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eCrop: A Novel Framework for Automatic Crop Damage Estimation in Smart Agriculture

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Abstract Natural disasters impact agriculture. Farmers incur large losses due to crop damage. Climate/weather driven natural events or disasters are happening often and are causing billions of dollars in losses. Crop insurance provides economic stability to the agricultural industry to make up for losses. A crop insurance claim is an extensive process and it takes time to process claims. In this paper, we propose a proof-of-concept of novel crop damage estimation method, *eCrop* which is a part of our proposed agriculture cyber physical system. eCrop is a grid based method. We also present a novel crop damage detection method. It is the core of *eCrop*. It is a Convolutional Siamese Neural Network (CSNN) based model. A meta learning approach has been taken to train the model. An accuracy of 92.86% has been achieved. Our *eCrop* method can be adapted to agricultural insurance claim processing to automatically estimate the crop damage. It is scalable to any size of the cropland and any type of crop.

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1 Introduction

Earth's climate has changed over time. The majority of these changes were due to minute difference in Earth's orbit that alter the quantity of solar energy received by our planet [1]. But the current climate era, started 11,700 years ago marking the beginning of human civilization, has mostly changed due to human actions since the mid-20th century. It is deteriorating at an unprecedented rate [8].

A stable climate is crucial for human civilization, especially for agriculture [20]. Human activities have contributed to the overall heating of the earth, including oceans, biosphere, and atmosphere. The observed impacts are melting of polar ice sheets and mountain glaciers, sea level rise, extreme natural events, e.g., extremely high temperatures, droughts, wildfire, floods, and extreme storms [38]. Fig. 1 shows some of the effects of climate change.

These extreme natural events or disasters due to climate change gravely impact agriculture. Temperature increase and change of rainfall patterns impact crop growth and yield which essentially stresses food supply chain [19]. The damage can happen at any stage of crop growth from early level of planting to harvesting. The loss due to crop damage costs billions of dollars to the agricultural sector of a country. Hence a protection umbrella is needed. Crop insurance provides the required financial protection to the farmers.

Fig. 1 Effects of climate change - Drought, Wildfire, Ice Melting at the Poles, Flood, and Storms

In this paper, we propose a proof-of-concept of crop damage estimation method for a large crop field. The method is automated and accurate. We also present a novel Siamese network based crop damage detection method which detects the damage type. Our model can detect the damages caused by natural events. Adaptation of our proposed method in processing the insurance claim will make the payment process easier, automated, and error free.

The rest of the paper is organized into eight sections. Section 2 presents the research question addressed in this paper along with an outline of the solution proposed. The novelty of the solution has also been discussed here. Existing work is discussed in Section 3. Section 4 states the proposed agro cyber physical system. Section 5 discusses the proposed proof-of-concept of *eCrop*. Our proposed crop damage detection method is presented in detail in Section 6. Experimental validation is discussed in Section 7 through a case study. Results are stated and analyzed in Section 8 along with a comparative study. Section 9 concludes the paper with suggestions for future work.

2 Novel Contributions of the Current Paper

2.1 Problem Addressed

When a crop field is affected by any natural event or disaster, the crop gets damaged, which in turn can cause huge financial losses to the farmers. To avoid such losses, farmers contact the insurer to initiate an insurance claim. The crop insurance company sends a loss adjuster for damage inspection. During inspection the adjuster takes photos, checks weather data, and talks to the neighbors to assess the damage [9]. The damage estimation profoundly depends on identification of Homogeneous Damage Zones (HDZs) and the extrapolation of data from the damaged sample of the HDZ to the total land [34]. The homogeneous damage zone selection is done manually by the loss adjuster. However, for a large land, identification of homogeneous damage zone without the extent of damage information is not fully accurate [34]. When a land is large, the damage is mostly heterogeneous. The process of extrapolation does not work properly. However, as the insurance money eases out some stresses on farmers, the process of insurance claim needs to be easy, seamless, and accurate.

USA is the largest corn producer of the world and according to a new NASA study corn yield will be reduced 24% due to climate change by 2030 [19]. Fig. 2 shows the projection of corn fields in 2070 where red color represents highly decreased corn production. Corn production in parts of both Americas, West Africa, Central Europe, and India and China in Asia will be severely affected [19]. As in near future, corn will be one of the most impacted crops, we use corn as a case study for evaluating our method. However, the method should be portable for it to be applied to any crop.

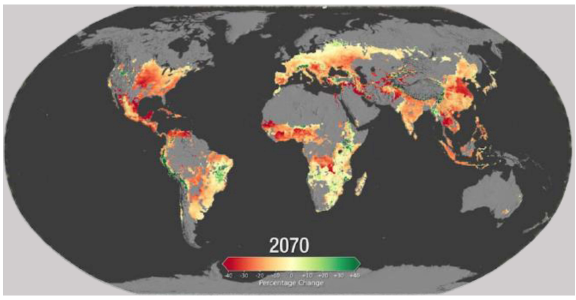

Fig. 2 Corn yield projection in 2070 [19]. In the color gradient scale, red means the mostly affected whereas green means not affected.

2.2 Proposed Solution

In this paper, we propose a grid-based method **eCrop** for estimating the crop damage across a large crop field as **proof-of-concept**. It is a part of the proposed **agro cyber physical system (A-CPS)**. In the future, with potentially available funding, permission, and collaboration, *eCrop* can be deployed in agricultural fields.

We also propose a simple convolutional neural network (CNN) structure for a Siamese network [16] based method to detect crop damage by natural causes and we evaluate it through a case study. When the loss adjuster from the insurance company comes to the damaged field to inspect crop status, our *eCrop* method assists in detecting the crop damage accurately and automatically.

2.3 Novelty of the Proposed Solution

The novel contributions of this paper are the following:

1. In general, deep learning based methods need a large number of data sets for training but application of artificial intelligence (AI) in agriculture is not in a mature state yet. As a result, the required data is not always available which in turn poses a bottleneck to transform agriculture to smart agriculture [28, 35]. However, our method does not suffer from the unavailability of data issue. The model for crop damage detection has been trained with very few data and high accuracy has been achieved. Our work can be a promising method for those research areas in agriculture domain where data scarcity is a problem.
2. Our proposed *eCrop* system is part of an agro cyber physical system. It precisely estimates the crop damage from the images taken by an Unmanned Aerial Vehicle (UAV). Hence, there is no need to set foot in the field for taking pictures. It reduces the risk of more damage to the crop land.
3. Our method is applicable to any stage of crop growth and to any crop type.
4. Real time processing is also possible as the data processing and computation is done at the edge server.

3 Related Works

In this section, some of the relevant papers which assess crop damages by different natural causes are discussed. Most of the papers present specific type of damage such as heat, frost, hail, storm, flood, pest, or crop diseases.

An unsupervised machine learning method has been used to detect hail damage using remote sensing data in [34]. Various indices have been calculated pre- and post-hail. K-means clustering has been used to determine the damage zone.

How drought affects the cropland has been studied in [24]. The relation between Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature has been studied in the areas of southeastern Germany from 20 years data. Different drought indices have been calculated with soil water content and crop yield discrepancies.

Some papers also address crop damage by floods, storms, crop diseases, and wild animals' attacks. Flood damage has been assessed in [15]. A simulated flood is generated using rainfall-runoff-inundation model. The water depth and the period for the flood have been considered to assess the damage of rice crops in the Stung Sen River basin of Cambodia.

Frost damage in lemons has been detected in [29]. Electrochemical resistance has been measured and different values of impedance were obtained for natural and freeze-thawed lemons. Statistical procedures have been used to differentiate between them. A prediction model has been presented using an artificial neural network.

Crop damage by wild animals has been presented in [26]. A photogrammetric reconstruction method has been used to segment the damaged part automatically. UAV taken images have been used to evaluate the method along with satellite data. Another work [32], also suggested taking pictures by UAVs and assessing crop damage by wild boars. A Random Forest classifier has been used to estimate the damaged land and corresponding loss. Geographic Object-Based Image Analysis has also been used. In [33], a Random Forest classifier has also been used to detect cyclone, earthquake, hailstorms, and flood damage. Sentinel I and II satellite data has been used. To estimate crop damage, crop layers along with NDVI have been considered. UAV images have also been used to detect crop damage by insects in [31]. K-means clustering algorithm has been used to detect the damage in an unsupervised learning way. Gaussian convolutional kernels help to reduce the high frequency noise.

Crop disease has been identified using convolutional neural networks in [36] whereas [17] addresses a more general approach. Disaster vegetation damage index (DVDI) has been utilized with MODIS images and USDA/NASS data to estimate crop damage. The damages are not specific to a cause. In [14] a distinct perspective has been considered. Here, the authors studied the feasibility of smart phone based photos for insurance processing. These photos are taken by the phones of the farmers. This approach has been suggested to reduce the cost.

Additional research works are discussed in Table. 1 along with our proposed *eCrop* method. These papers also address specific types of damages. Majority of the papers use satellite images. However, our goal is to find the related damage in real time when the loss adjuster sees the damage at the field. We wanted to find out ways to assess crop damage other than using satellite images.

Table 1 A Comparative Perspective of Existing Works with eCrop

Works	Year	Cause of Damage	Method	Remark
Sosa et al. [34]	2021	Hail	Unsupervised learning with K-means clustering + Satellite Images	Specific to one type of damage.
Kwak et al. [27]	2015	Flood	Flood depth and duration + MODIS time series images	Specific to damage type
Bell et al. [12]	2019	Storm, Hail and damaging winds	Synthetic Aperture Radar (SAR) + MODIS image + NOAA/NWS severe weather reports	Specific to damage type
Di et al. [17]	2018	Natural Disaster	Disaster vegetation damage index (DVDI) + MODIS images + USDA/NASS data	Provides overall estimation
Sawant et al. [33]	2019	Cyclone, earthquakes, hail storms, and flood	Random forest classifier + Min. and Max. NDVI + Sentinel 1 and 2 data	Specific to damage type
Yang et al. [39]	2019	Cold	Hyper spectral image + Convolutional neural network	Specific to damage type
Hsuan et al. [22]	2018	Fluctuating weather, heavy rainfall and typhoon	UAV aerial images + NDVI calculation	Focused on specific damage type
Pallagani et al. [30]	2019	Crop disease	CNN + Plant Village dataset	Specific to one damage type
Udutalapally et al. [36]	2020	Crop disease	CNN + Image Transformation + Plant Village dataset	Specific to one type of damage
eCrop	2022	Any natural causes like heat, frost, diseases and insect	Convolutional Siamese Network + Contrastive Loss + Few Data	Covers all damage type under MPCI. Scalable to any type of crop.

MODIS → Moderate Resolution Imaging Spectroradiometer
NDVI → Normalized Difference Vegetation Index
NWS → National Weather Service
STRM → Shuttle Radar Topography Mission
NOAA → National Oceanic and Atmospheric Administration

4 Proposed Agro Cyber Physical System (A-CPS)

A cyber physical system is the integration of physical systems and computational resources. When the Internet-of-Things (IoT) is implemented in a physical system, it forms a cyber physical system. As CPS comprises of various heterogeneous objects, connection and communication among the devices play a key role. CPS increases the efficiency, scalability, and usability of any system. Application of CPS in any industry not only reduces the cost [4], but it also makes the system more adaptable and seamless. It advances the industrial growth towards automation.

A-CPS is the cyber physical system in agriculture. It integrates the Internet-of-Agricultural-Things and computing elements. Our proposed A-CPS is shown in Fig. 3. A-CPS is the foundation stone of smart agriculture. It increases the efficiency of agricultural systems, predicts the yield precisely, estimates the damage automatically, and presents solutions for sustainable agriculture. It makes the process more efficient, adaptable, risk free, and resilient.

Our proposed A-CPS in Fig. 3 presents different granularity of data at various levels. Different stakeholders e.g., farmers, horticulturists, environmental scientists, and insurance providers access different levels of data. It makes the process more secure and robust.

The proposed A-CPS has 3 layers : agro layer, edge layer, and cloud layer. They are connected through the connectivity layer [28] Internet of Agriculture Things (IoAT) form agro layer. Sensors, robots, UAVs [25], and RFID tags are the IoAT devices. The agro layer is connected to the edge layer via a connectivity layer e.g., near range ZigBee or long range SigFox and LoRaWan. Edge layer processes the data and computes time sensitive operations. This layer comprises of IoAT edge servers. These edge servers are equipped with hardware accelerators. Machine learning models run in these devices. For authentication of these devices Physical Unclonable Functions (PUF) are used. Blockchains are used for data integrity purposes. Agro layer IoAT devices are connected to the IoAT edge servers through LoRA Gateways. Finally, all data are stored at the IoAT cloud servers for future use.

Crop damage estimation is part of this A-CPS. Here, farmers and insurance providers are the related stakeholders, UAV is the IoAT device, IoAT edge server computes the damage, and finally IoAT cloud server saves the data. For this specific solution, no sensor data has been used. In future, collecting sensor data and incorporating them in the solution will strengthen the approach.

5 Proof-of-Concept of eCrop: A Novel Method to Evaluate the Extent of Crop Damage

5.1 Proof-of-Concept

In this section, we propose the proof-of-concept of the *eCrop* method for evaluating the extent of damage. Fig. 4 shows the grid and Fig. 5 shows the overall *eCrop* pipeline.

In the event of crop damage due to natural causes, crop damage estimation is performed at different times and crop growth stages for different damage type. For hail and wind damage, damage estimation is done using eCrop just after the disaster whereas for heat, drought, frost, and fungal diseases, estimation is done near to the harvest time.

A UAV is sent to take photos throughout the large field following the proposed *eCrop* method. The data collected by the UAV is then sent to the IoAT edge server which processes the data and estimates the damage.

5.2 eCrop Grid

1. The large crop field is divided into a grid system as in step-1 of Fig. 5.
2. For each grid, the adjuster takes several photos of the crop through a UAV, as shown in step-2 of Fig. 5.
3. Any existing Machine Learning (ML) method can detect the damaged area as in step-3 of Fig. 5.
4. Damage type is detected using our proposed damage detection method discussed in Sec. 6 and shown in Fig. 6. The process is repeated for all the images of the grid as in step-4 of Fig. 5. (In case of crop kernel level approach, 50% of the damaged area is sufficient to check the damage type. But for smaller crops, head or panicle level approach is advisable.)
5. Final damage type for the grid is calculated from average similarity score of that grid.
6. If any damage type is identified, the grid is updated with 1 as in step-5 of Fig. 5.
7. The entire process is repeated for all grids and an overall estimate is calculated for the damage as in step-6 of Fig. 5.

The method is scalable to any crop. For more general method, a crop selection module with various stages of crop growth such as planting, growth, and harvesting can be added in the eCrop system. To avoid identifying deformed grains as damaged grains, an elimination module can be added too. The module will detect the deformed grains and not allow the system to detect the damage on those grains.

5.3 eCrop Grid Generation

The first step of estimating crop damage is *eCrop* grid generation. Fig. 7 describes the proposed *eCrop* grid generation method for detecting the crop damage. First, the map of the crop field is uploaded in the eCrop system. The (*latitude, longitude*) of the four corners of the land are retrieved. The distance between the corners is calculated using the *Haversine formula*.

If the (*latitude, longitude*) of two points P and Q are denoted as (ϕ_1, λ_1) and (ϕ_2, λ_2) respectively, the *great-circle* distance between them is calculated using *Haversine formula* as in Eq. 1 assuming the points are on a sphere:

$$d_{P,Q} = 2R \arcsin\Big(\sin^2(\frac{\phi_1 - \phi_2}{2}) + \cos(\phi_1).\cos(\phi_2).\sin^2(\frac{\lambda_1 - \lambda_2}{2})\Big)^{1/2}. \quad (1)$$

In the above expression, $d_{P,Q}$ is expressed in km, the radius of the earth R is 6371 km, and the (*latitude, longitude*) angles are in radians.

Once the distances are calculated, Algorithm 1 is followed. Then, $N = n \times m$ number of grids, each of size (100×100) sq.meter, are drawn and photos are captured. Finally, crop damage is detected for the entire grid.

5.4 Extent of Damage Calculation

For each (100×100) sq.meter grid, several images of the crop are taken through UAV. Once the damaged area in each image is detected, the average damage type is identified. Grid score value is updated with 1 if any damage is detected, otherwise it is 0. The damage type is also noted. This process is repeated for each grid. As the images are taken through UAV, the process of imaging is easy. If the number of damaged grids out of total N grids is u, then the extent of damage e_{damage} is given by Eq. 2:

$$e_{damage} = \frac{u}{N}. \quad (2)$$

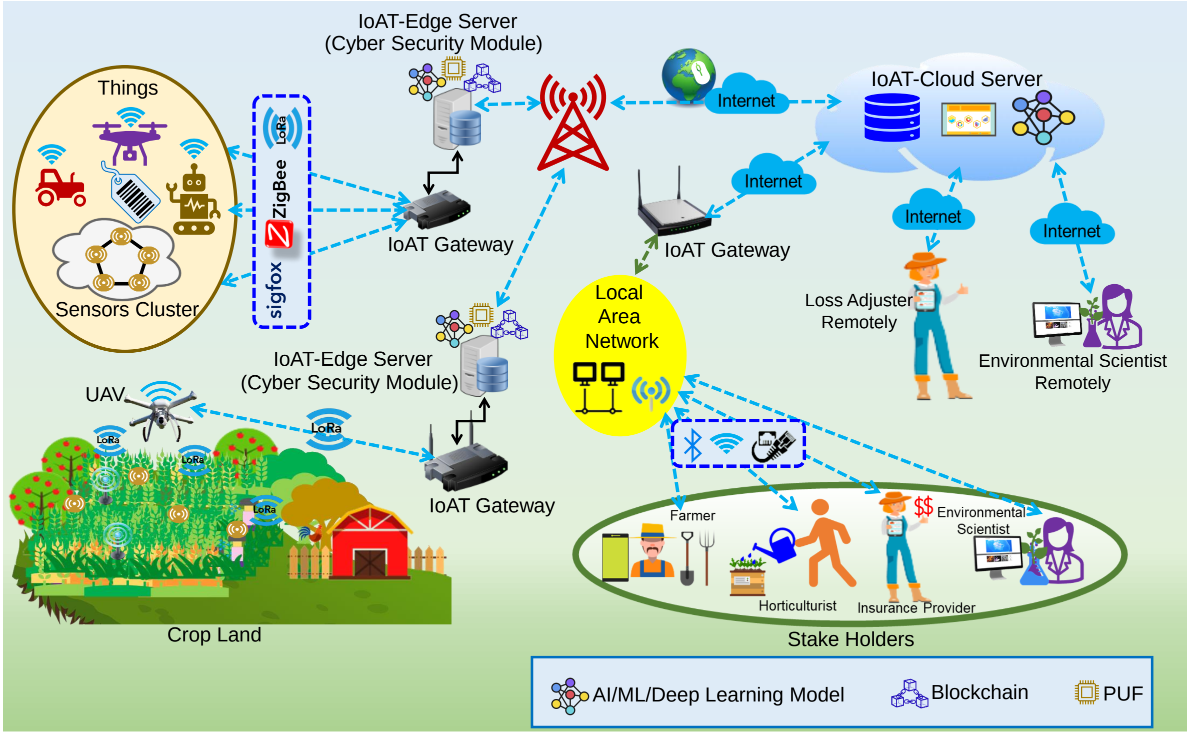

Fig. 3 Proposed Agro Cyber Physical System (A-CPS). eCrop is a part of A-CPS.

Algorithm 1: Procedure to Detect Crop Damage for the entire Grid

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Function `eCrop` (*length, width*):
  Declare variables n, m, *count*, *damagetype*, *similarityscore*, and *griddamagetype*, *grid* and initialize them to 0
  Declare a variable *imagecount* and set a value for it
  Draw a rectangle with sides *length, width*
  Set l $\leftarrow$ round($\frac{length}{100}$)
  Set w $\leftarrow$ round($\frac{width}{100}$)
  Draw $l \times w$ grids on that rectangle
  Set *row* to 0
  for $m \in w$ **do**
    Set *column* to 0
    for $n \in l$ **do**
      for *count* $\in$ *imagecount* **do**
        Take *photo* of the crop at position (*row, column*)
        Detect *damagetype* and note *similarityscore*
        Save *damagetype*, *similarityscore*, and *count*
      Update *griddamagetype* from average *similarityscore*
      Save *griddamagetype* and value of n and m in *grid*
      column $\leftarrow$ *column* + 100
    row $\leftarrow$*row* + 100
  return *grid*

---

1 1	2 1	3 1	4 1
5 1	6 1	7 1	8 0
9 1	10 1	11 1	12 0
13 1	... 1	... 0	N 0

Fig. 4 eCrop for Evaluating the Extent of Crop Damage.

The claim value M is calculated using Eq. 3:

$$\begin{aligned} M &= c \times e_{damage} \times N \times 10,000 \\ &= c \times u \times 10,000 \end{aligned} \tag{3}$$

In the above expression, c is the insured claim value in dollars per sq. meter of the field.

A hypothetical case is assumed to present the effectiveness of our proposed grid method. The average size of the crop lands varies across the globe. In USA, the average cropland varies from coast to coast. Most of the fields located west of the Mississippi are $(\frac{1}{2} \times \frac{1}{2})$ sq.mile and they were combined with time. Some are of size (1×1) sq.mile and separated by roads. According to USDA report [37], the average cropland size was

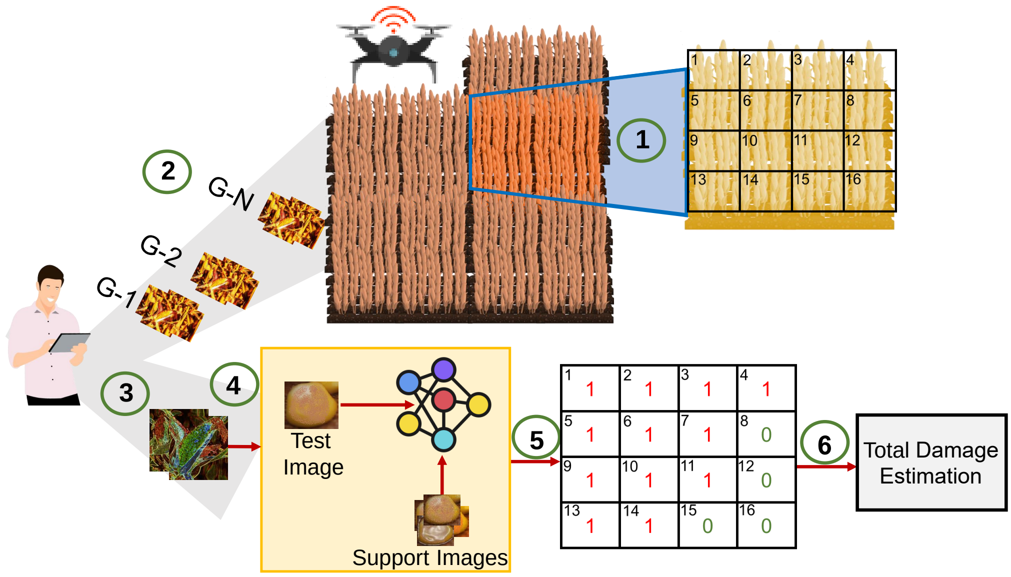


Fig. 5 eCrop System Overview.

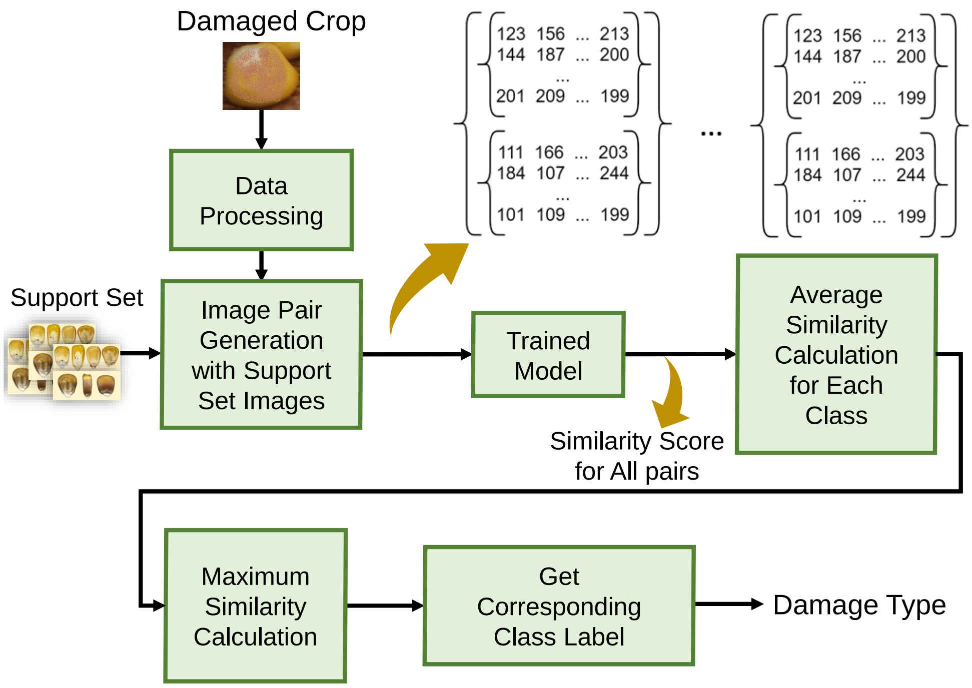


Fig. 6 Automatic detection of crop damage for each grid.

444 acres or 1.79 sq. km as per 2020 data whereas in Argentina the average crop land size is 500 acres [34]. We take a value 1.69 km square size with sides of (1300×1300) sq.meter, close to USA data as an example. It is divided into $13 \times 13 = 169$ unit grids, each of size (100×100) sq.meter. If 150 out of 169 grids have damaged crops, then e_{damage} will be 0.89 and the total money claimed will be $\$0.89X$ instead of $\$X$ where $\$X$ is the original claimed insured money for that damaged crop land. This grid method will help the insurance company to calculate the claimed money accurately and automatically.

6 Meta Learning Based Detection of Crop Damage for Each Grid : Architecture and Method

Here, we present the architecture and the learning protocol of our proposed crop damage detection method.

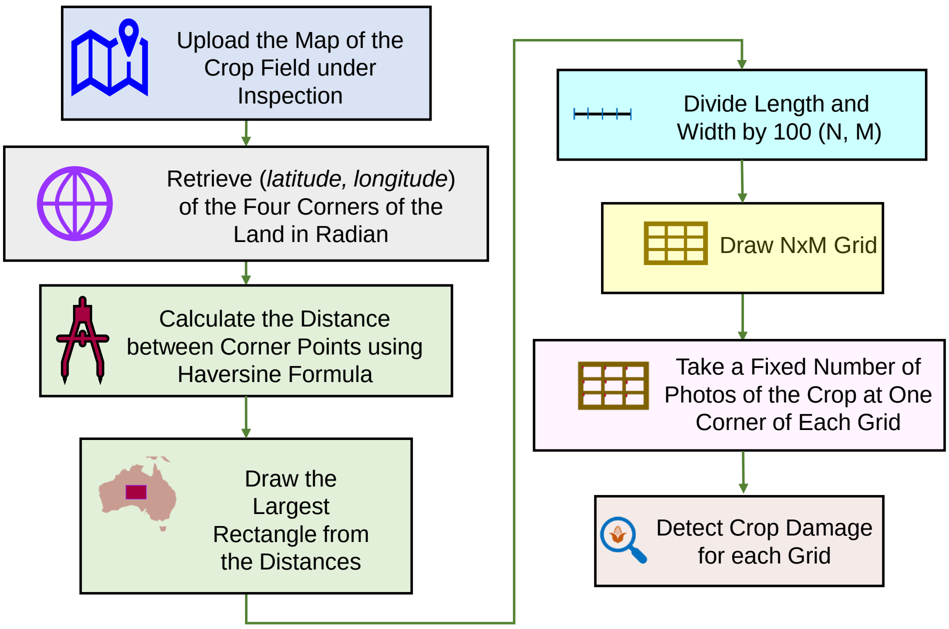


Fig. 7 Grid Generation of eCrop system for detecting crop damage.

We apply this method to detect the crop damage for each grid of a crop land.

6.1 Architecture

We propose a Convolutional Siamese Network Based framework as damage detection network. A Siamese network [13] is composed of two co-joined twin networks. The twin networks are called sister networks. They are identical and they share weights and network parameters. They are joined with an energy function at the top but accept different inputs or an image pair. The energy function can be a Euclidean distance or cosine similarity. They calculate the similarity score between the two images.

In our work, a shallow convolutional neural network (CNN) has been used to extract the features from the images. Fig. 8 shows the proposed CNN structure used in the sister networks of damage detection system.

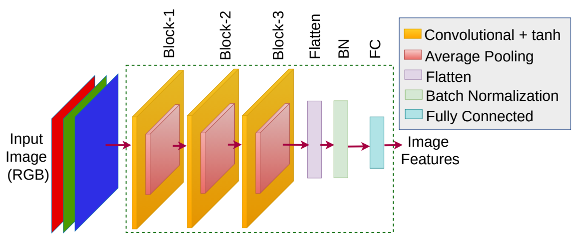


Fig. 8 CNN Structure used in Sister Networks of Damage Detection System.

It has 3 *convolutional* blocks. Each block consists of a *Convolutional* layer with tanh activation and *AveragePooling* layer. The pooling layer reduces the spatial dimensions. The number of filters varies in each block, but the kernel sizes are kept the same. Finally a *Flatten* layer, followed by a *BatchNormalization* layer with default parameters, and followed by a *Fully Connected* layer form the sub-network. The parameters of the layers are presented in Table. 2. Two of these structures have been used as the sister networks of the Siamese network as in Fig. 9 and they share weights between each other. The total number of trainable parameters are $4,514$. The network accepts inputs as a pair. Each sister network accepts an RGB input image of size 28×28. The output of each sub-network is a 16-dimensional feature vector.

Table 2 Sister Network Architecture Details of eCrop Siamese Network

Layers	Parameters	Output Shape
Conv2D	f=16, k=3, s=1, p=1	(28,28,16)
Averagepooling2D	k=2, s=2	(14,14,16)
Conv2D	f=8, k=3, s=1, p=1	(14,14,8)
Averagepooling2D	k=2, s=2	(7,7,8)
Conv2D	f=8, k=3, s=1, p=1	(7,7,8)
Averagepooling2D	k=2, s=2	(4,4,8)
Flatten	-	(128,)
BatchNormalization	-	(128,)
Fully Connected	u=16	(16,)

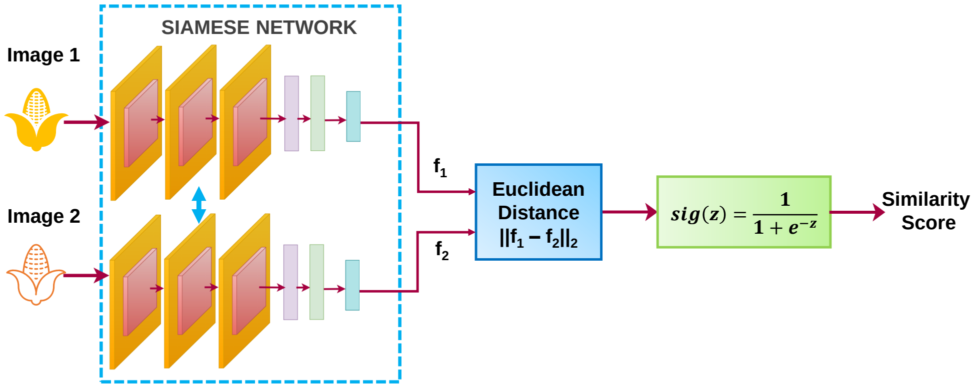


Fig. 9 eCrop Network consisting of CNN structure in Fig. 8 as sister networks.

6.2 Data Pair Generation

As a Siamese network accepts a pair of images as inputs, data pair generation plays a significant role for the training of this network. If the two images are from the same class, they form a positive or similar pair and if the images are from different classes, a negative or dissimilar pair is formed. Each pair is labeled. The label value of the pair is denoted by Y. It is expressed in Eq. 4:

$$Y = \begin{cases} 1, & \text{for similar images} \\ 0, & \text{for dissimilar images} \end{cases} \tag{4}$$

Before making the data pair, RGB images are resized to 28×28 and normalized. This step has been done to reduce the computational time.

6.3 Energy Function and Similarity Score

To know the similarity score between the image pair, the *Euclidean distance* has been used as the energy function. It measures the distance between two images in feature space. If the feature space is w dimensional and p_i and q_i are two points in that space, then the *Euclidean distance* D_w between those two points is given by Eq.5:

$$D_w = \sqrt{\sum_{i=1}^{w} (p_i - q_i)^2} \tag{5}$$

For our case w is 16. Eq.6 shows the *Euclidean distance* in our case:

$$D_{16} = \sqrt{\sum_{i=1}^{16} (p_i - q_i)^2} \tag{6}$$

A smaller distance means the similarity score is high and the images are similar. Similarity is measured through a *Fully Connected* layer with 1 node and sigmoid activation function as in Fig. 9.

6.4 Method and Training Protocol

Though AI has significantly advanced in recent years, application of AI in agriculture is in budding stage. Deep neural networks need large training datasets to predict accurately. But in reality, gathering a large dataset for training a deep learning network is not so easy or the required data is not always available. In such cases deep neural networks fail to function accurately. In agriculture, the unavailability of necessary datasets is one of the many reasons for the slow digital transformation of agriculture although datasets are available in concentrated areas of research e.g., plant disease [10], soil health [11], groundwater nitrate contamination [7], and disaster analysis [6]. Due to limited availability of data, agriculture is yet to harvest the full benefits of AI.

Crop damage by natural causes is one of such issues - where large public dataset is not available. To overcome this issue, we applied the concept of *meta learning*. In *meta learning* machine learning model learns the new task seeing only few data instead of being trained with a large dataset.

We apply a *few shot* learning approach. For classification problem, *few shot* learning is stated as N-way-K-shot classification where N denotes the number of classes with K images in each class. The network learns from a small dataset, called *support set*, with N classes and K samples in each class and is evaluated using a *query set*. *Support set* is usually a part of large dataset. An *episodic training* process is usually followed where in each episode different but small *support sets and query sets* from a large dataset are shown to the model. By this method, the model learns how to classify a new unseen class from the test query set when the test support set is available.

In our case, we have a small dataset and damages are known and specific. Known and specific crop damages remove the necessity of training the network in a true episodic manner of few shot learning as no unknown class is needed to be detected. We train the network with few images and detect the damage correctly.

6.5 Loss

Contrastive loss [21] has been used to train our Convolutional Siamese network. If there is an image pair of two input images x_1 and x_2 with pair label Y and D_w is the *Euclidean distance* between those two images in feature space, the Siamese network can find image similarity by measuring D_w. D_w is optimized by minimizing the *contrastive loss* L_{con} expressed in Eq. 7. The margin value m is set to 1 for *contrastive loss* L_{con}.

$$L_{con}(x_1, x_2) = (1-Y)\frac{1}{2}(D_w)^2+(Y)\frac{1}{2}\{max(0, m-D_w)\}^2 \tag{7}$$

6.6 Proposed Algorithm

To detect the type of damage, we propose Algorithm. 2. Whenever the UAV sends images to the IoAT edge server, the damage is detected.

Algorithm 2: How to Detect Crop Damage Caused by Natural Events?

Input: Image *testimage*
Output: Label *cropdamagetype*

Declare the *supportimages* path and Model $\tilde{M}$ path
Declare and initialize variables f, i, c, *label similarity* to 0
Declare *average similarity* as a list
Read *testimage*
Resize *testimage* to 28×28
Normalize *testimage*
Load Support Images *supportimages*
Call *makePair*()
Load Model $\tilde{M}$
Predict *similarity* for all *imagepair*
Get the similarity score between pairs with $30th$ percentile and $80th$ percentile to avoid any outlier
Get *average similarity* for each class from the range
Find maximum *average similarity* from the *average similarity*
Get corresponding *foldername* value for maximum *similarity*
Get the *label* name from *foldername* value
Set ***cropdamagetype*** to correct *label*
Function `makePair()`:
    Declare *imagepair* and f as list and initialize to 0
    Declare $foldername$ as list and initialize to 0
    for *images* $\in$ *supportimages* **do**
        for $i \in$ *images* **do**
            Read image i
            Normalize image i
            Make *imagepair* with *testimage* and image i
            Update $foldername$ with f
    return *imagepair*, *foldername*

7 Evaluation of the Proposed Crop Damage Detection Method for Each Grid

In this section, we present the experimental validation of our crop damage detection method. To evaluate our method, we did a case study on corn. We used corn kernels to detect the damage type. With proper availability of ear level data, the procedure is the same.

7.1 Dataset

In practice, images taken by the UAV camera will be used for training and inferring. But to evaluate our system, we train our neural network with available images.

We chose four types of damages such as heat, frost, disease (fungal), and insect infestation for evaluating our method. Other types of natural events, e.g., flood, hail, and storms can also be included here. Crop diseases are crop specific. So, to evaluate our method, we chose only one crop, corn, and heat, frost, cob rot, and insect damages have been considered. Corn kernels images from [3] and [5] have been used for training and evaluating our method.

The resolution of the images in our dataset is low, as those images are collected from the pdf copy of the reports [3,5]. We used the corn kernel images as is without doing much image enhancement. The dataset details for our work are mentioned in Table. 3. Fig. 10 shows some of the sample training images [5]

Table 3 Dataset Details

Cause of Damage	No. of Total Images
Disease (Cob Rot)	10
Frost	10
Heat	10
Insect	10

7.2 Validation

In this section, we present the validation details of the proposed crop damage detection method. The pipeline in Fig. 11 has been followed. Collected data are saved

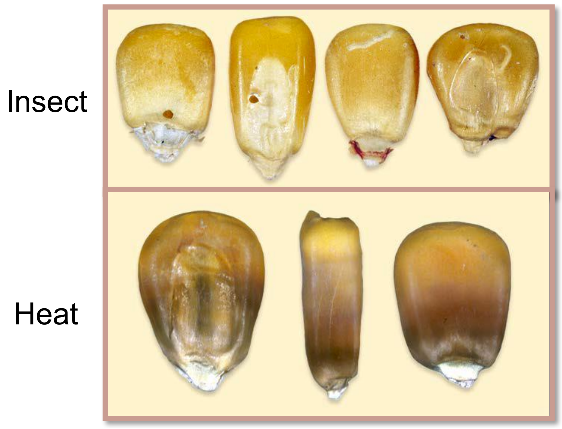


Fig. 10 Sample damaged grain images used for training [5]. In practice images taken by UAV will be used.

in different folders with the damage name. The folder names provide the class labels.

As we did not have much data to train, the same data used for training has been used as support images during testing too. The RGB images are resized to 28×28 and normalized. Similar and dissimilar pairs are then formed with normalized images.

Once the pairs are formed, they are used in training and evaluating the network mentioned in Fig. 9. The Euclidean distance between the pairs has been optimized using *contrastive loss*. The margin for the *contrastive loss* is kept at the default value 1. An *Adam* optimizer with learning rate 0.001 has been used. We trained the model with different values of N (number of ways/number of class types) and with different values of K (number of shots/number of images per class). Algorithm. 2 is used to detect the damage. The implementation has been done in Python. The training of the Siamese network for crop damage detection has been performed using a Jupyter Notebook (Python front-end) of a Dell G5 Windows 10 laptop with NVIDIA® GeForce® RTX 2060, 6GB GDDR6 video card and 16 GB memory. The model has been evaluated on a 4GB Raspberry Pi 4 using TensorFlow Lite Converter. Batch size has been varied from 4 to 32. Number of epochs has also been changed from 50 to 100.

8 Results and Comparative Study

8.1 Experimental Results

We evaluated our system by varying N and K. Fig. 12 and Fig. 13 show the accuracy vs number of shots (K) plots for two different values of N whereas Fig. 14 and Fig. 15 show the training time vs number of shots (K) plots for those two values of N. N is set to 3 and 4.

N is 4 in Fig. 12. The four classes we chose here are *Cob Rot, Frost, Heat* and *Insect*. Each class has 10 images. We varied the number of training samples for each class in different evaluation scenario by changing K. We changed the value of K to 4, 5, and 6 keeping the number of validation images to 2 for all cases. Hence the number of test images varied from 4 to 2. However, as our learning approach is based on meta learning, the Siamese network learns how to differentiate between two data samples. The similarity of the test image with the support images (in our case the training images) is compared. Therefore, the number of testing combinations is much higher than the number of test images. For example, let us assume the case when the number of classes N is 4 (all classes are considered) and $K = 4$ i.e., number of images per class is 4. Hence for a specific training scenario:

- number of training images = 4.
- number of validation images = 2.
- number of test images = $(10 - (4 + 2)) = 4$.

Evaluating a model with only 4 images does not perform the accurate validation. Here, the working of Siamese network plays a significant role.

- We have total 4 classes.
- Each class has 4 images.

Therefore, the total number of test combinations T is expressed as in Eq. 8:

$$\begin{aligned} T &= N \times K \times testimage \\ &= 4 \times 4 \times 4 \\ &= 64, \end{aligned} \tag{8}$$

where, N is the number of classes, K is the number of images in each class, and *testimage* is the number of test images. Hence the ratio of test combinations and total training images is expressed in Eq. 9:

$$\begin{aligned} \frac{\text{number of test combinations}}{\text{number of total training images}} &= \frac{T}{NK} \\ &= \frac{64}{16} \\ &= \frac{4}{1} \end{aligned} \tag{9}$$

The whole process is repeated for $N = 3$ as shown in Fig. 13. Here the classes are *Cob Rot, Frost*, and *Heat*. Table. 4 shows the number of images used for training, validation, and testing for each case.

We noted accuracy with different epochs. The training was complete for epoch value of 100. After that, the model started to overfit as the *contrastive loss* became

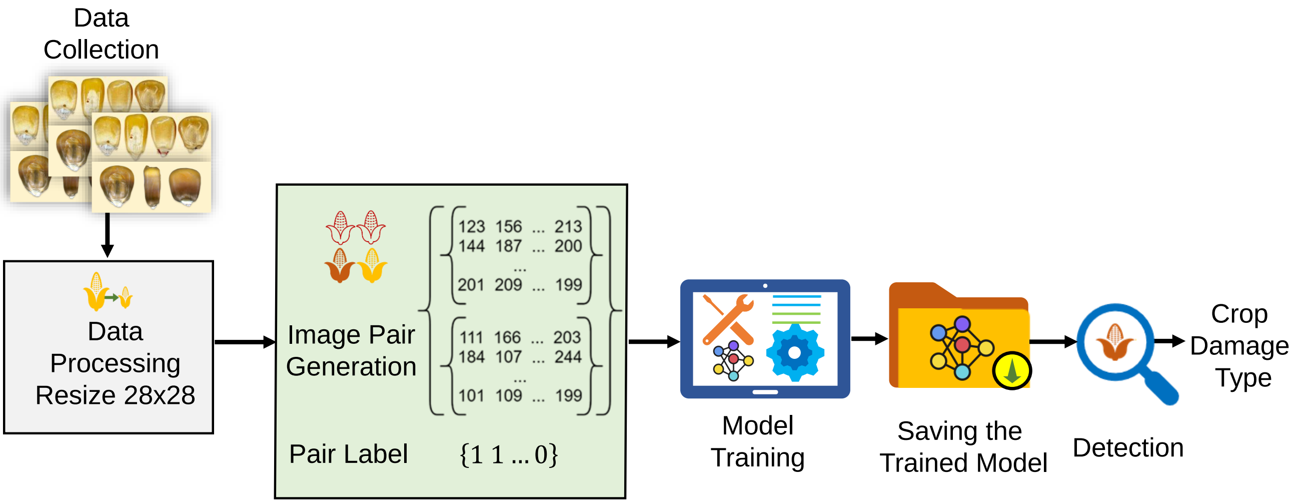
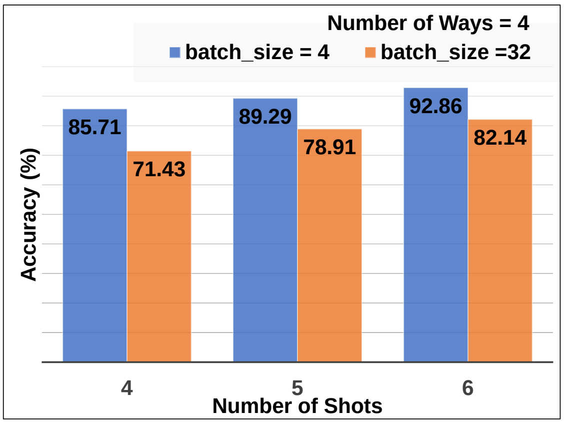
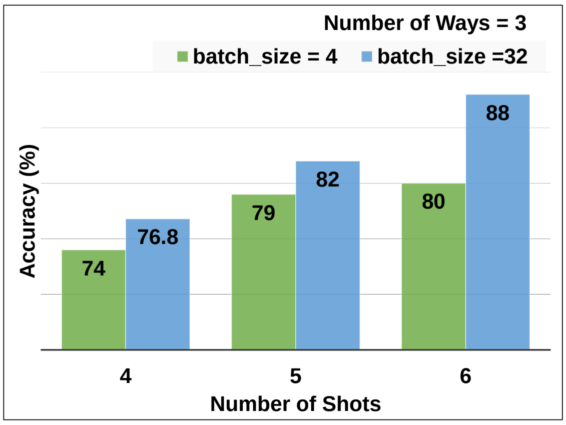


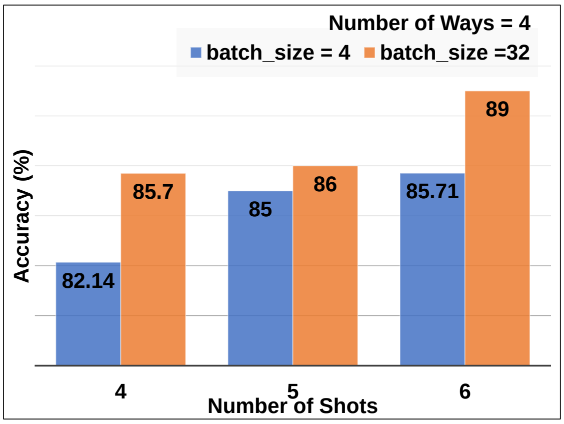
Fig. 11 Crop Damage Detection Pipeline.



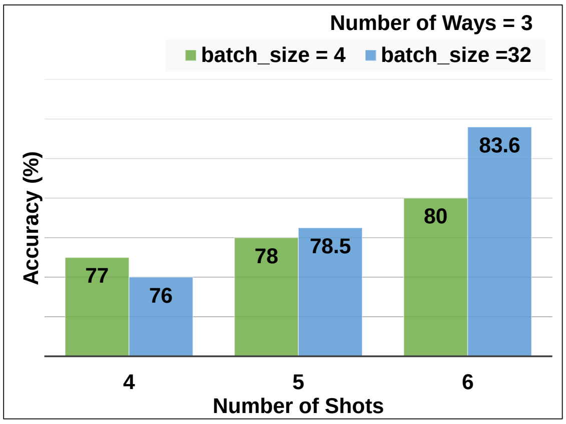
(a) For Epoch=100



(a) For Epoch=100



(b) For Epoch=50



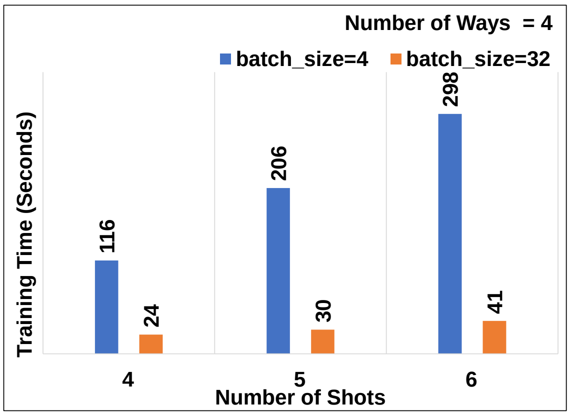
(b) For Epoch=50

Fig. 12 Accuracy vs Number of Shots (K) for Number of Ways (N)=4

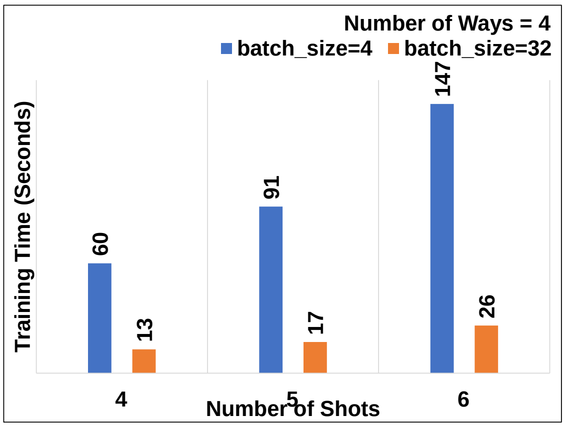
Fig. 13 Accuracy vs Number of Shots (K) for Number of Ways (N)=3

Table 4 No. of Images for Training, Validation, and Testing

N	K	No. of Train Images	No. of Validation Images	No. of Test Images	No. of Testing Combinations (T)
	4	4	2	4	64
4	5	5	2	3	60
	6	6	2	2	48
	4	4	2	4	48
3	5	5	2	3	45
	6	6	2	2	36



(a) For Epochs=100

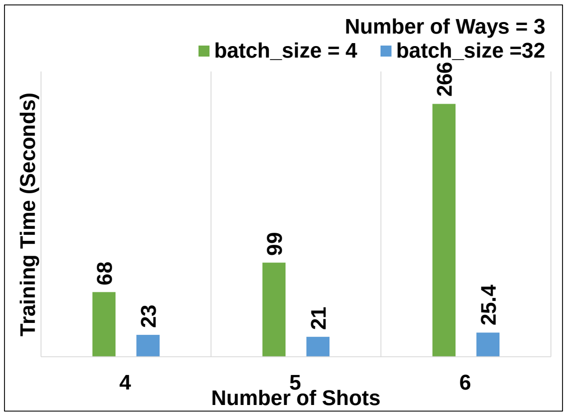


(b) For Epoch=50

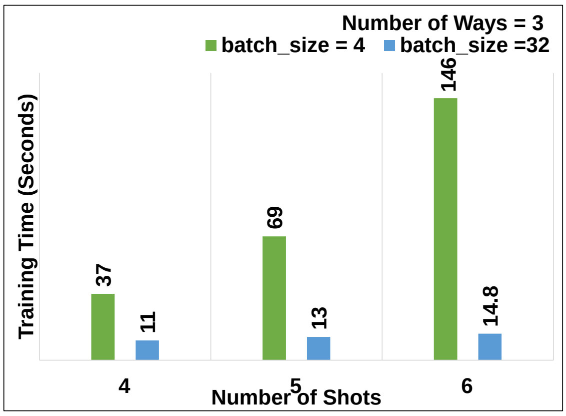
Fig. 14 Training Time vs Number of Shots (K) for Number of Ways (N) =4

erratic. The best model was obtained for both N with learning rate 0.001. Fig. 16 shows the first 3 features of the support images obtained from the trained model for $N = 4$.

Fig. 12 and Fig. 13 show that the accuracy increases with N even if the number of support class types increases. In our case, as the support set is same as training set, the number of training images also increases with increase of N. As a result, the model learns better.



(a) For Epochs=100



(b) For Epoch=50

Fig. 15 Training Time vs Number of Shots (K) for Number of Ways (N) =3

With an increase of K, the accuracy increases as the model has more data to learn. As in Table 5, we obtained the highest accuracy of 92.86% for $N = 4$ and $K = 6$. It was achieved when the model was trained with epoch=100 and batch size=4. For $N = 3$ the highest accuracy 88% is obtained when the model is trained with epoch=100 but batch size=32 and $K = 6$.

Table 5 Accuracy for Different N and K

N	K	Accuracy (%)
4	6	92.86
3	6	88

To evaluate the performance of the model we plot the confusion matrix in Fig. 17(a) for this multi-class problem. *Accuracy*, *precision*, *recall*, and *F1-score* have also been calculated in Fig. 17(b).

We varied the batch size to see the effect of batch size on training time. The training time is low for higher batch size as expected. Fig. 14 and Fig. 15 confirm that.

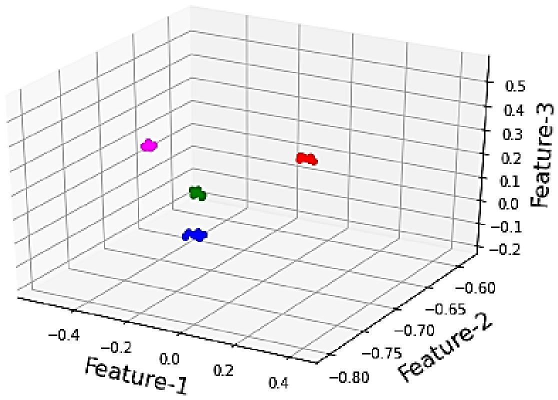


Fig. 16 First 3 Features of Support Images from the Best Trained Model for N=4

Fig. 14 and Fig. 15 show that the training time increases with N for both higher and lower batch sizes. It is expected as for higher number of N, the number of training images increases.

8.2 Comparative Study

Table. 6 shows a comparative study between the existing works and our proposed method. Most of the papers present crop damage estimation for a single type of damage. They are not suitable for at-location real-time estimates. But our proposed damage detection method addresses those issues. It automatically detects the crop damage from the UAV taken images at the IoAT edge server with high accuracy. It also includes more damage types compared to the existing works. Our *eCrop* system can estimate the crop damage over a large crop field.

8.3 Challenges

Crop damage estimation is an important area of research in agriculture. However, when we started the work, no public datasets were available. This challenge turned into motivation to propose a method which can work with few training data. We were able to find two reports containing few images. The clarity of the images was not very good. But, in this preliminary experiment, those images were used without any image enhancement methods. Along with the training data, there is also scarcity of test data. However, we overcame this issue by intuitively designing the detection method. The similarity of the test images with the training images has been calculated. As a result, the number of testing combinations has increased. For our experiment, the number of testing combinations was 4 times higher than the training data. Another challenge was unavailability of field data. However, for a more exhaustive model, field data is necessary.

9 Conclusion and Future Work

The agricultural industry may struggle to feed the world population which will reach to 9.7 billion by 2050. The condition will be aggravated due to the vulnerability of agriculture to climate change [2]. More and more researches are required to address various crop damage related issues for future sustainable agriculture.

In this paper, we propose an agro cyber physical system and bring all agricultural research problems under one CPS. We address one such agricultural research problems: estimation of crop damage caused by natural disasters. We propose a proof-of-concept of a grid based system. It can estimate the crop damage of a large crop field precisely and automatically. We also evaluate the damage detection method used at the grid level. Our method can detect the crop damage with a higher success rate and is scalable to any crop.

Higher accuracy can be obtained with higher quality and more number of training images which cover all types of damages for a specific crop. Integration of blockchain and PUF based methods will be explored in future for robust cyber-attack resilient smart agriculture Cyber-Physical System (A-CPS) [18, 23].

Implementation of the total *eCrop* system will be an important and relevant future work for estimating crop damage due to natural disaster. As eCrop system reduces the work of the loss adjuster by making the process automated with high accuracy, we believe our work has the potential to be applied to assess the crop damage in practice.

Compliance with Ethical Standards

The authors declare that they have no conflict of interest and there was no human or animal testing or participation involved in this research. All data were obtained from public domain sources.

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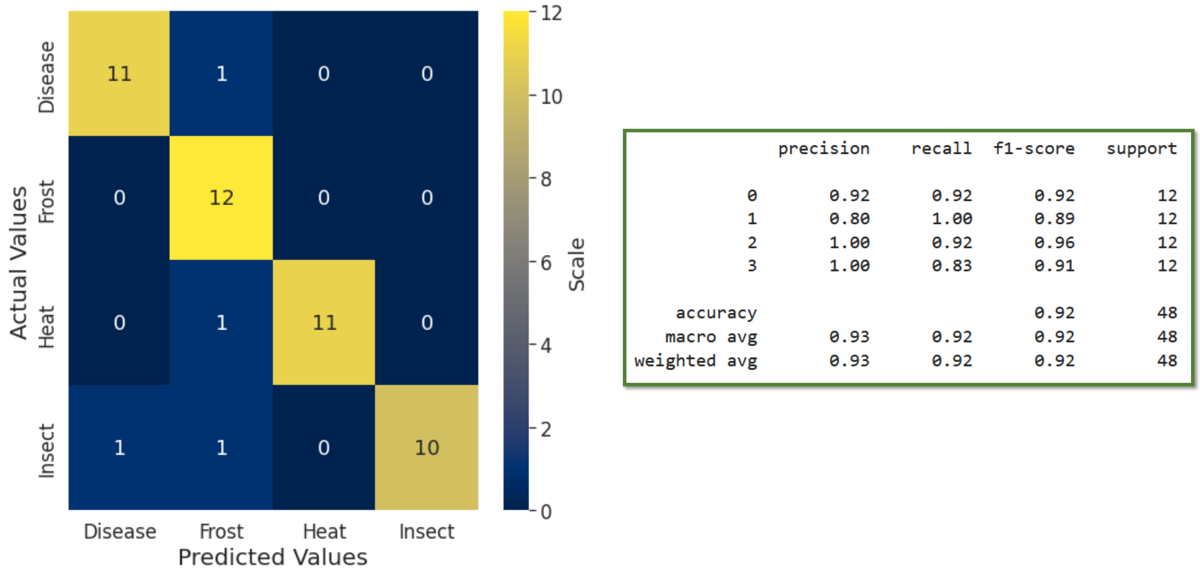

	precision	recall	f1-score	support
0	0.92	0.92	0.92	12
1	0.80	1.00	0.89	12
2	1.00	0.92	0.96	12
3	1.00	0.83	0.91	12
accuracy			0.92	48
macro avg	0.93	0.92	0.92	48
weighted avg	0.93	0.92	0.92	48

(a) Confusion Matrix (b) Performance Metrices

Fig. 17 Performance Evaluation of the Best Trained Model when N=4 and K=6

Table 6 A Quantitative Comparison of the Current Paper with Existing Works

Works	**Year**	**Damage Type**	**Accuracy (%)**	**Real Time**
Sosa et al. [34]	2021	Hail	87.01	No
Kwak et al. [27]	2015	Flood	80.00	No
Di et al. [17]	2018	Natural Disaster	95.00	No
Sawant et al. [33]	2019	Cyclone, earthquakes, hailstorms, and flood	87.23, 92.22	No
Yang et al. [39]	2019	Cold	82.19	No
Hsuan et al. [22]	2018	Heavy rain and typhoon	NA	No
Pallagani et al. [30]	2019	Crop disease	99.24	Yes
Current Paper (eCrop)	2022	**Any damage type: heat, frost, diseases, and insect**	**92.86**	**Yes**

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10. Plant Disease. URL https://www.kaggle.com/saroz014/plant-diseases. Accessed on 23 December, 2021
11. Soil Health. URL https://new.cloudvault.usda.gov/index.php/s/7iknp275KdTKwCA. Accessed on 23 December, 2021
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