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Early disease detection of leaves using Deep learning and drones - Cyber physical systems approach

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ARTICLE INFO

Edited by Dr Spyros Fountas.

Keywords:
Artificial Intelligence
Generative AI
Federated learning
5G
6G
Swarm of Drones
Cyber Security
Trans Disciplinary
Edge Computing

ABSTRACT

Agriculture is the major source of food and livelihood of many countries. In the recent years many developing countries are adopting technology to improve farming. Farming Drones are currently being used for spraying pesticides, seed bombing, data gathering for precision agriculture, etc. Farming drones are also used for aerial imagery to estimate the count of fruits and other produce. Extensive research has been done to use drones for aerial imagery and estimate of leaf disease proliferation in farms. Most of the research focuses on image gathering on front side of leaves as drones fly above the leaf foliage. However, there are several leaf diseases that proliferate in the rear side of the leaf. Few examples include Mildew and Cabbage Looper. In this work we propose a novel drone design (patented already) that captures rear side of the leaf images. Early disease detection can help in reducing the use of pesticides, increasing the quantity and quality of the yield. In the proposed solution, camera can go below the leaves - to capture the image of the affected area. The drone captured images are resized to 224x224. Feature extraction frameworks using Deep learning models including VGG16, efficientNetBo, ResNet or AlexNet were used to classify if the leaf is healthy or unhealthy. Experimentation provided Validation accuracy of 98 % and model training accuracy of 89 %.

1. Introduction

Burgeoning population is exerting pressure on agriculture, (Yan ping wang et al., 2021) which is facing impact through climate change, water shortage and diseases in plants. Predominant diseases that could affect plants include Powerly Mildew (cucumber), Downy Mildew (cauliflower), Blackspot (flowers), Mosaic Virus (Potato), Rust and Fusarium Wilt (Tomato). Normally, front side of the leaves (fig. 1) is affected by fungi.

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In the following two cases rear side of the leaf gets affected initially. .In case of Downy Mildew (Carla colque little, 2021) which is caused by *Pseudoperonospora cubensis*, spores appear on the rear side (fig . 2 (a)) of the leaves and sporulation on leaf surface may occur after 3 days only. The spread of disease is very fast in wet and high humidity conditions. This disease affects cauliflower, maize, grapes, melon, pumpkin, squash, soybeans, sunflower etc.

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In the following two cases rear side of the leaf gets affected initially. .In case of Downy Mildew (Carla colque little, 2021) which is caused by *Pseudoperonospora cubensis*, spores appear on the rear side (fig . 2 (a)) of the leaves and sporulation on leaf surface may occur after 3 days only. The spread of disease is very fast in wet and high humidity conditions. This disease affects cauliflower, maize, grapes, melon, pumpkin, squash, soybeans, sunflower etc.

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In case of cabbage looper pest (Saini Mayanglambam, 2021), moths lay their eggs on the rear side of the leaves . Newly hatched larvae (fig 2.(b)) start eating the small areas of the rear side of the leaves, before affecting the front side of leaf. This affects cabbage looper , broccoli, bok choy (chinese cabbage), cauliflower , Brussels sprout, mustard plant , raddish, maca (edible plant of south America) , black mustard , white mustard , turnip, choy sum (chinese vegetable). At the earliest distribution, severity and virulence of these two have to be enervated. Delay in identification of these may lead to major loss. Globally, 22 % of annual crop yield loss is due to plant diseases (Savary et al., 2019).

At this juncture, FAO (Food and Agriculture Organisation) has predicted that crop yield has to be doubled between 2020 and 2050, to feed the expected global population of 9 . 7 billion by 2050. It is a (B-HAG) Big hairy audacious goal (Jim Collins, 1994) and cannot be achieved by traditional methods.

Fig 1. Image of front side of affected leaf

Lot of research has been done in detecting plant diseases from images of leaves using Machine Learning (ML) and Deep Learning (Geoffrey Hinton, 2015) techniques. Most of the past works have used the images of the front view of leaves, using unmanned ground vehicles (UGV) or drones (Bini Darwin, 2021) with camera . But, the rear view of the images is equally important to draw a conclusion and extract meaningful information. While UGVs are good at capturing high quality images due to being on a stable ground, they're generally slower than Unmanned Autonomous vehicles (UAV) or drones and might have a hard time taking photos of the top cover of plants, if the plants are too tall. They could also face issues in locomotion if the ground is too wet and slippery causing the wheels to slip, wasting precious battery power. While significant work has been done in the field of drones in agriculture, no solutions have been deployed for capturing high quality close up photographs of rear side of the leaves, from drones. Proposed Innovative solution, which uses the cyber physical system for data collection (Indian patent got published on 31st July 2020 titled Drones for Smart farming, No. 202041031483 A).

Fig 2 (a). Spores on the rear side of affected leaf

Fig 2 (b). Cabbage looper on the rear side of the leaf

As of now, many Indian farmers use physical inspection (time consuming). It can be compensated by using camera for image detection (Dworak et all, 2015), for disease detection . Computer vision and mechanical add - on like a reel mechanism combined with the UAV, allows us to achieve this goal and save lot of time, for farmers. If the need arise, Intelligent up - scaling of low resolution images to high resolution (Generative AI) is possible, to help in getting maximum accuracy. Generative AI refers to use of AI algorithms, to create new content from existing images. Hybrid Algorithms (sherly, 2019) can also be used, to identify severity of disease. Swarm of drones can detect plant disease in large fields, 20 times faster (Stav, 2019) with 6G , through deployment of connected robotics and autonomous systems, by saving time on drone battery charge . Scientists from Norway (FFI) and US company are working on drone swarm (Stav, 2019), with patented technology (kinetic mesh and foreign function interface), which can communicate in a decentralized way. Early identification of disease (A.Y. Khaled, 2017), to result in enhanced productivity and reduced input cost

2. Backgrund

Experts suggest that agriculture industry has to change gears, thrive on chaos (Tom peters, 1987), by adopting creative destruction (Joseph Schumpeter, 1942), resulting in enhanced productivity (Mayer et all, 2015) and higher farm income. Audacious Innovation (Amy C. Edmondson, 2016) and adoption of technologies in farming (smart farming) is the need of the hour, as internet mobility has penetrated into rural areas of India (grown from 100 to 450 million users, between 2011 and 2019). Smart farming has a market size of US $ 20.8 billion by 2026 with a Compounded annual growth rate (CAGR) of 10.1 % from 2021. Smart farming to generate lots of data and the same can be processed in real time , using Edge computing ; To ensure trustworthy smart device, federated learning , "Feng Huo Lun" (machine learning), could also be used.

Downy Mildew disease could be confused (Gary, 2012) with gray mold (or) with Powderly mildew. Images of any new disease (which emerge , due to climatic changes) could also confuse. These challenges of agriculture can be tackled effectively by multi - stakeholder partnership (UNDP Agenda 2030 - point no. 17), through creative destruction (Johnson, 1995). Multiple stakeholders (Government, Corporate, SME's, Academia, Financial Institutions, NGO's, Farmers, Domain experts, and Scientist) to join and focus on Innovation and Design Thinking (Rim Razzouk, 2012) is Trans Disciplinary Approach (Jean, 1970). Trans Disciplinary (TD) team wanted to explore the possibility of combining available technology solutions (R . Murugesan, 2018) like IoT (John Deere tractors with sensors), Agriculture Robot (Fiona, Scientist 2015), Artificial (AI) Intelligence Rina Dechter, Professor, USA), Crop dusting drones (Abraham, 1980) etc… for farming . This has resulted in use of drones (Unmanned autonomous vehicles) to spray pesticides (Sane, 2021), to prevent locust attack (Matthieu, 2021), weed removal (Samarth Prabhu, 2021) etc.. Autonomous system (UAV) is part of the Cyber Physical system (CPS) and the deployment of the same, with AI is termed as Agriculture 5.0 (R. Murugesan, 2019)

3. Cyber Physical System and Trans Disciplinary Approach

Cyber - physical system (CPS) involves Trans Disciplinary (TD) approach (R.Murugesan, 2019) to digitize and automate the world. In last decennium, it garnered importance among Academia, FORTUNE 500 companies and Researchers, due to its potential impact on economy. CPS is nothing but orchestrate*ng networked computational resources with physical systems (Dr. Edward A. Lee, 2013). CPS has potential applications in a broad range of field i.e..." MASTER"

a) Manufacturing (Guodong Huang , 2021)
b) Medical Monitoring (Fulong Chen, 2021)
c) Aerospace (Roberto Sabitini, 2020)
d) Automotive (Yoo ho son, 2021)
e) Autonomous Tractors (with LIDAR - for obstacle avoidance), (Nelson H. carreras , 2019)
f) Agriculture (Kelly Rigswijk, 2021),
g) Autonomous Vehicles (Vlasios Tsiatsis, 2019)
h) Armed Services (sandeep, 2019)
i) Smart Building (Leepakshi Bindra, 2021)
j) Security (Sandhya C. P , 2021)
k) Surveillance (Chuang Yao, 2021)
l) Supply - using reinforcement learning (Peng Peng Sun, 2021)
m) Swarm Support (World's 1st 5G and AI platform - Qualcomm Flight RB5),
n) Transportation (Muhammed Mazar, 2021)
o) Education (Liping Guo, 2021)
p) Energy (Van Den Berg, 2018),

CPS is expected to give competitive advantage (Michael Porter,1980) to corporate and its market size is expected to reach $ US 9.5 billion by 2025 . USA is a market leader in CPS, followed by Europe and Japan. The great potential of CPS is motivating many developing countries like India, to forge ahead in the field.

Tectonic Shift & latest applications of CPS in India include ..

1) Robotic Surgery in CURI Hospital, Chennai,
2) Use of Robot in Hyundai Factory ,
3) Weather monitoring in Bangalore Airport ,
4) Smart grid pilot project for 1000 consumers in Ajmer,
5) MEMS for remote healthcare by ST Microelectronics,
6) Driverless Electric Tractor by AutoNxt in Maharashtra and Use of Agricultural drones, to kill locust in night - by Govt. of India

Agri Drone market value is expected to reach $ 3. 7 billion , by 2022 (Winter Green Research 2016) . China has used 13,000 drones in farming, to deliver pesticide and fertilisers in 7 million hectares of land ("The Green Future Index", MIT Technology Review , USA, 2021). Cyber-physical systems are being increasingly developed and adopted in the agriculture industry , due to the promise of increased yield.. Numerous papers can be found based on including various sub - fields such as AI , IoT and robotics of CPS in agriculture Examples of such applications include plant disease detection , yield estimation , automated irrigation and fertigation , precise pesticide spraying , soil condition monitoring and produce harvesting.

Table 1
Characteristics of Cyber Physical System (Farming)

Tool	Use
Complexity / Heterogeneity Encapsulation	Communication and Connectivity
Sensors, Camera, server, Reel mechanism, mobile	Prudent decision making
Generate (Photos) Communicate (Cloud) and evaluate data (ML, DL) of ongoing Process (spread of disease , Weed identification)	Real time data from agriculture field and feedback from cyberspace

Table 2
Application of soft computing in smart farming

Tool	Use
Federated Learning	To train ML algorithms across multiple distributed devices (each with unreliable and relatively slow mobile network onnections.), while preventing data leakage; This can be used for disease outbreak detection, in farming
Generative	System can detect the underlying pattern and AI generate Similar images and System can help in intelligent up gradation of low resolution to high resolution images (to identify disease)

Social problems like agriculture to be solved using TD approach (Basarab Nicolescu, 2002), to achieve sustainable development (UNSD Agenda, 2030).

In line with this approach, DRDO, Ministry of Defense, India has signed a Bilateral Innovation Agreement with DDR & D of Israel, to accelerate innovation in SME's to develop dual use technologies like drones with AI , for smart farming (India Defense News - 10/11/21),

4. Challenges and Solutions in Disease identification and use of drones

4.1 Major challenges include capturing the images of rear side of leaves and enhancing the identification accuracy of infected leaves . Major and associated challenges in use of Drones in agriculture is shown in Fig. 3.

4.1.1 It is difficult to get the images of the rear side of the leaves and so it was mentioned as a limitation (Sharada P. Mohanty et al., 2016) ; It is difficult to get both the model validation accuracy (value of closer to 100) and model training accuracy (value closer to 99) using DL.

4.1.2 As per FAO (Gerald, 2018), Drone flight time is around 30 minutes per battery block and so cannot cover large acreage from base station.

4.1.3 As per the Drones rules - published by Ministry of Civil Aviation (MoCA), India in August 2021 , Drone promotion council to be set up in future . This will enable Academia , Startup and other stakeholders to join together (i.e.. Trans disciplinary approach); this step will help but delay the process of innovation , incubation (due to delay in formation of team, by Government).

4.1.4 Indian farmers literacy level is very low and so the adoption rates of drones is also low.

load of 4 kg. These technologies are yet to be commercialized and is not available in countries like India.

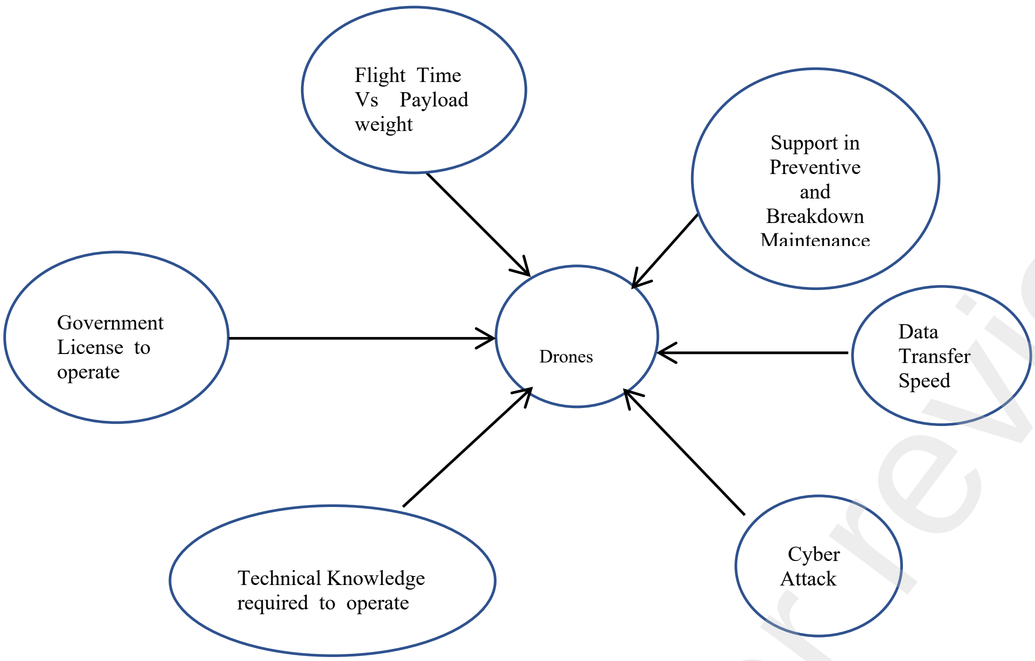

Fig. 3 Constraints for usage of drones

Focus area :-
The paper to focus on analysis of rear side of the plant leaf images (deep learning), taken by drones.

4.1.5 Lack of instant support during breakdown maintenance (PwC , 2020) and support for preventive maintenance are the main challenges in adoption of drones, by Indian farmers.

4.1.6 Ministry of Telecommunications, Government of India has confirmed that 37,439 out of 5 ,97,000 inhabited villages of India is still waiting (Indian Lok Sabha Questions , Feb. 2021) for 3G ; i.e. Maximum of 8,947 villages of Odisha and minimum of 1 village of Punjab, Haryana - don't have 3G. Only 33 % of the rural population has access to 3G network in 46 Least developed countries (LDC), across 4 continents (Nikola , FAO, 2019) ; This will have major impact on data transfer speed.

4.1.7 Cyber threat is also a main concern in use of drones (Forbes , Feb. 2021); Cyber data theft is possible , from the mobile phone of farmers through Wi - fi connections (while Operating drones, from base station). Cyber-attacks could be 1 of the following...

a) False data injection attack (K .Demestichas, 2020),
b) Misinformation attack (O.E. Oche, 2020),
c) Radio frequency jamming attack - i.e... GPS with real time Kinematics, to enhance the precision of data (Y. Arjoune, 2020),
d) Malware injection attack (A. Yazdinejad, 2021),
e) Denial of service attack (S. Sontowski, 2020),
f) BOTNET of Things (Maanak Gupta, 2020).

4.2 Solutions in use of drones

4.2.1 Disease Identification - Our solution use the camera , which is attached to drone - using pulley mechanism ; The system can capture the images of the rear side of the leaves . By using feature extraction network of efficient Net BO , model validation accuracy and model training accuracy can be enhanced considerably (by extracting the area of interest)

4.2.2 Long range drones - following solutions are available (US).
a) Gasoline powered drone (MIT, USA) with a flight time of 5 Days,
b) Petrol electric hybrid drone (weighing 16kg) which can fly for 2 hours - with a pay load of 2kg,
c) Hydrogen fuel cell drones that can fly for 1 hour - with a Pay

4.2.3 Trans Disciplinary Approach

Team of Academia (Faculty, Students, Research Scholars and Students club members), to identify NGO's, SME's to form a team and help farmers - in using drones ;

Breakdown maintenance to be attended by end of day (or) on Saturdays by students of Engineering Institution ; Preventive Maintenance of drones (e.g. battery replacement) can be done on periodic schedule , as drone promises unique benefits to farmers (Bedir, 2021), in developing countries ; This is possible as Ministry of Human Resources Development (MHRD), Government of India has launched " Unnat Bharat Abhiyan " (in 2017) , to connect Institute of higher education with nearest villages and to address the development challenges .

4.2.4 5G

5G is a radical innovation (Souto, 2015) . It can give download speed of up to 10 gigabits per second and can connect more devices. This could benefit farming as it is likely to get data about soil nutrients, irrigation, pest attack etc. .. in the form of numbers, images and videos collected through sensors , camera. Mobile Edge computing (MEC) or Multi - access Edge Computing unleashes the power of 5G by enabling the data processing and computing capabilities closer to user, resulting in low latency and deterministic compute times for the use cases .

5G to help in bringing the following use case into reality (Fig . 4) Drones fitted with HD and AI - powered cameras which can measure the health of the crops. 5G powered drones help to transmit high bandwidth live stream video to long distance to farmer's device in real time, by leveraging low latency and high bandwidth characteristics.

Performance indicators for 5G is (mMtc) massive machine type communications, which focus on supporting extremely high connection density for scenarios like massive IoT sensor deployments (i.e. In smart farming). developed economies like UK , China are using 5G drones in farming.

4.2.5 6G

6G will become the new Electricity (Forbes, Sep. 2021); It will offer " SCALE". i.e. Security, Cognition, Agility, Latency, Efficiency. Purdue University , USA with partners have deployed broadband to nearby farms (David Broecker, 2021), through the Initiative " Lab to Life (L2L) 6G Digital Innovation", in Aug. 2021. Autonomous vehicles like swarm of drones , should be supported with ultra-low latency (less than 1 milli second) and the same can be provided by 6G only (Agbotiname, 2021)

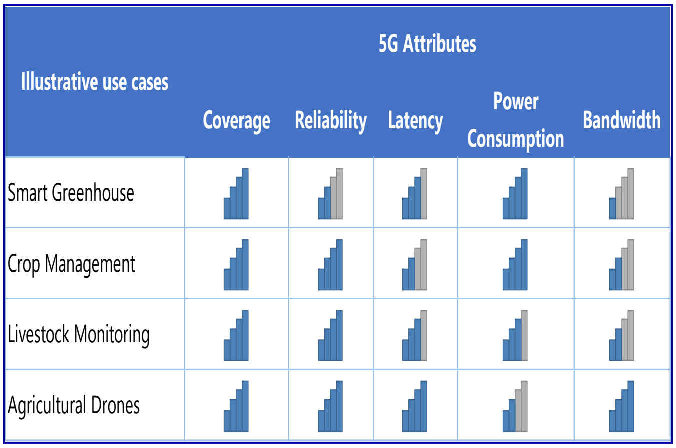

Fig 4. 5G Use case and attributes

4.2.6 Cyber Security Solutions include...

a) Light weight device authentication solution where public and Session keys to expedite encryption and decryption tasks (A.R.A. Zenello, 2020),
b) 2 factor user authentication (H. Khalid, 2021)
c) Use of blockchain technology (T. Alladi, 2020)
d) Use of Intrusion detection system (X.Yang, 2021),
e) Use of XPath and Fast XPath (A.R.A. Zenello, 2020)

5. Drones with Reel Mechanism

There has been a lot of research done on detecting diseases in plants from photographs of leaves as well as photography using drones. However, a problem that occurs while deploying drones in agriculture to take close , clear photos of plant leaves is that the wind from the drone's propellers blows around the leaves and possibly the whole plant , preventing any chance of taking a good close-up photograph . Flying too close to the plant may also cause damage to more delicate crops, which is undesirable. On the other hand, if the drone is too far away, the quality of photos aimed at a patch of leaves starts to degrade the farther the camera is from the target for the picture. In this paper, proposed solution to hover the drone at a safe, high altitude (Fig. 5) that would produce minimal shaking of the leaves , and lowering a camera through a reel system that has been designed and patented[70]. This will allow for close - up photographs with very less shaking of leaves . A visual representation of the idea is shown in Fig 6.

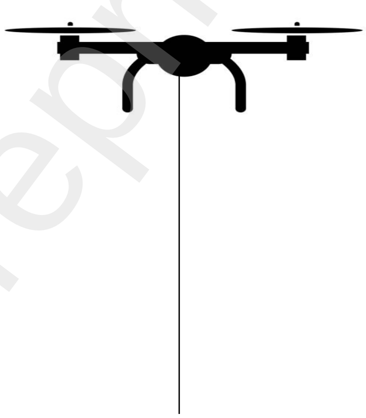

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Fig 5. Drone with a camera on a reel

The system proposed in this paper is a controller for the reel mechanism made with the following constraints in mind:

A) Low cost

The system should be as cheap as possible to allow for use in orchards and farms, across India.

b) Low weight

Lighter components not only make it possible to use on smaller drones but also reduce power consumption .

c) Small size

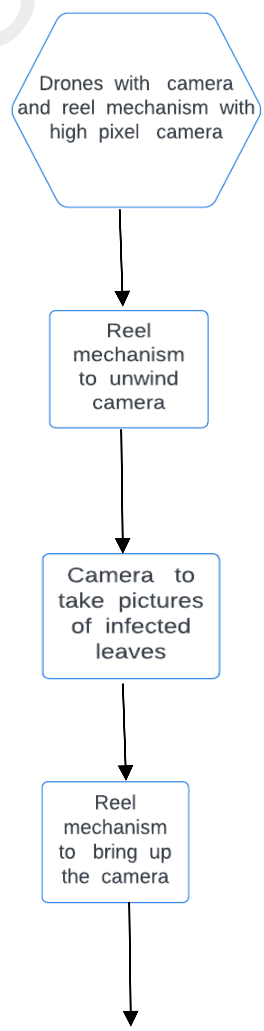
Being a small component allows users to fit many other components they might want . This helps especially when making multifunctional products such as drones that can take photos of crops as well as spray pesticides.

d) Low power

Drones have strict power constraints since there's a limit on battery capacity that can be used due to size , weight and cost constraints. Due to this , each and every component on a drone must be as low - powered as possible to increase flight time.

e) Ease of use

Now a days drones are built and used , not just by knowledgeable and skilled engineers , but even hobbyists . Hence , the ease of use of a component is necessary for community growth . Keeping this in mind , our system is made to be able to quickly understand and start working with.



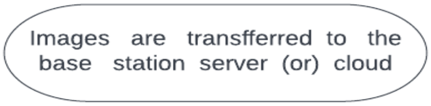


Fig. 6. Drone with reel mechanism

Our mechanism can be controlled using just two signal wires as shown in Fig 7 . In fig. VCC represents the voltage common collector, CK / CCK control represents clockwise / counter clockwise control respectively and GND represents Ground or common drain. Giving a positive signal to each signal wire makes the motor spin in a particular direction allowing for both winding and unwinding of the reel. To make the mechanism low powered , low weight and small – sized , proposed system to use a simple H - bridge based MOSFET configuration . Choosing the right MOSFET is critical as it can allow for using PWM based speed - control making it possible to control the speed of winding or unwinding . The reel mechanism makes use of special structures for the reel to keep the camera steady even when it is extended away from the body. The sheer simple and low - profile nature of our proposed system is shown in our circuit diagram in Fig 8 in fig. M1, M2, M3, M4 represents DC motors.

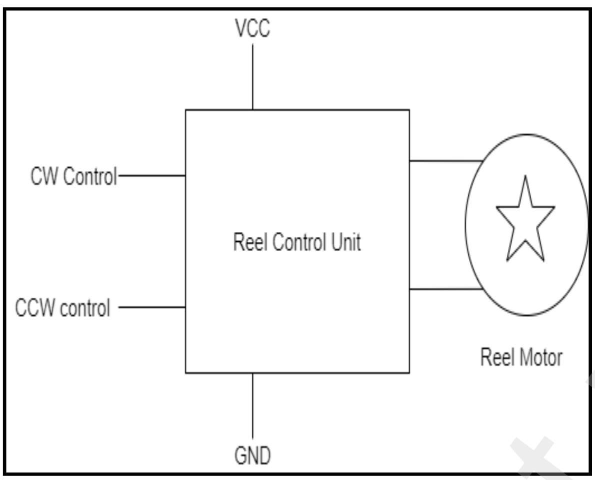


Fig. 7 . Motor Circuit

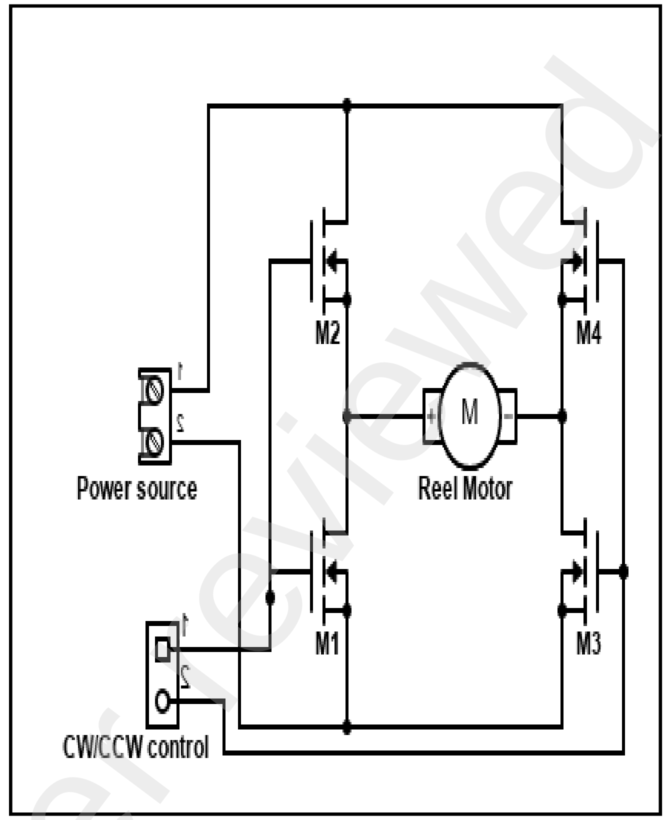


Fig . 8. Circuit Diagram

5. Data Analysis for Disease Detection

The experiment was done on Windows and Mac OS with Python 3.7+ version and pyTorch 1.9.0 with cuda 10.2, alongside a GPU GeForce 3090 ti embedded into the system.

5.1 Dataset Description

In the experiments performed, 58, 806 photographs of plant leaves have been analyzed (Source: - Dataset from Harvard, USA, https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/8BP9L2)with the provided 38 class labels of the Plant Village Dataset. A plant disease pair is provided as each class label, and our paper aims to predict the disease and the crop when either rear and front sided leaf image is given as input.

Researcher took up sample of the database - rear view images of leaves from Jena Leaf Images 17 of Harvard Data verse, followed by resizing images to 224 × 224 pixels, and perform both model improvements and predictions for these reduced images. Fig 9 shows two examples of an image in our training dataset, from our database used.

A bias in the database obviously exists due to the normal data collection process in the Plant database environment, which is likely in any database. Hence, our model uses a robust segmentation process to remove any potential bias and make our database more accurate. Researcher have used a segmentation method based on a set of masks produced to analyze color , brightness and saturation of different parts of the images in multi-colored areas along with convolutional models for precise disease prediction.

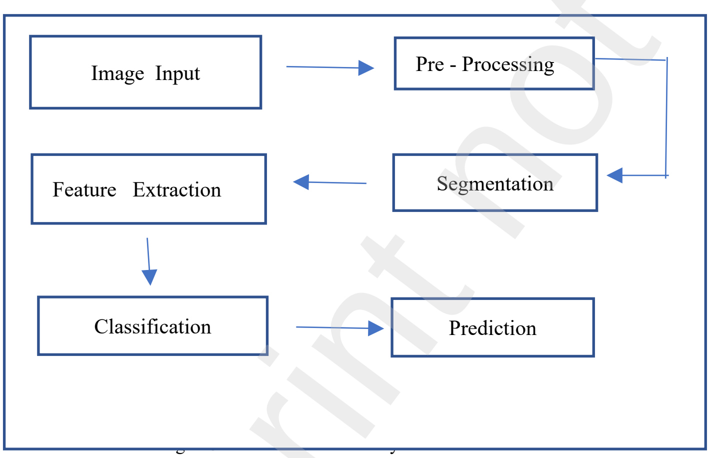
5.2 Methodology

There has been existing works in the field but the efficiency of them and the easy implementation of them in hardware components has not come up to the very advanced and manifold stages. Now a days, combining deep learning techniques with IoT based technology has been increasingly gaining the focus , hence the models and methodologies researcher used should also be in favor of easy implementation into microprocessors or any hardware device.

Fig. 9 Example images from our plant database

The Feature extraction frameworks of vgg16, efficientNetB0, ResNet or AlexNet are all state of the art neural network models which are greatly used in recent deep learning based works. Some key things to consider here is a check on the number of parameters used, its ease of implementation in hardware components, its scalability and its efficiency all of which are considered in the backbone selection, in our proposal.

We have noticed EfficientNetBO performing better among the options. Both the front and the rear view of the images are equally important to draw a conclusion and extract meaningful information . Here, we have used an ensemble of them both for achieving more real - life and accurate predictions. The overall workflow of the methodology used has been described in Fig 10 and the remaining methodology section of the paper has been divided in the same manner.



5.3 Preprocessing

The Preprocessing pipeline primarily consists of a series of data cleaning and image alteration algorithms . The intent of this pipeline is to reduce the noise of the leaf images and sample all the types of images to reduce bias in the neural network. Apart from the bias removal methodology elaborated in previous section , the pipeline also tries to balance the images from both the datasets , by replicating via changing orientations and lighting conditions .

The next part of the process involves resizing the images in 224 x 224 for faster and efficient computations in the neural network and keeping the image data as loss less as possible. Further , every pixel of the image is passed into a normalization sub pipeline , where the Z-scores are computed by calculating the standard deviation and mean of the same. The images are also cropped in such a way to try to maintain the region of interest. It was also observed that the picture had a lot of noise, so every image was passed through a denoising algorithm which primarily uses a Gaussian filter and an extended SmoothGrad filter. The algorithm works on smoothening of every pixel using a 2-D distribution as a point spread function, achieved by multiple convolutions . The filter resembles a blur mask on the image.

Additionally , the algorithm was precisely applied to the non – area of interest parts to keep the most relevant features of the image. The target is to make the neural networks extract the area of interest and neglect the non – essential parts. The whole preprocessing pipeline aids and fastens this process.

5.4 Image Segmentation and Feature Extraction

Image segmentation is an important stage of any computer vision and image detection cycle as it helps in localization of a specific part or portion of an image which author really want to focus upon which can be used for further processing steps. Isolation of a desired object from an image is the main outcome of segmentation for example in our case isolation of a defected area of a leaf from the entire leaf. Feature extraction is an essential step too as selecting a set of more well defined set of features to work upon rather than the entire image as a whole is definitely more efficient and less computationally expensive.

Author can work on a reduced set of important and relevant information of an image and also get rid of redundant data using the process of feature extraction. Our model uses a hybrid pipeline of Faster R - CNN with any one of the backbone {Resnet - 101, VGG 16, AlexNet, EfficientNetB0} and Feature Pyramid Networks (FPN) for the tasks of image segmentation, feature extraction, object detection and classification. The most important framework is the feature extractor selection as it in turn affects the entire performance of the model .

Faster R-CNN applies a region proposal network (RPN) to sample the bounding boxes which replaces the slower and less efficient selective search algorithm . RPN uses sliding window technique to move across the feature maps and generates regions based on an aspect ratio of anchor boxes. Fig 11 shows the heatmap after image segmentation where the disease infected portion of the leaf is clearly visible.

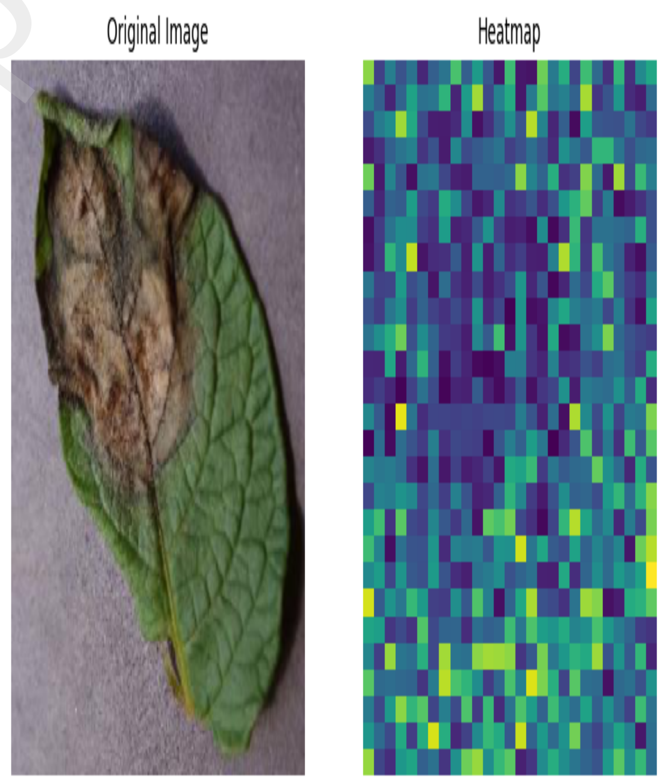


Fig. 11. Heatmap visualization of a disease - infected leaf After image segmentation

The proposals are then fed into the Fast R-CNN model with a pooling layers, FC layers and classification and regression layers . Each feature extractor is trained using a FPN architecture with a bottom-up pathway which pays higher value to low level features as well. Feature maps are preprocessed with a 3*3 convolutional layer , the output of which is added to the current stage of the top-down pathway with the help of a lateral connection , then fed to the RoI pooling layer. For training, a pre trained model of Faster RCNN (M Saqib, 2017) with resnet-101 and FPN on coco dataset is used with batch size of 1 and number of extracted regions to be 256. SGD optimizer and LR scheduler are used during training and the extension of FPN helped for smaller defected region detection in leaf images.

However , a different feature extraction backbone like that of EfficientNet is also used in our model experiment owing to a more advanced scaling approach. Efficient Net uses a new scaling called compound scaling which scales up depth(layers), width(channels) and resolution simultaneously instead of just scaling up the depth by addition of new layers.

ResNet used skip connections to increase depth of the network but still had 26 million parameters while EfficientNet has only 5.3 million parameters which is quite a drop while keeping the efficiency intact . Keeping the scaling coefficient as 1.20, 1.10 and 1.15 EfficientNet has also been used as a backbone in our model. The Fig 12 depicts the entire architectural diagram of our model

5.5 Classification and Prediction

ROI pooling layer takes feature maps from the feature extractor backbone and region proposals from the RPN and resizes the feature maps to a fixed uniform size. The proposals and feature maps can be of varied width, height and aspect ratios and which need to be uniformed for a further processing. The output channel and input channel number is the same in this layer. The ROI pooling extracts a fixed size feature vector from the maps.

ROI pooling is followed by ROI align to remove any quantization using bilinear interpolation. This ROI align head can also be used to get the segmentation mask. Then the final feature vector is passed down to classification / prediction and regression heads for the bounding box offset for the disease infected regions on a leaf and classification to classify the leaf as healthy or unhealthy and predict the disease the leaf is infected with.

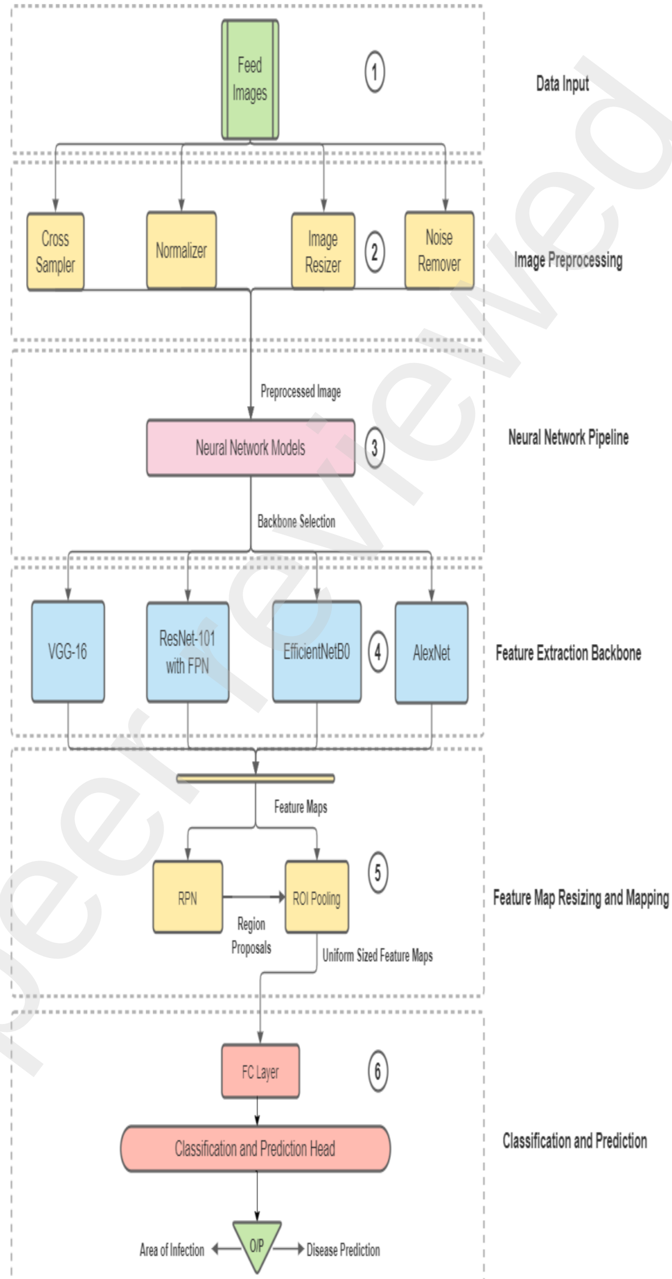


Fig . 12. Model Architecture

5.6 Results

Out of the several feature extraction neural network backbones used in our model , EfficientNet provides the best accuracy the lowest loss and overall greater performance evidently in our model too as it has a relatively increased number of flops , is faster (time taken for training completion is 3 hours 45 minutes) and also much deeper ten VGG nets with much lesser parameters.

The results have also shown the outputs using AlexNet and VGG16 as the feature extraction backbone in our model. The results of our model experiments have been described in this section. The training and validation accuracy and loss curves can be found in the Fig . 13 and Table 3, below. The model validation accuracy stands at 98% and the model training accuracy is 88.92%. The training and validation losses surmount to 0.585 and 0.492 respectively.

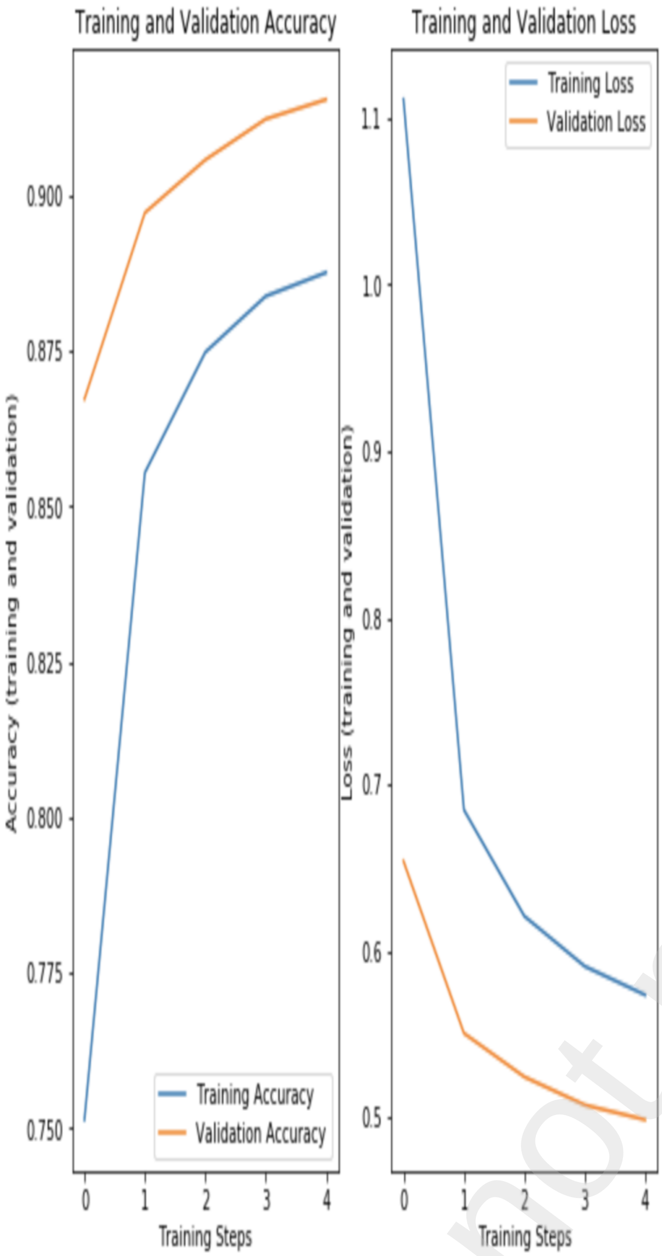


Fig. 13. Training and Validation Accuracy, Loss

Table 3
Training and Validation Accuracy, Loss

Training Steps	Training Accuracy in %	Variation Accuracy in %	Training Loss	Validation Loss
1	68	90	0.972	0.897
2	77.7	91.3	0.777	0.82
3	85.6	95.6	0.621	0.626
4	88. 9	98.0	0. 585	0. 492

The contour and edge mapping visualization have also been plotted and visualized in Fig 14 for AlexNet and VGG-16 backbones.

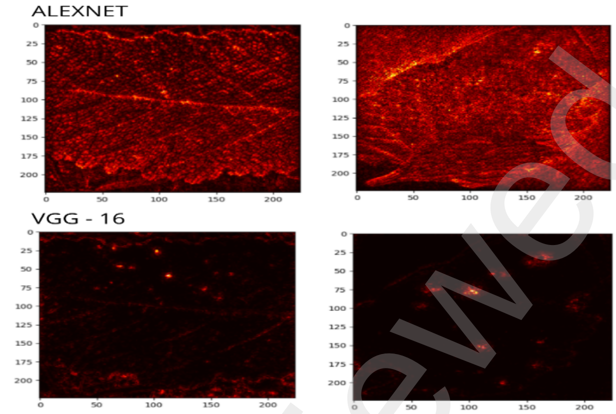


Fig. 14. AlexNet and VGG16 Feature Extractor Backbone Contour Visualizations

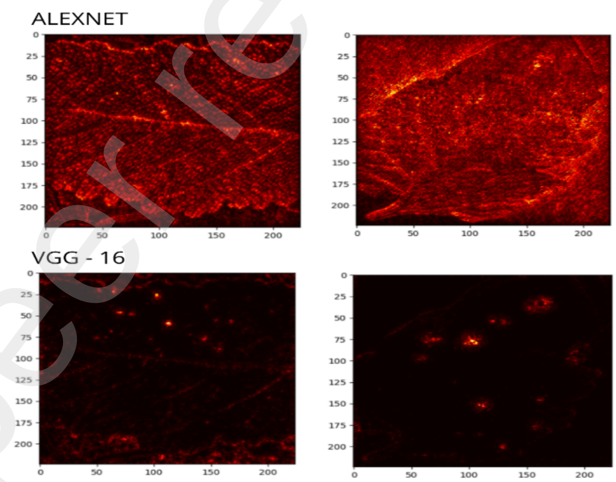


Fig . 15. Faster RCNN with Resnet - 101 Backbone - Smooth Grad Saliency Map

Next Author have plotted the saliency maps with and without SmoothGrad for our backbone networks, namely ResNet and EfficientNet seen in Fig 15 - 18. Saliency maps are essentially analytical methods that estimate the pixel importance , making use of one forward and one backward pass in the network. Fig 19 is the main output of the convolutional neural network architecture that we have used in our model where clearly and precisely the disease infected region of a leaf is highlighted.

Fig 16. Faster RCNN with Resnet - 101 Backbone - Saliency Map

Fig 17. Faster RCNN with EfficientNetB0 Backbone - SmoothGrad Saliency Map

Fig. 18 Faster RCNN with EfficientNetB0 Backbone - Saliency Map

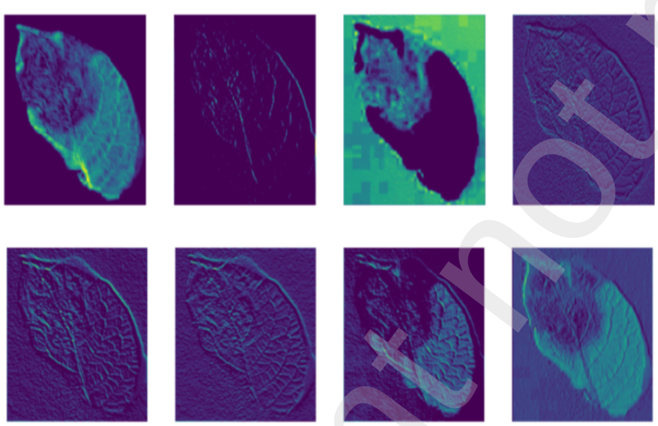


Fig 19 . Neural network identification of disease infected areas Of rear - sided leaf

6. Discussion

The work has given us more insights. Types of disease and intensity varies from one place to another, within a state; So, Deep learning goes with challenges like

a) Use of same algorithm will not give desired results,
b) Support of domain expert is required, to train the model
c) Data transfer speed from remote location might be slow
d) Date transfer and processing in cloud, cost money (farmers)
e) Use of "edge computing" might need a server in the village.

Validity of results depends on the training with the available dataset. New disease emerge because of various reasons including climate change . The images of this new disease have to be provided by domain experts, scientist . If this is not updated at the right time, results of the deep learning analysis may not be accurate.

7. Conclusion

This research is focused on detection of plant diseases, using the images of rear and front side of the leaves. FR - CNN and FPN were used. It took 3 hours to 45 minutes, to train the model and to achieve the training accuracy of 89% and valiation accuracy of 98 % . EfficientNet provides the best results and images of the rear side of the leaves could also give the desired results, to help the farmers. During COVID Pandemic, Agriculture is the only sector which has grown in the 1st quarter of financial year of India (i.e. April to June 2020), when the country's GDP shrank by 23. 9 % (RBI report released in July 2020). With right support from members of Trans disciplinary group and by adoption of disruptive technologies in agriculture , profits of Indian farmers can be increased This will lead to better standard of living, social progress and can change the trajectory of farmer's life.

Future work of this research includes the use of Generative AI (to enhance the accuracy of predictions), Edge Computing (to save image processing time and cost), Reinforcement learning (beyond Visual line of sight , in farms), Fuzzy Logic (to identify the level of infection, in leaves), Transfer learning on synthetic data (to improve the performance of algorithms), Hybrid algorithms (to identify severity of plant disease) and Swarm of Drones (to speed up the monitoring process), with the support of 6G.

Instead of identifying the infected leaves (at a very early stage), predicting the leaves disease, can help farmers t this can lead to zero loss in crop yield. So, this also could be taken as the next major step of this research. Such a transformation, to stop migration of farmers , help them move towards society 5.0 and possibly help India achieve the target of US $ 5 trillion economy.

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