threat by 2050 as the world population is estimated to touch 9 billion [3]. Except some practices in Slash and burn technique, most of the traditional farming methods [4] are focused on protecting soil fertility and the ecosystem. It is very difficult to fulfill the global food demand by traditional farming.It is an ancient practice to use traditional agricultural knowledge for food production [5]. Presently, adverse impacts due to climate change emerge as the greatest threats to global food security [6]. Maize crop, fisheries, fruit and vegetable production are at serious risk due to changes of meteorological characteristics. Potential physical and biological consequences on fisheries due to climate change and implication on food security was reviewed by [7] with the help of a specific example in Sub-Saharan African (SSA) countries. According to the report ”Climate Change and Agriculture in India” by Government of India 62% of cropped land in India is rainfed, and even the irrigated system is dependent on monsoon rain. A report by the Parliamentary Standing Committee on Agriculture, 2017 estimated that overall GDP loss of 1.5% due to climate change. Adverse effect on Indian agriculture sector due to climate change reviewed elaborately [8].

Apart from the chaotic nature of monsoon, small land holdings of farmers, primary and secondary processing, supply chain, the infrastructure supporting the efficient use of resources and marketing, etc. are the significant challenges in Indian agriculture. The Indian government and other organizations are endeavoring to equip the difficulties of agriculture in India. Modern technology-based agriculture, including climate-smart agricultural practices (CSAPs) is essential for sustaining Indian agriculture. Substantial efforts have been made by both national and international agricultural organizations to promote CSAPs in India. But transforming towards these new model is disappointing [9]. Sustainable Intensification is a mechanism by which we can produce more yields without increasing cultivated land, and without conflicting environmental ecosystem [10][11].

Growth, inclusiveness, and sustainability are the primary goals of agricultural development in India. In India, most farmers still monitor the crops, diagnosis the diseases manually which is not only time consuming but also difficult to detect exact situation accurately. These agricultural problems are solvable by IoT-based technology. Microcontrollers like Arduino, Raspberry Pi minicomputers with a camera and Wifi module, temperature sensors, humidity sensors, pH sensors, soil moisture sensors, water level sensors, and infrared sensors are commonly used as hardware components in IoT-based smart agriculture technology. Zigbee, Xbee protocols for cellular connectivity, and some machine learning algorithms are used for the decision support system [12]. Basics like seeds, fertilizers, credit, water, technology, etc. are essential for agriculture, and they should not be forgotten [13].

Every farmer wants to maximize the production. To achieve the target farmers, need to protect their crops from diseases. Plant diseases are regarded as dangers because they frequently result in substantial yield, economic, and environmental losses around the world. According to FAO, dropping of global agricultural productivity from 20% to 40% are related to pests and diseases. Infectious parasites including nematodes, fungi, oomycetes, viruses, and bacteria are the fundamental cause of plant diseases. Currently, fungi account for over 83% of known plant infectious diseases, whereas viruses and phytoplasmas cause 9% and, bacteria account for more than 7% [14]. Because a large range of organisms can produce a variety of symptoms, accurate pathogen identification is fundamental to building a management plan.

Crop diseases detection is one of the vital and time-consuming tasks in agriculture. Skilled labour and experienced farmers can identify the diseases by visual inspection. They take the necessary measures from their knowledge base. Disease control initiatives may result in a waste of time and resources without accurate identification. Ineffective disease control measures may subsequently result in increased plant losses. Therefore, it is essential for farmers, managers, and decision-makers to identify, monitor, and assess plant diseases early and accurately.

Modern IoT based technology can able to monitor constantly moisture, temperature and humidity. Imbalance of these parameters lead to deteriorate of plant’s health. Unhealthy plants are more vulnerable to pathogen invasion. Infected plant is more at risk to secondary pathogen attack. Smart agriculture alerts the farmers in whenever there is any imbalance of above-mentioned soil & climatic parameters. Detection of this imbalance by visual inspection is very difficult in time. So IoT enabled technology is useful to monitor the plant’s health without human labour. Thus automatic but accurate diseases detection by just analysing the image of the crop is not only helpful to farmers but also drew the attention to the researchers. Recently Deep Learning (DL) outperforms human in case of image classification.

TABLE I: List of abbreviations used

Abbreviation	Full Form
AI	Artificial Intelligence
ANN	Artificial Neural Network
CBAM	Convolutional Block Attention Module
CMPE-SE	competitive SE
CNN	Convolution Neural Network
CRAFT	Character Region Awareness For Text detection
DL	Deep Learning
DT	Decision Tree
DSSD	Deconvolutional Single Shot Detector
FC	Fully Connected
FPN	Feature Pyramid Network
G-CNN	Grid Convolutional Neural Network
G-RCNN	Granulated RCNN
HOG	Histogram of an Oriented Gradient
ION	Inside-OutsideNet
IRCNN	Inception-Recurrent CNN
ILSVRC	ImageNet Large Scale Visual Recognition Challenge
IoT	Internet of Things
KNN	K-Nearest Neighbors
MAE	Mean Absolute Error
mAP	mean Average Precision
MSE	Mean Square Error
MCD-SORT	Multi-Class Deep SORT
ML	Machine Learning
MLKP	Multi-scale Location-aware Kernel Representation
MR-CNN	Multi-Region CNN
MS-CNN	Multi Scale CNN
NiN	Network In Network
OCR	Optical Character Recognition
OHEM	Online Hard Example Mining
PFPNet	Parallel Feature Pyramid Network
PSPNet	Pyramid Scene Parsing Network
RCNN	Region-based Convolutional Neural Networks
ResNet	Residual Network
ReLU	Rectified Linear Unit
RF	Random Forest
RFBNet	Receptive Field Block Network
RMSE	Root Mean Square Error
RMSLE	Root Mean Squared Logarithmic Error
RNN	Recurrent Neural Networks
RNN	Recurrent Neural Network
RRCNN	Recurrent Residual Convolutional Neural Network
SENet	Squeeze-and-Excitation Network
SOTA	State Of The Art
SPP-Net	Spatial Pyramid Pooling Network
SSD	Single Shot detector
SVM	Support Vector Machine
VGG	Visual Geometry Group
YOLO	You Only Look Once

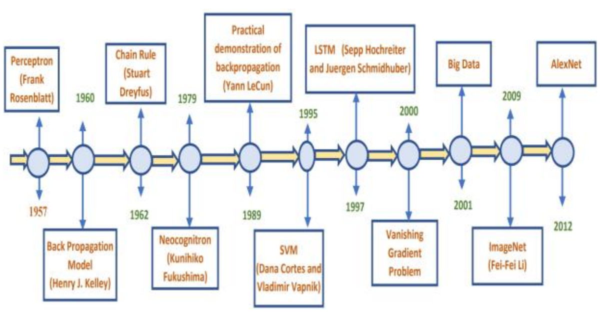

Fig. 3: Evolution of DL: 1943-2012

Deep Learning (DL) is a subsection of Machine Learning (ML). Nowadays DL becomes popular choice of researchers. But it has not appeared overnight. Over the past 70 years, it has slowly and progressively transformed to its present state. The idea of DL was initiated by American logician Walter Pitts and American neuroscientist Warren McCulloch, in the year 1943. They tried to replicate the human thought process using a set of mathematical formulas and algorithms named as ”threshold logic.” The first phase(1943-2012) of DL evolution is shown in figure 3.

After winning ILSVRC in the year 2012, AlexNet achieved a milestone. The evolution story after AlexNet is shown in table :

TABLE II: Evolution of DL: 2012-2022

Year	Developed Model
2012	AlexNet
2013	ZFNet, NiN, OverFeat, Xception
2014	GoogleNet, Inceptionv2, Inceptionv3, Inceptionv4, InceptionResNet, VGG, MultiBox, SPP-Net
2015	HighwayNet, SegNet, U-Net, MR-CNN,DeepBox, AttentionNet
2016	DenseNet, SSD, OHEM, YOLOv1, G-CNN,AZNet, ION, HyperNet, CRAFT, MS-CNN
2017	FractalNet, ResNet, DenseNet, CapsuleNet, DSSD, IRCNN, IRRCNN, RefineNet, PSPNet,Mask-RCNN, WideResNet, PolyNet, PyramidalNet, YOLOv2, RetinaNet
2018	Fast-RCNN, DCRN, R2UNet, SENet, CMPE-SE,Residual Attention Module, CBAM,ChannelBoostedCNN, YOLOv3, MLKP, Relation-Net, CascadeR-CNN, RFBNet, CornerNet,PFPNet, HKRM, R-DAD
2019	ResNext-50, M2Det
2020	YOLOv5
2021	YOLOP, YOLOR
2022	YOLOv7

Artificial neuron is the most fundamental unit of NN. NN estimates the nonlinear and complicated relationship between input x and output y by integrating a lot of neurons. A DNN is made up of multiple hidden layers between one input and one output layer. Normally, there are several identical neurons in each layer.

Each neuron has an activation function that is used for nonlinear transformation. Most commonly used non-linear activation functions are shown in the figure.

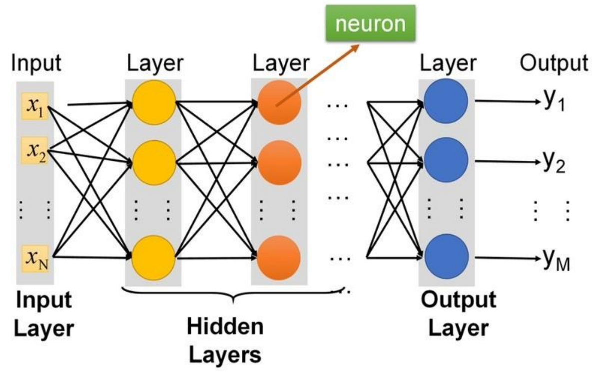

Fig. 4: A typical architecture of DNN [15]

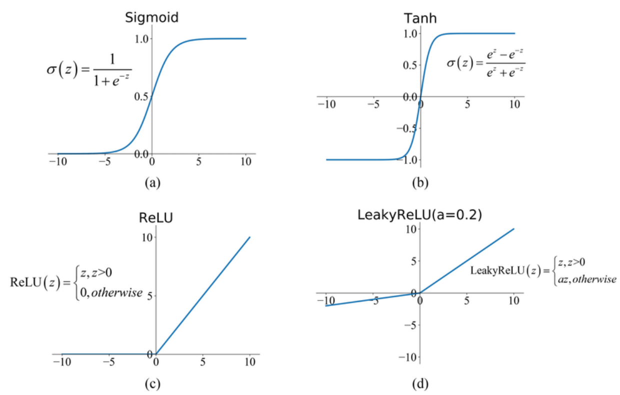

Fig. 5: Commonly used non-linear activation functions: (a) Sigmoid (b) Tanh (c) ReLU and (d) LReLU [15]

CNN is a subset of DL and a member of the ANN. The convolutional layer is the backbone of a CNN. Convolution is the mathematical term for the process of combining two functions to create a third function. It is widely used for various image filtering techniques such as sharpening, blurring, edge detection, and so on. In CNN, both the kernel and filter are the same, and it is nothing but a small matrix. The feature map is the outcome of applying one filter to the previous layer. Various features of the input images are extracted at various levels during the convolution process.

Pooling layers are used after the convolutional layer. The main objective of pooling is to reduce the dimension of feature maps, which in turn speeds up computation by reducing the number of training parameters. The two most popular pooling strategies are average pooling and max pooling. Max pooling selects the maximum value from the feature map while average pooling selects the average value. Since max pooling selects most prominent features then it is usually used for dark background. Since average pooling returns average the features in a region then it is effective when harsh edges in a image are immaterial. Another type of pooling is named ”min pooling,” which selects the minimum value from the feature map. Min pooling returns dark pixel value from image having lighter background.

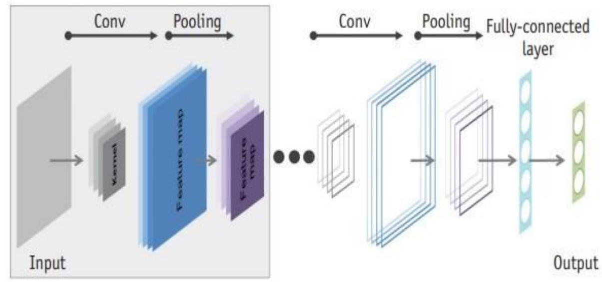

Fig. 6: A conceptual CNN architecture [16]

The fully connected layers, also known as dense layers, link the extracted features by the pooling and convolutional layers to the model’s final outputs. CNN is widely used in OCR [17][18], sentiment analysis[19][20], medical image recognition [21] [22], and object detection from videos [23] [24].

Most significant two stage object detection deep learning models:

TABLE III: Major two stage object detection DL models

Year	Model Name
2014	RCNN and SPPNet
2015	Fast RCNN and Faster RCNN
2017	Mask R-CNN, Pyramid Networks FPN
2021	G-RCNN

Most significant one stage object detection deep learning model:

TABLE IV: Major one stage object detection DL models

Year	Model Name
2016	YOLO, SSD
2017	RetinaNet
2018	YOLOv3
2020	YOLOv4
2021	YOLO-R
2022	YOLOv7

The most widely used DL models for object detection include YOLO, RCNN, MaskR-CNN, MobileNet, and SqueezeDet.

The architecture of Alexnet, VGG-16 and Resnet50 are sown in Figure 7, Figure 8 & Figure 9 respectively.

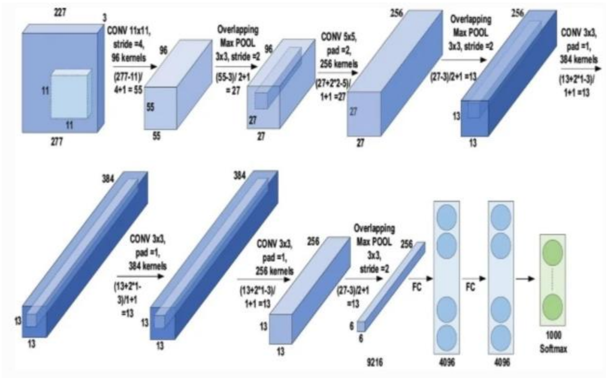

Fig. 7: Architecture of Alexnet model [25]

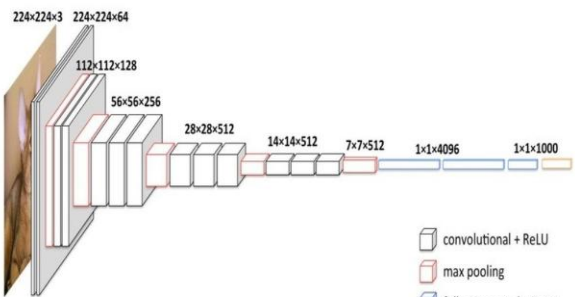

Fig. 8: Architecture of VGG-16 model [26]

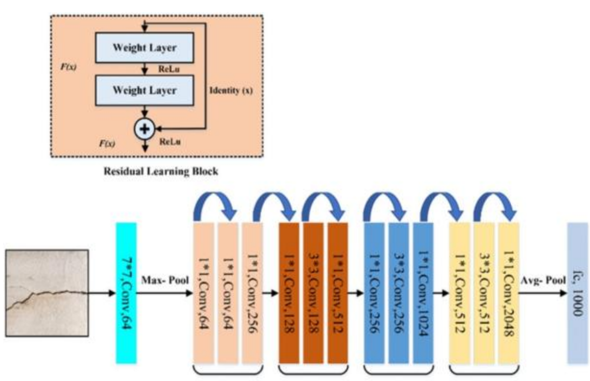

Fig. 9: Architecture of ResNet50 model [27]

In the following table we make a feature comparisons between 3 commonly used CNN model.

TABLE V: Feature comparisons AlexNet, VGG-16 and ResNet 50

Model	Model's details	
AlexNet	Size(M)	238
	Layers	8
	Parameters (Million)	60
	Model description	5 conv + 3 fc layers
	Learning time	3 m 48s
	Processing time	12.90 ms
	Accuracy	98.53%
	Top-1/Top-5 error	41.00/18.00
VGG-16	Size(M)	540
	Layers	16
	Parameters (Million)	138
	Model description	13 conv + 3 fc layers
	Learning time	16 m 14 s
	Processing time	16.55 ms
	Accuracy	97.84%
	Top-1/Top-5 error	28.07/9.33
ResNet 50	Size(M)	100
	Layers	50
	Parameters (Million)	25.6
	Model description	49 conv+ 1 fc layers
	Learning time	43 m 27 s
	Processing time	13.83 ms
	Accuracy	96.8%
	Top-1/Top-5 error	22.85/6.71

In the context of computer vision, the advantages of deploying CNNs over other conventional neural networks are as follows:

(i) CNN holds the weight sharing feature which lowers the volume of trainable parameters and leads to handle the overfitting problem.

(ii) Powerful feature extraction layers and classification layer result the output of the model is both extremely organised and trustworthy.

Apart from applications in various domains, CNN has some limitations as follows:

(i) The position and orientation of an object are not captured by CNN.

(ii) CNNs trained on ImageNet and other well-known datasets struggle to recognise object when they are observed from different perspectives and in changing lighting conditions with noisy background.

Developing and training a CNN from scratch requires a huge amount of data. Training with large and complex data set makes the models costly. A lot of sophisticated hardware is also required to do complicated mathematical calculations. To overcome this problem researcher's interest switch over transfer learning to solve image recognition and image classification related problem.

Transfer learning is the most popular technique to training a newly developed model by using previously trained models [28].In general, transfer learning involves shifting a model's understanding of knowledge in the source domain to the target domain using less data for quicker training [29].

These are the following steps to be followed for transfer learning :

(i) Select a pre-trained CNN model as base model.

(ii) Replace the existing classifier with new classifier.

(iii) Freeze the convolutional base and train the newly inserted classifier.

(iv) Unfreeze the top few layers of the convolutional base.

(v) Fine tune the unfreeze top layers as well as added classifier.

Figure 10 represents the transfer learning process from a pre-trained CNN model.

Performance of the newly developed model can be optimized by adjusting the following hyperparameters: number of neurons in each hidden layer, choosing the activation function, selection of proper optimizer function, adjusting learning rate, batch size and number of epochs.

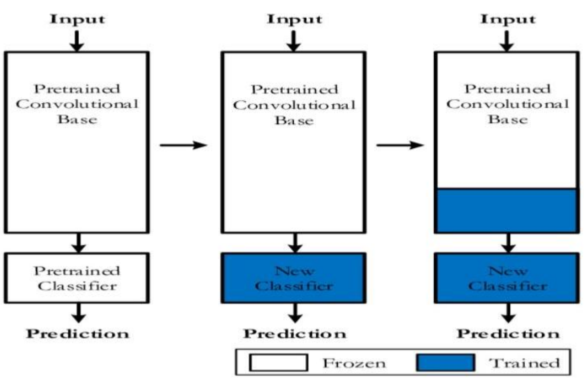

Fig. 10: Block diagram of transfer learning from a pretrained CNN model [30]

DL using CNN gained popularity among the research community after the formation of PlantVillage dataset in 2015[31].

While solving a classification problem, the target variable is partitioned into a finite number of classes; however, when solving a regression problem, the target variable possesses continuous values, and we have to minimise the deviation from actual values.

Most commonly used performance metrics for classification problems:

Confusion matrix:

Confusion matrix is a 2D-matrix which gives us a comprehensive understanding of the effectiveness of our classification model and the types of mistakes it is committing. Each row of the confusion matrix represents a predicted class while each column is associated with actual class. For binary classification problem, confusion matrix size will be 2 x 2. If N be the number of target class then confusion matrix becomes N x N. Confusion matrix associated with following variables:

TP : predicted correctly and it is true.

TN : predicted incorrectly and it is true.

FP : predicted correctly and it is false.

FN : predicted incorrectly and it is false.

Accuracy:

For properly balanced classification problems accuracy is a fair choice and it is defined as,

$$Accuracy = \frac{TP + FN}{TP + FP + TN + FN} \tag{1}$$

Precision: It represents how % of the positive classes we accurately predicted correctly and is defined as,

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

Model with high precision value is highly accepted.

Recall / Sensitivity: It represents What % of actual Positives are actually classified correctly?

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

Value of Recall should be as possible.

F1-score: It represents% of actual Positives are actually classified correctly.

$$F1\_score = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

Value of F1-score generally in between 0 and 1. For a perfect model F1-score = 1, while F1-score = 0 means complete failure. Model with high F1-score indicates low FP and low FN means model is correctly identifying real threats.

AUC-ROC: Figure 11 shows a typical ROC curve. Closeness of the graph to the top and positive TPR axis measures the higher accuracy of the test. Graph closer to the diagonal implies less accurate test. For a perfect classifier, area under the ROC curve (AUC) = 1.

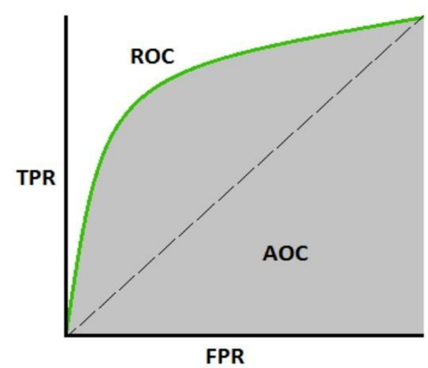

Fig. 11: A typical ROC curve [32]

LogLoss: When the model gives a probability for each class, as opposed to merely the most likely class, LogLoss is applied. It is also known as Cross Entropy. LogLoss/Cross Entropy is calculated using the follwing formula,

$$Logloss = \frac{-1}{N} \sum_{i=1}^{N} \sum_{j=1}^{n} x_{ij} * log(P_{ij}) \tag{5}$$

Gini_coefficient: The Gini Coefficient is an indicator to measure inequality. From the area under ROC curve Gini coefficient can be computed using the formula,

$$Gini\_Coefficient = (2 * ROC\_Curve) - 1) \tag{6}$$

Most commonly used performance metrics for regression problems:

MAE: It represents a measure of how inaccurate the predictions are.

$$MAE = \frac{1}{N}\sum|Y - \hat{Y}| \tag{7}$$

where $\hat{Y}$ = Predicted output
where Y = Actual output

MSE: It is an average of the squares of the errors. MSE is differentiable and it can be used as loss function.

$$MSE = \frac{1}{N}\sum(Y - \hat{Y})^2 \tag{8}$$

RMSE: It is frequently used to confirm experimental findings forecasting, and regression analysis. It illustrates how densely the data is clustered around the line of best fit.

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(y_j - \hat{y}_j)^2} \tag{9}$$

RMSLE: RMSLE is preferred for objectives with exponential growth.

$$RMSLE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(log(x_i + 1) - log(y_i + 1))^2} \tag{10}$$

II. Review of Literature

Early identification of crop diseases and Optimal use of pesticides at the proper time are significant factors of smart agriculture. Remote Monitoring System(RMS),a web-based as well as mobile application prediction model proposed by authors [33] with the help of IoT to achieve this. Real-time data(temperature, soil moisture,pH) were collected from crop area through Ubi_Sense_mote. Plant images were captured by webcam, and the spectral analysis of these images states the plant's health. But which machine learning model was used in DSS(Decision Support System) remains unmentioned.

Analyzing 119 research papers from well-reputed journals related to crop disease forecasting, it was concluded [34] that most used algorithm in an agricultural context is Decision Tree, followed by Support Vector Machine, Artificial Neural Network, and Bayesian networks.

A feature extraction algorithm using HOG was developed [35] to detect anomalies on plants in both natural or greenhouse environments. Model was trained by RF on 160 papaya leaves using Histogram of an Oriented Gradient. 70% accuracy was achieved just by training with 160 observations.

Multidimensional feature compensation residual neural network (MDFC-ResNet) model [36] for accurate identification of the stages of crop diseases. In the data processing stage - (i) after rotating and flipping images data set was enhanced from 36258 pictures to 63265 images. (ii) normalization for converting all the images to a uniform size of 224x224 pixels. (iii) Singular Value Decomposition(SVD) for extracting important features from the original image and eliminating noise. Identification of the category of the species was performed by an optimized ResNet-34 network. ResNet-50 was used for speedy but accurate disease recognition.

For classification and symptoms visualization of tomato disease [37], authors selected 14828 tomato leaves images as data set from the website www.PlantVillage.org and used NVidia DIGITS as a deep learning framework. [38] identified tomato leaf diseases with 97.28% accuracy by using deep CNN.

CNN model was used to identify the plant diseases only individual lesions and spots were considered instead of the entire leaf [39]. Improved deep CNN [40] was used for maize leaf disease detection, and modified LeNet architecture was proposed for maize leaf disease classification [41].

Authors [42] developed a seven-layer sequential transfer learning CNN model to identify the potato diseases with more than 99% accuracy from leaf images. Three channels RGB images from PlantVillage dataset were converted to single channel grey scale images. Keras ImageDataGenerator was used for converting tensor images according to batch size. Custom model was tested separately over several pretrained models such as MobileNet, VGG-16, ResNet50, InceptionV3 and InceptionResNetV2. Accuracy in each case was measured from confusion matrix. Developed model was not tested over real time dataset with noisy background.

In [43] authors applied transfer learning separately using pretrained CNN model such as VGG-19, Xception and ResNet-50 on PlantVillage dataset to detect the tomato leaf diseases. Recall, precision and F1 score metrices were used to measure the performance in each case. In case of models using VGG-19 and Xception achieved the accuracy more than 95% while model using ResNet50 accuracy was 60%. Less accuracy in ResNet50 as compared to other model probably due to losses in training and validation phase.

A light weight CNN model consisting with 8 layers was proposed [44] by compressing VGG16 model. The authors claimed that SOTA CNN models were created to identify a variety of classes. However, in reality, the majority of plants have no more than 15 types of diseases. Created a hidden layer with less number of filters by removing insignificant filters. To remove the insignificant filters, authors added the the absolute values of weights associated with filters from hidden convolution layers. Filters having sum value = 0 were discarded and treated as irrelevant filters for the new model. The filters selected for new layer assigned with original weights. Using this technique, the 94 MB weight file for the VGG16 model was downsized to 9 MB and the number of Convolution layers was lowered from 13 to 5. Accuracy of the model was improved from 93.5% to 94% after 1000 epoch for training purpose.Traditional ML with k-NN produces maximum accuracy of 94.9% and 93.5% using pre-trained VGG model. But, the developed model achieved 98.4% accuracy for detecting tomato leaf disease on PlantVillage dataset. All the images having white/gray background were tested over the model. In case of multiple diseases within a single leaf model had been able to detect the most likely disease.

Using transfer learning on InceptionV3 model authors [45] developed a prototype to identify the health conditions of tomato plants by analysing the images taken from drone.

ZigBee protocol was used to send the captured images to the system. The system classified the images into 3 categories: good, bad, and average. 500 photos from nearby farms and 2100 images of tomato leaves from web are included in the dataset. Model achieved 99% accuracy when training to testing data ratio was 9:1 but accuracy dropped down to 72% when it was 9:11. But detailed architecture of the proposed transfer learning CNN model was not described.

Authors[46] proposed a prediction model for apple scab disease prediction in the apple orchards of Kashmir valley with the help of a linear regression model in an IoT-based platform. IRIS fitted MTS420 sensor board, embed with DHT22 are used as nodes which were deployed over the entire orchard maintaining 100 meters distance with other to collect data such as temperature, humidity, barometric pressure, ambient light sensor, and dual-axis accelerometer. MIB 520 fitted with an IRIS which was programmed via MoteConfig and acts as a gateway in order to communicate with the computer. The tools provided by MOTE-VIEW monitoring software were used for easier monitoring and visualization of sensor network deployments. PostgreSQL, an open source object-relational database system loaded on a PC, is used as a remote server. Analyzing the collected data, a prediction model was developed based on the three parameters- temperature (T), time span of wetness (W), and incubation period of the infection causing pathogen (I), respectively. This paper did not mention the implementation cost.

SCA based RideNN [47], an IoT driven automated model was developed to detect bacterial spot disease from the images of bell pepper.

Maydis Leaf Blight (MLB), Turcicum Leaf Blight (TLB), and Banded Leaf and Sheath Blight (BLSB) are the most serious, widespread, and destructive fungal diseases of Maize crop. To identify the diseases in their early stages, authors [48] analyzed a total of 5939 digital images which were taken from experimental fields of ICAR-IIMR, Ludhiana, India. Images were captured with the help of DSLR and Smartphone cameras with minimum 12 MP resolutions. Out of 5939 images 59%, 20%, 11% and 10% were MLB affected, BLSB affected, TLB affected, and healthy leaves, respectively. CNN model using 'Inceptionv3' was used to classify the images, and the global average pooling layer (Inceptionv3_GAP) was able to identify the targeted disease exceeding 95% accuracy with 200 epochs. This proposed model need to validate by integrating with a mobile application to become more farmers friendly.

"Early Blight" disease of tomato was successfully identified [49] with 99.735% and 99.952% accuracy using ResNet and Xception respectively. As feature extractors, YOLOv3, YOLOv3-tiny, and YOLOv3-SPP are applied to identify the affected area of tomato leaves.

DA-ActNN-YOLOV5[50] an improved yolov5 model was proposed to identify accurately of early and late potato blight in different scenarios. A compression algorithm was used to compress activation parameters which had been considered as negligible impact on the performance of the model. The dataset is divided into 8:1:1 for training, validation and testing purposes. Highest accuracy of the model was achieved for a batch size of 64.

Model developed by [51] successfully identified very tiny bacterial spot on bell peeper leaf. It was a light weight faster model based on YOLOv5.

Authors [52] developed an improved YOLOv5 model for accurate classification and identification of two different types of widespread epidemics for rubber tree. Images of infected leaves and healthy leaves were captured at different visibility by Sony digital ILCE-7m3 camera.

YOLOJD [53], a deep learning-based image recognition model for detecting jute diseases. Image dataset consist with 4418 images covering 8 common jute diseases and two pests. A Canon Powershot G16 camera and the camera of a Samsung Galaxy S10 were used to capture the images from the field of Jamalpur and Narail districts in Bangladesh. YOLOJD able to identify more than one class of diseases and pests within the single image.

An improved image classification model [54] using VGG was proposed for detecting diseases from diseases affected leaves, collected from the field of Nashik, Maharastra, India. The model attained an accuracy more than 95% for both the crops.

A lightweight, faster and perfectly fitted with low end device transfer learning-based disease detection model [55] was trained with the data taken from PlantVillage Dataset which contains 18160 tomato leave images, out of which 1591 number of healthy leave images and the remaining 16569 images of infected leaves with 8 different types of diseases.

The summary of reviewed literature along with limitations were displayed in a tabular form on Table VI.

III. Discussions

From the literature survey it was observed that PlantVillage dataset to be the most widely used dataset. However a large section of researchers from the assessed papers have chosen to obtain private, customised datasets. In this section few publicly accessible datasets have been summarized for the benefit of researchers.

A. PlantVillage dataset :

A total of 54,309 images, taken under controlled lab conditions, of 38 distinct diseases in 14 crops are included in the dataset. Crops consist of Apple, Blueberry, Cherry, Corn, Grape , Orange , Peach, Bell Pepper, Potato, Raspberry, Soybean , Squash, Strawberry , Tomato.

B. Digipathos dataset :

A total of 46513 images (2326 number of images were taken under controlled lab conditions) of 171 distinct diseases in 21 crops are included in the dataset [56]. Dataset can be accessible through the link: https://www.digipathos-rep.cnptia.embrapa.br

TABLE VI: Summary of reviewed literatures with limations

Sl. No	Limitations Identified	Model Used	Dataset Used	Publication Year with Reference
1	(i) Unable to identify multiple diseases within a single leaf. (ii) Model was not tested with images having noisy background. (iii) Diseases severity were not measured	[42]: VGG-16, ResNet-50, MobileNet [42]: Inceptionv3, InceptionResNetv2 [47]: RideNN [49] : YOLOv3 [50] : HybridYOLOv5 [51] : YOLOv5 [55]: MobileNetv2	PlantVillage	2022: [50],[51],[55] 2021: [47] 2020: [49] 2019: [42]
2	Require more performance optimization	[36]: ResNet-34, ResNet-50; [39]: GoogleNet [50]: HybridYOLOv5 ; [52] : MobileNetv2 [53] ; YOLO-JD	[36]: AI-Challenger [39]: Digipathos [50]: PlantVillage [52] ; Private (Rubber) [53] : Private (Jute)	2022: [50],[52],[53] 2020: [36] 2019: [39]
3	High initial implementation cost with minimum technical knowledge	[46]: IoT + ML	[46]: Private(Maize)	2021: [46]
4	Require larger dataset	[35]: HOG	[35]: Private(Papaya)	2018: [35]
5	Require performance metrices value of the model combining InceptionV3 and ResNet	[54]: VGG	[54]: PlantVillage	2022: [54]

C. PlantDoc dataset :

A total of 2598 images, captured under field conditions, of 17 distinct diseases, for 13 plant species are included in the dataset [57]. Leaf images from Apple, Bell Pepper, Blueberry, Cherry, Corn, Grape, Peach, Potato, Raspberry, Soybean, Squash, Strawberry, Tomato are in the dataset.

D. CD&S dataset:

A total of 4455 images, captured under field conditions, of 3 distinct diseases, for corn are included in the dataset[58].

E. NLB dataset:

The NLB dataset[59] contains 18222 maize crop images taken under field conditions for a single disease.After annotations,the dataset contains 105705 images.

F. AI Challenger dataset:

A total of 36258 images, captured under natural field conditions, of 49 distinct diseases, for 10 different plants are included in the dataset. Online images available at the foloowing URL: https://pan.baidu.com /s/1TH9qL7Wded2Qiz03wHTDLw#list/path=%2F

Apart from above mentioned crop leaf image dataset other agriculture related datasets are available on web. In [60] authors presented a large scale aerial datset consist of 94,986 high-quality aerial images from 3,432 farmlands across the US. A rice disease dataset [61] includes 3355 images under controlled lab conditions of 3 diseases may be helpful for researchers. In the DeepWeeds dataset[62], there are 17,509 labelled images of eight nationally significant weed species across eight different regions of northern Australia.The dataset gained popularity due to increased researcher interest in robotic weed control. Additionally, sample images for each type of weed are accessible at the following URL: https://github.com /DigitalAgricultureDiscovery/AgBotSamples.

IV. Conclusion and Future direction

After the public release of the PlantVillage dataset, research on crop disease detection using deep learning gained its momentum. The majority of researchers used tomato or potato leaves from the PlantVillage dataset to test their own models. In most cases, the accuracy of the models was nearly 98%when training, testing, and validation were done on the same dataset. But if models were trained on one dataset and validated with another dataset, then accuracy would drop remarkably. So, data fusion is one of the challenges in this area of interest. Plant leaves affected by a single disease were identified with high accuracy using surveyed papers. However, disease detection algorithms could not detect disease with the same accuracy in leaves with a noisy background. Additionally, the current algorithm only recognises the disease with the most significant symptoms in leaves with numerous disorders. Based on the area of leaves covered by lesions, researchers have employed deep learning-based image classification to solve the problem. To estimate the degree of plant disease severity, several algorithms were developed by the researcher. To calculate disease severity, many research have suggested different definitions of severity. The majority of studies determined severity as the percentage of the total leaf area that was taken up by symptoms. Based on this definition, researchers claimed their model's accuracy.However, the severity of the disease in the leaf depends on the species and age of the crop. So, to effectively evaluate disease severity,a standard approach must be created. Most of the developed models are crop-specific. Based on the findings of the study, we can conclude that a lightweight, multi-disease detection model will benefit society by detecting and estimating the severity of diseases.

References

[1] B. S. Chauhan, G. Mahajan, V. Sardana, J. Timsina, and M. L. Jat, "Productivity and sustainability of the rice–wheat cropping system in the indo-gangetic plains of the indian subcontinent: problems, opportunities, and strategies," *Advances in agronomy*, vol. 117, pp. 315–369, 2012.

[2] A. Ganeshamurthy, "Soil changes following long-term cultivation of pulses," *The Journal of Agricultural Science*, vol. 147, no. 6, pp. 699–706, 2009.

[3] H. C. J. Godfray, J. R. Beddington, I. R. Crute, L. Haddad, D. Lawrence, J. F. Muir, J. Pretty, S. Robinson, S. M. Thomas, and C. Toulmin, "Food security: the challenge of feeding 9 billion people," *science*, vol. 327, no. 5967, pp. 812–818, 2010.

[4] H. Hamadani, S. M. Rashid, J. Parrah, A. Khan, K. Dar, A. Ganie, A. Gazal, R. Dar, and A. Ali, "Traditional farming practices and its consequences," in *Microbiota and Biofertilizers, Vol 2*. Springer, 2021, pp. 119–128.

[5] M. Banoo, B. K. Sinha, G. Chand, S. Dogra, and R. Sinha, "Traditional agriculture: Alternative practices for climate change mitigation."

[6] A. Tripathi, D. K. Tripathi, D. Chauhan, N. Kumar, and G. Singh, "Paradigms of climate change impacts on some major food sources of the world: a review on current knowledge and future prospects," *Agriculture, ecosystems & environment*, vol. 216, pp. 356–373, 2016.

[7] E. Y. Mohammed and Z. B. Uraguchi, "Impacts of climate change on fisheries: Implications for food security in sub-saharan africa," *Global Food Security, Nova Science Publishers, Inc*, pp. 114–135, 2013.

[8] P. Datta, B. Behera *et al.*, "Climate change and indian agriculture: A systematic review of farmers' perception, adaptation, and transformation," *Environmental Challenges*, p. 100543, 2022.

[9] J. P. Aryal, M. L. Jat, T. B. Sapkota, A. Khatri-Chhetri, M. Kassie, S. Maharjan *et al.*, "Adoption of multiple climate-smart agricultural practices in the gangetic plains of bihar, india," *International Journal of Climate Change Strategies and Management*, 2018.

[10] J. Pretty and Z. P. Bharucha, "Sustainable intensification in agricultural systems," *Annals of botany*, vol. 114, no. 8, pp. 1571–1596, 2014.

[11] H. C. J. Godfray and T. Garnett, "Food security and sustainable intensification," *Philosophical transactions of the Royal Society B: biological sciences*, vol. 369, no. 1639, p. 20120273, 2014.

[12] G. Balakrishna and N. R. Moparthi, "Study report on indian agriculture with iot," *International Journal of Electrical and Computer Engineering*, vol. 10, no. 3, p. 2322, 2020.

[13] S. M. Dev *et al.*, "Transformation of indian agriculture: Growth, inclusiveness and sustainability," in *Presidential Address at the 78th Annual Conference of the Indian Society of Agricultural Economics, November*, 2018, pp. 1–3.

[14] A. Khakimov, I. Salakhutdinov, A. Omolikov, and S. Utaganov, "Traditional and current-prospective methods of agricultural plant diseases detection: A review," in *IOP Conference series: earth and environmental science*, vol. 951, no. 1. IOP Publishing, 2022, p. 012002.

[15] J. Feng, X. He, Q. Teng, C. Ren, H. Chen, and Y. Li, "Reconstruction of porous media from extremely limited information using conditional generative adversarial networks," *Physical Review E*, vol. 100, no. 3, p. 033308, 2019.

[16] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolutional neural networks: an overview and application in radiology," *Insights into imaging*, vol. 9, no. 4, pp. 611–629, 2018.

[17] N. Sarika, N. Sirisala, and M. S. Velpuru, "Cnn based optical character recognition and applications," in *2021 6th International Conference on Inventive Computation Technologies (ICICT)*. IEEE, 2021, pp. 666–672.

[18] M. A. KO and S. Poruran, "Ocr-nets: variants of pre-trained cnn for urdu handwritten character recognition via transfer learning," *Procedia Computer Science*, vol. 171, pp. 2294–2301, 2020.

[19] S. Liao, J. Wang, R. Yu, K. Sato, and Z. Cheng, "Cnn for situations understanding based on sentiment analysis of twitter data," *Procedia computer science*, vol. 111, pp. 376–381, 2017.

[20] A. M. Alayba, V. Palade, M. England, and R. Iqbal, "A combined cnn and lstm model for arabic sentiment analysis," in *International cross-domain conference for machine learning and knowledge extraction*. Springer, 2018, pp. 179–191.

[21] S. P. Singh, L. Wang, S. Gupta, B. Gulyas, and P. Padmanabhan, "Shallow 3d cnn for detecting acute brain hemorrhage from medical imaging sensors," *IEEE Sensors Journal*, vol. 21, no. 13, pp. 14 290–14 299, 2020.

[22] P. Tiwari, B. Pant, M. M. Elarabawy, M. Abd-Elnaby, N. Mohd, G. Dhiman, and S. Sharma, "Cnn based multiclass brain tumor detection using medical imaging," *Computational Intelligence and Neuroscience*, vol. 2022, 2022.

[23] K. Kang, H. Li, J. Yan, X. Zeng, B. Yang, T. Xiao, C. Zhang, Z. Wang, R. Wang, X. Wang *et al.*, "T-cnn: Tubelets with convolutional neural networks for object detection from videos," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 28, no. 10, pp. 2896–2907, 2017.

[24] Y. Chen, W. Li, C. Sakaridis, D. Dai, and L. Van Gool, "Domain adaptive faster r-cnn for object detection in the wild," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2018, pp. 3339–3348.

[25] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamar´ıa, M. A. Fadhel, M. Al-Amidie, and L. Farhan, "Review of deep learning: Concepts, cnn architectures, challenges, applications, future directions," *Journal of big Data*, vol. 8, no. 1, pp. 1–74, 2021.

[26] B. Shi, R. Hou, M. A. Mazurowski, L. J. Grimm, Y. Ren, J. R. Marks, L. M. King, C. C. Maley, E. S. Hwang, and J. Y. Lo, "Learning better deep features for the prediction of occult invasive disease in ductal carcinoma in situ through transfer learning," in *Medical imaging 2018: computer-aided diagnosis*, vol. 10575. SPIE, 2018, pp. 620–625.

[27] L. Ali, F. Alnajjar, H. A. Jassmi, M. Gocho, W. Khan, and M. A. Serhani, "Performance evaluation of deep cnn-based crack detection and localization techniques for concrete structures," *Sensors*, vol. 21, no. 5, p. 1688, 2021.

[28] S. J. Pan and Q. Yang, "A survey on transfer learning. ieee transactions on knowledge and data engineering," *22 (10)*, vol. 1345, 2009.

[29] B. Neyshabur, H. Sedghi, and C. Zhang, "What is being transferred in transfer learning?" *Advances in neural information processing systems*, vol. 33, pp. 512–523, 2020.

[30] G. Khademi and D. Simon, "Convolutional neural networks for environmentally aware locomotion mode recognition of lower-limb amputees," in *Dynamic Systems and Control Conference*, vol. 59148. American Society of Mechanical Engineers, 2019, p. V001T07A005.

[31] D. Hughes, M. Salathe´ *et al.*, "An open access repository of images on plant health to enable the development of mobile disease diagnostics," *arXiv preprint arXiv:1511.08060*, 2015.

[32] S. Narkhede, "Understanding auc-roc curve," *Towards Data Science*, vol. 26, no. 1, pp. 220–227, 2018.

[33] K. Patil and N. Kale, "A model for smart agriculture using iot," in *2016 international conference on global trends in signal processing, information computing and communication (ICGTSPICC)*. IEEE, 2016, pp. 543–545.

[34] D. C. Corrales, J. C. Corrales, and A. Figueroa-Casas, "Towards detecting crop diseases and pest by supervised learning," *Ingenier´ıa y Universidad*, vol. 19, no. 1, pp. 207–228, 2015.

[35] S. Ramesh, R. Hebbar, M. Niveditha, R. Pooja, N. Shashank, P. Vinod *et al.*, "Plant disease detection using machine learning," in *2018 International conference on design innovations for 3Cs compute communicate control (ICDI3C)*. IEEE, 2018, pp. 41–45.

[36] W.-J. Hu, J. Fan, Y.-X. Du, B.-S. Li, N. Xiong, and E. Bekkering, "Mdfc–resnet: an agricultural iot system to accurately recognize crop diseases," *IEEE Access*, vol. 8, pp. 115 287–115 298, 2020.

[37] M. Brahimi, K. Boukhalfa, and A. Moussaoui, "Deep learning for tomato diseases: classification and symptoms visualization," *Applied Artificial Intelligence*, vol. 31, no. 4, pp. 299–315, 2017.

[38] K. Zhang, Q. Wu, A. Liu, and X. Meng, "Can deep learning identify tomato leaf disease?" *Advances in multimedia*, vol. 2018, 2018.

[39] J. G. A. Barbedo, "Plant disease identification from individual lesions and spots using deep learning," *Biosystems Engineering*, vol. 180, pp. 96–107, 2019.

[40] X. Zhang, Y. Qiao, F. Meng, C. Fan, and M. Zhang, "Identification of maize leaf diseases using improved deep convolutional neural networks," *Ieee Access*, vol. 6, pp. 30 370–30 377, 2018.

[41] R. Ahila Priyadharshini, S. Arivazhagan, M. Arun, and A. Mirnalini, "Maize leaf disease classification using deep convolutional neural networks," *Neural Computing and Applications*, vol. 31, no. 12, pp. 8887–8895, 2019.

[42] F. Islam, M. N. Hoq, and C. M. Rahman, "Application of transfer learning to detect potato disease from leaf image," in *2019 IEEE International Conference on Robotics, Automation, Artificial-intelligence and Internet-of-Things (RAAICON)*. IEEE, 2019, pp. 127–130.

[43] L. Aversano, M. L. Bernardi, M. Cimitile, M. Iammarino, and S. Rondinella, "Tomato diseases classification based on vgg and transfer learning," in *2020 IEEE International Workshop on Metrology for Agriculture and Forestry (MetroAgriFor)*. IEEE, 2020, pp. 129–133.

[44] M. Agarwal, S. K. Gupta, and K. Biswas, "Development of efficient cnn model for tomato crop disease identification," *Sustainable Computing: Informatics and Systems*, vol. 28, p. 100407, 2020.

[45] M. Hasan, B. Tanawala, and K. J. Patel, "Deep learning precision farming: Tomato leaf disease detection by transfer learning," in *Proceedings*

of 2nd international conference on advanced computing and software engineering (ICACSE), 2019.

[46] R. Akhter and S. A. Sofi, "Precision agriculture using iot data analytics and machine learning," *Journal of King Saud University-Computer and Information Sciences*, 2021.

[47] M. Mishra, P. Choudhury, and B. Pati, "Modified ride-nn optimizer for the iot based plant disease detection," *Journal of Ambient Intelligence and Humanized Computing*, vol. 12, no. 1, pp. 691–703, 2021.

[48] M. Haque, S. Marwaha, C. K. Deb, S. Nigam, A. Arora, K. S. Hooda, P. L. Soujanya, S. K. Aggarwal, B. Lall, M. Kumar *et al.*, "Deep learning-based approach for identification of diseases of maize crop," *Scientific reports*, vol. 12, no. 1, pp. 1–14, 2022.

[49] A. S. Chakravarthy and S. Raman, "Early blight identification in tomato leaves using deep learning," in *2020 International conference on contemporary computing and applications (IC3A)*. IEEE, 2020, pp. 154–158.

[50] G. Dai, L. Hu, J. Fan *et al.*, "Da-actnn-yolov5: Hybrid yolo v5 model with data augmentation and activation of compression mechanism for potato disease identification," *Computational Intelligence and Neuro-science*, vol. 2022, 2022.

[51] M. P. Mathew and T. Y. Mahesh, "Leaf-based disease detection in bell pepper plant using yolo v5," *Signal, Image and Video Processing*, vol. 16, no. 3, pp. 841–847, 2022.

[52] Z. Chen, R. Wu, Y. Lin, C. Li, S. Chen, Z. Yuan, S. Chen, and X. Zou, "Plant disease recognition model based on improved yolov5," *Agronomy*, vol. 12, no. 2, p. 365, 2022.

[53] D. Li, F. Ahmed, N. Wu, and A. I. Sethi, "Yolo-jd: A deep learning network for jute diseases and pests detection from images," *Plants*, vol. 11, no. 7, p. 937, 2022.

[54] A. S. Paymode and V. B. Malode, "Transfer learning for multi-crop leaf disease image classification using convolutional neural network vgg," *Artificial Intelligence in Agriculture*, vol. 6, pp. 23–33, 2022.

[55] S. Ahmed, M. B. Hasan, T. Ahmed, M. R. K. Sony, and M. H. Kabir, "Less is more: lighter and faster deep neural architecture for tomato leaf disease classification," *IEEE Access*, vol. 10, pp. 68 868–68 884, 2022.

[56] J. G. A. Barbedo, L. V. Koenigkan, B. A. Halfeld-Vieira, R. V. Costa, K. L. Nechet, C. V. Godoy, M. L. Junior, F. R. A. Patricio, V. Talamini, L. G. Chitarra *et al.*, "Annotated plant pathology databases for image-based detection and recognition of diseases," *IEEE Latin America Transactions*, vol. 16, no. 6, pp. 1749–1757, 2018.

[57] D. Singh, N. Jain, P. Jain, P. Kayal, S. Kumawat, and N. Batra, "Plantdoc: a dataset for visual plant disease detection," in *Proceedings of the 7th ACM IKDD CoDS and 25th COMAD*, 2020, pp. 249–253.

[58] A. Ahmad, D. Saraswat, A. E. Gamal, and G. Johal, "Cd&s dataset: Handheld imagery dataset acquired under field conditions for corn disease identification and severity estimation," *arXiv preprint arXiv:2110.12084*, 2021.

[59] T. Wiesner-Hanks, E. L. Stewart, N. Kaczmar, C. DeChant, H. Wu, R. J. Nelson, H. Lipson, and M. A. Gore, "Image set for deep learning: field images of maize annotated with disease symptoms," *BMC research notes*, vol. 11, no. 1, pp. 1–3, 2018.

[60] M. T. Chiu, X. Xu, Y. Wei, Z. Huang, A. G. Schwing, R. Brunner, H. Khachatrian, H. Karapetyan, I. Dozier, G. Rose, D. Wilson, A. Tudor, N. Hovakimyan, T. S. Huang, and H. Shi, "Agriculture-vision: A large aerial image database for agricultural pattern analysis," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2020.

[61] H. B. Prajapati, J. P. Shah, and V. K. Dabhi, "Detection and classification of rice plant diseases," *Intelligent Decision Technologies*, vol. 11, no. 3, pp. 357–373, 2017.

[62] A. Olsen, D. A. Konovalov, B. Philippa, P. Ridd, J. C. Wood, J. Johns, W. Banks, B. Girgenti, O. Kenny, J. Whinney *et al.*, "Deepweeds: A multiclass weed species image dataset for deep learning," *Scientific reports*, vol. 9, no. 1, pp. 1–12, 2019.