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RESEARCH ARTICLE

Detection of Disease in Maize Plant Using Deep Learning

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ABSTRACT

Agriculture is vital to the Indian economy as over 17 percent of total GDP and employs more than 60 percent of the population relies on agriculture. This research focuses on plant diseases as they create a major threat to food production as well as for small-scale farmer's livelihood. Expert workers are employed in traditional farming to visually evaluate row by row to identify plant diseases, which is a time-consuming, labor-intensive activity that is potentially error-prone because it is done by humans. The aim of this research is to develop an automated detection model that uses a combination of image processing and deep learning techniques (Faster R-CNN+ResNet50) to analyze real-time images and detect and classify the three common maize plant diseases: Common Rust, Cercospora Leaf Spot, and Northern Leaf Blight. The proposed system achieved 91% accuracy and successfully detects three maize diseases.

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Introduction

Agriculture is vital to the Indian economy as over 17 percent of total GDP and employs more than 60 percent of the population relies on agriculture. In India, more than 70 percent of rural small households depend on agriculture [1]. The Continual growth in India's population has increased the demand for food, resulting in a situation where crop production is insufficient to meet the demand. The major factors which reduce food production are climatic changes, plant diseases, weeds, and so on. This research focuses on plant diseases as they create a major threat to food production as well as for small-scale farmer's livelihood.

To avoid disease-related yield loss, a variety of approaches have been developed, whereas to avoid epidemics, a preventive method at the seedling stage is insufficient, but strict visual monitoring is required for early disease detection in the crop. Expert workers are employed in traditional farming to visually evaluate row by row for plant diseases, which is a time-consuming, labor-intensive activity that is potentially error-prone because it is done by humans. Furthermore, plant pathology experts are not always available, particularly in segregated and impoverished areas. To address this issue, researchers devised a number of solutions based on the introduction of new technologies like image processing, computer vision, object detection and classification, and so on for crop quality assessments.

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Precision farming is the new Agricultural Evolution that uses science and technology to increase crop production, which strives to reduce pesticide and fertilizer use, while also lowering farm costs. Precision farming has proven benefits in several agricultural areas as it transitions from traditional methods to new ways[17]. It entails strategies for efficiently detecting and curing diseases or pests by accurately focusing the amount of fertilizers or insecticides required. Precision farming's main objective is to obtain real-time data in order to boost agricultural productivity and maintain crop quality. Sensors and remote sensing, high precision positioning systems, mapping and surveying, Automated steering systems mapping, Global navigation satellite systems, variable-rate, and computer-based applications are some of the technologies utilized in precision agriculture. Drone's integration into precision farming operations has completely altered the market landscape. The Drone can be used for a variety of tasks in farming, including fertilizer and pesticide spraying, seed sowing, and crop growth monitoring. To carry out these tasks, a drone must be outfitted with a camera, a sprayer, and pesticide/fertilizer canisters[18][19]. Drones can be used to monitor crop health on a regular basis and detect anomalies early stage. To determine overall crop growth patterns and estimate the yield, the Drone acquired data (image/video) can be processed in real-time with the help of a video/image analytics system based on deep learning or machine learning technology.

The purpose of this study is to develop an automated detection model that uses a combination of image processing and deep learning techniques to analyze real-time images captured by the simple camera and detect and classify the three common maize plant diseases: Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot. Maize is India's third-largest food crop, after rice and wheat. Maize is a staple food for the human-being, as well as primary raw material to thousands of industrial goods, including oil, starch, alcoholic beverages, pharmaceutical, food sweeteners, cosmetics, textile, film, gum, paper, and package sectors. Maize is farmed throughout the year in all states for fodder, grain, sweet corn, green cobs, pop corn and baby corn in peri-urban areas. Andhra Pradesh, Uttar Pradesh, Himachal Pradesh, Karnataka, Bihar, Rajasthan Maharashtra, Madhya Pradesh, are the leading states that grow maize, supplying over 80 percent of India's total maize production [2][13][14][23]. Diseases and pests that found in fields can easily infect maize. Abiotic (non living) and biotic (living) agents are the two types of agents that can affect maize plants.[16][20] Bacteria, Insects, Viruses, and fungi are examples of living agents. Various environmental factors such as excess moisture, rapid temperature change, high humidity conditions, poor soil pH, and insufficient nutrients are examples of non-living agents.

Problem Statement

The problem discussed in this study is detecting anomalies in cultivated land, particularly in the detection and classification of maize diseases. Plants are articulated bodies in general; nevertheless, defining a single model that detects and distinguishes different diseases and plants could be difficult. Because of their non-rigid structure, crop growth is not uniform, and intra-class variability between crops is enhanced. The research focuses on applying deep learning approaches to develop disease detection and classification models that capture the prominent features of diseases and distinguish them from other items of interest, such as crops.

Mathematical statement is as follows,

$$\boldsymbol{Y}\text{out} = \text{for}\begin{cases} \text{X}[\mathbf{I}]\ \mathbf{0} \text{ if disease} \\ \mathbf{1} \text{ if normal} \end{cases}$$

$\text{X}[\mathbf{I}]$: Maize leaf images as input $\boldsymbol{Y}\text{out}$ = 0 if leaf has a disease

$\boldsymbol{Y}\text{out}$ = 1 if leaf is healthy

Objectives

- To propose a more appropriate deep learning model for detecting diseases in maize plants, specifically Northern Leaf Blight, Common Rust, and Cercospora Leaf Spot using 1269 images obtained with various resolutions by camera devices at early and late stages and fed to deep detector: Faster R-CNN (Faster Region-based Convolutional neural-network).
- To recognize maize diseases, integrate deep learning model plus "deep feature extractor": ResNet50.
- To train and test the proposed system from start to end on the maize disease dataset described in this paper, which includes challenging photos of several maize diseases, as well as intra- and extra-class variations.

The following is a summary of the rest of the paper: Section 2 studies the influence in this field, Section 3 explains the methodology, Section 4 presents the experiment results, and Section 5 conclusion.

Literature Survey

This section summarizes the results of numerous studies in plant diseases and pests detection in deep learning technology. Deep learning offers a lot of potential for classifying plant diseases severity automatically.

In [3], the authors gathered a 1090 comprehensive real-time image dataset of tomato leaves infected by four diseases (Septoria Leaf spot, Leaf curl, Septoria, Bacterial Spot, and Early Blight), where images have been captured by camera devices with various resolutions (48MP, 12MP), different lighting conditions, and all stages of tomato disease (early, medium, and final) and fed into a deep learning model detector: Faster R-CNN plus "deep feature extractor": ResNet50 to recognize tomato diseases. Faster R-CNN with ResNet50 was identified as a viable approach to identify the type and location in tomato plants disease. Also, they trained and evaluated the deep learning system from start to end on the tomato disease dataset described in their paper, which includes complex photos of various tomato diseases, as well as extra- and intra- class variations.

The author of [4] used the PlantVillage dataset to extract photos of tomato leaves. There are 14828 photos are grouped into nine diseases in the dataset. The author used

CNN as a learning technique to train classifier, which allows for the direct usage of images and avoids the use of hand-crafted features. Visualization methods were used to analyze the deep models (GoogleNet and AlexaNet) in order to fully understand symptoms and locate diseased areas in the leaf. The PlantVillage dataset's photos were captured in a lab. under controlled conditions, which is a flaw in this model.

The authors [6][20] developed a CNN model to detect tomato diseases and pests based on VGG16+Transfer learning. The authors created an image dataset with 11 categories totaling 7040 photos, each disease with 640 photos. To detect pests and diseases in tomato images, the (VGG16+SVM) algorithm uses VGG16 as an image feature extractor and combines it with an SVM classifier; End to end classification system was developed by using fine tuning method. The overall maximum performance, on the other hand, is dependent on substantially higher quality test images, rather than low-quality test images.

In [4][6] the authors collected 5000 images from different farms in Korean Penisula. The authors aim to build a deep-learning system for detecting and recognizing the disease and pest types and where anomalies are located in images. For the purpose the authors built an, Meta architectures R-FCN (Region-based Fully Convolutional Network), Faster R-CNN (Faster Region-based Convolutional Neural Network), and SSD (Single Shot Multibox Detector) and various deep feature extractors (VGGnet, ResNet) are considered to detect and classify pests and diseases in maize leaf images. In addition, to improve accuracy and reduce FP's (false positives), data augmentation, global and local class annotation methods were used during the training stage, which is trained and tested with Tomato Pests and Diseases Dataset. The system is capable of detecting nine distinct types of pests and diseases. Because there aren't enough samples, some classes with a lot of pattern variation get mixed up with others, resulting in false positives.

The authors in [6][7] used a diverse dataset that includes images from the nursery, PlantVillage dataset, and farm. Convolutional Neural-Network was trained to identify 3 diseases. Using the Softmax activation function, a classification model was used to calculate the class confidence score. All of the feature maps from the preceding layers are entirely connected by fully connected layers and classifies images into 3 diseases (powdery mildew, downy mildew, and early blight). Remarks: Images in the PlantVillage dataset are collected under a controlled condition which holds a drawback of the model. The authors of [8] considered a tomato dataset that included 500 photos from nearby farms and 2100 photos from the internet. In order to classify tomato disease photos into good, bad, average types, Google's Inception Model was retrained with transfer learning and in turn, increased system execution speed.

In their work [8], the authors examined 1,796 photos of maize leaves, with 768 photos of non-infected leaves, and1,028 NLB (Northern Leaf Blight) infected photos. The authors built a technique that can identify NLB disease automatically in maize plants photos. In order to detect early stage of NLB disease regions in photos, several CNN's are trained with tiny parts of photos, and separate heat maps (with disease and healthy) are generated, which is fed to final trained CNN on entire photo to detect disease or not. Remarks: To train CNN, one should classify images manually, which is time-consuming and error prone.

The authors of [10] collected 3823 photos of maize disease leaves from the plant's website and annotated them for four different types of maize disease. Using AI methods such as Random Forest (RF), K-Nearest Neighbor (KNN), Decision Tree (DT), Support Vector Machine (SVM), Naive Bayes (NB), and the authors predicted early disease detection in crops. When compared to all other models, Random forest achieved 80.68 percent accuracy. Remarks: However, each model in the classification process has its own set of problems that may or may not apply to other available datasets.

Methodology

The approach for the proposed maize plants disease detection system is presented here. More appropriate deep learning architecture to detect diseases in maize plants using 1239 photos taken with varied resolutions using mobile phone camera at all stages (early, late) is fed to deep detector: Faster R-CNN (Faster Region-based Convolutional neural network), and combines with "deep feature extractor: Residual Network-50 (ResNet-50)".

System Overview

The goal of this research is to detect three types of diseases i.e Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot, that impact maize plants by using Deep-Learning as the primary body to the proposed system. Figure 3.1 depicts a high-level picture of the system. Each stage in proposed system is described in depth below.

Data Collection

Maize dataset has images of Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot diseases occurs in maize plants, which were collected using a simple phone camera under a variety of situations depends on place (e.g., nursery, farms), season (humidity, temperature), time (illumination), and we visited a number of maize fields in Piller, Mangapuram, and Kallur in Andhra Pradesh. Maize dataset contains data like, various resolutions images (48MP, 12MP), medium, last and early infection status of maize leaves, complex background (e.g soil), images where the desired object (disease) is partially obscured, overlapped with something else (leaves, stems), or only halfway in the image. The table (Table 3.1) summarizes the symptoms of Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot.

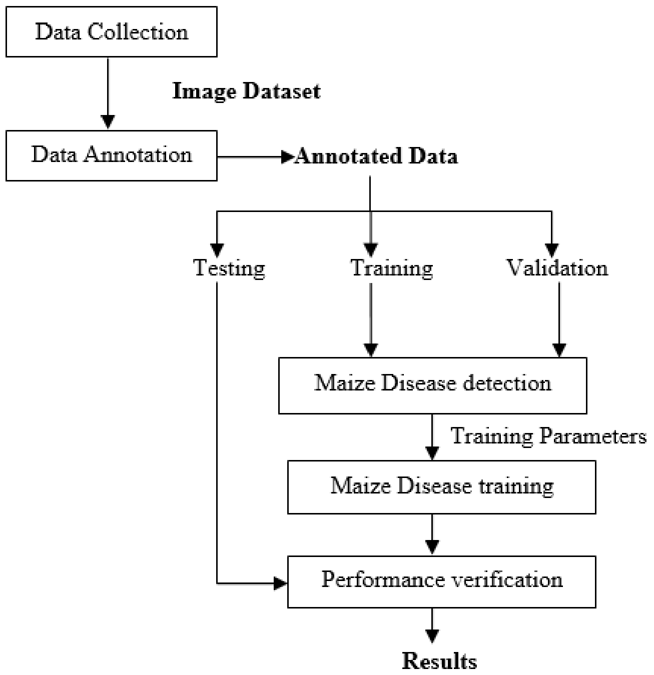


Figure 3.1. High-level picture of proposed system for maize disease detection

Table 3.1. Database for infected maize samples for disease detection

Disease	Symptoms	Collected sample
Cercospora Leaf Spot	A little necrotic spot on the leaf that grows into a rectangular lesion as it ages and become browned and eventually grey.	
Common Rust	Small tan spots on lower and upper surfaces of leaves, as disease matures turns from dark brown to black	
Northern Leaf Blight	Elliptical gray-green lesions on leaves	

Data Annotation

Using the LabelImg tool (which is a great tool for labeling pictures) manually marked disease regions in all images by bounding-box's and class type to which the disease belongs. The data annotation stage output is the coordinates of differing sized bounding boxes with their respective disease class, which will be evaluated by the IoU (Intersection-over-Union) with the proposed system and predicted result during testing.

Faster-RCNN Maize Disease Detection

The aim is to detect and identify three disease classes and their locations in maize plant images. To get accurate results from the system, the bounding boxes that include disease should be correctly defined to which the disease belongs. Faster R-CNN generates essential (Region of Interest) ROI's for maize disease detection using the Region Proposal Network (RPN).

The steps are followed in a Faster RCNN approach for maize disease detection in a image:

1. Give an image to the ConvNet, that will return feature maps for the image to RPN.
2. RPN creates k fixed size anchor boxes with varying sizes and shapes in a maize disease image by sliding windows on obtained feature maps at each window, and predict the probability that an anchor is disease and a bounding-box regressor to best fit the anchor for disease.
3. ROI collects fixed size feature maps to all the anchors after obtaining various types and sizes of bounding boxes (object proposals) and cropping each proposal in such a way that each proposal comprises tomato diseases.
4. A fully connected layer with a softmax and a linear regression layer receives the collected fixed size feature mappings. At the end, the maize disease is classified (Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot) and bounding-boxes to the identified maize diseases are predicted.

RPN Training and Loss Functions

When an anchor meets one of the following two criteria, it is deemed a "positive (disease)" sample: a) It has the greatest Intersection_over_Union (IoU) with a ground truth-box; b) When the IoU more than 0.5 with any ground truth-box. If the IoU on all ground truth-boxes was much less than 0.5, anchor is labelled as 'negative (healthy)'. For RPN training, rest all anchors are ignored (either negative or positive). Each RPN mini-batch is made from a single image. In order to avoid bias learning, a batch should be formed with 128 healthy (negatives), 128 disease (positives) samples. The RPN training loss is estimated by:

$$L(\{ p_i \}, \{ t_i \}) = \frac{1}{N_{cls}} \sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}} \sum_i p_i^* L_{reg}(t_i, t_i^*) \quad (1)$$

Here,

i - Index of anchor in mini-batch

$L_{cls}(p_i, p_i^*)$ - Classification loss is the log loss over two classes (disease v/s healthy)

p_i - Output score from the classification branch for anchor *i*

p_i^* - Ground truth label (1 or 0)

$L_{reg}(t_i, t_i^*)$ - Regression loss

When anchor truly includes a disease, i.e., if ground truth p_i^* is 1, then the regression loss $L_{reg}(ti, ti^*)$ gets activated. The t_i refers to regression layer's output prediction, which is made up of four variables [t_x, t_y, tw, t_h].

The t_i^* (regression target) is estimated by:

$$t_x^* = \frac{(x^* - x_a)}{w_a},\ t_y^* = \frac{(y^* - y_a)}{h_a},\ t_w^* = \log \frac{(w^*)}{w_a},\ t_h^* = \log \frac{(h^*)}{h_a} \quad (2)$$

Here,

h : bounding-box height

x^*, x_a: coordinates of anchor-box and related ground-truth bounding-box.

w: bounding-box width

(x, y): top-left coordinates of bounding-box

Experiments and Results

The proposed system uses Faster R-CNN with ResNet-50 to detect three common maize diseases. Firstly, the proposed system's performance is evaluated using the Pascal VOC Challenge's [11] IoU (Intersection_over_Union) and AP (Average Precision).

$$IoU(A, B) = \left|\frac{A \cap B}{A \cup B}\right| \tag{3}$$

Here,

A - Annotated Coordinates of Ground-truth-box

B - Predicted result of the network

The predicted result is deemed as true positive (TP), when estimated IoU exceeds 0.5 (threshold value), or it is deemed as false positive (FP). The proposed system is considered efficient, when there are low numbers of FP's from the images which contain disease regions. IoU is a regularly used approach for determining an object detector's accuracy. AP is calculated by taking precision average across a range of [0, 0.1,..., 1] recall levels, and the mean Average Precision (mAP) is the AP calculated for Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot maize diseases.

$$AP = \frac{1}{11}\sum_{r\in\{0,0.1,\ldots,1\}} p_{interp}(r) \tag{4}$$

$$P_{interp}(r) = \max_{\tilde{r}:\, \tilde{r}\geq r} p(\tilde{r}) \tag{5}$$

Where $p(\tilde{r})$ is the precision measure at $\tilde{r}$ recall shown in Figure 2 for each maize disease. The mAP computed for *IoU* = 0.5 and the proposed detection system achieved more than 91% Faster RCNN with ResNet50 results achieved for Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot maize diseases is shown in the Table 1. The proposed system mAP gave a performance more than 91%. The performance can be improved by training proposed system with more samples. Tensorboard [12][22] is an tensorflow visualization toolkit provides visualization and tracking of total loss, the Figure 1 shows the resultant loss curve for an fifty two thousand epoch's and shows that proposed is capable of learning maize data by achieving a smaller error-rate less than 0.1 at fifty one thousand epoch. The qualitative results achieved by the proposed system to detect three common maize diseases is shown in Figure 3.

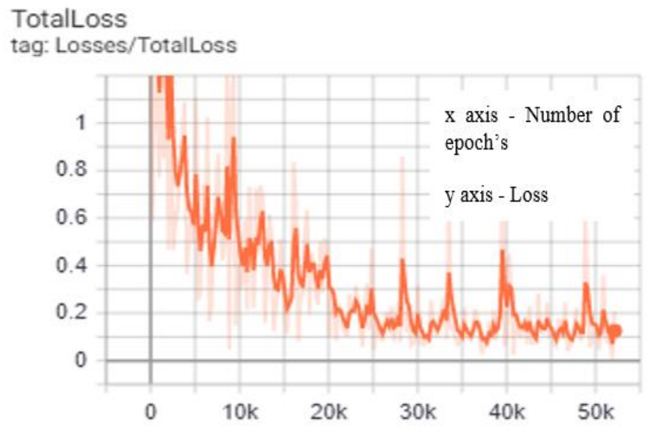
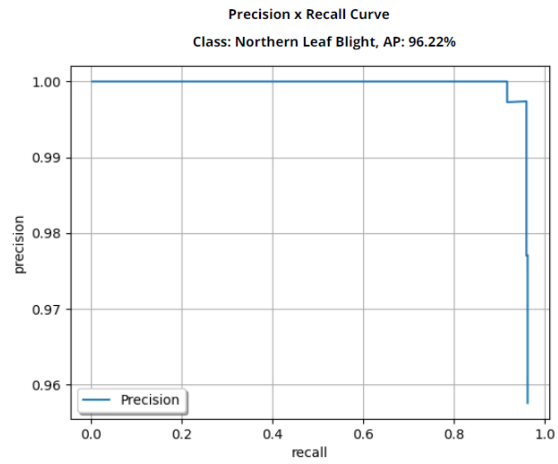


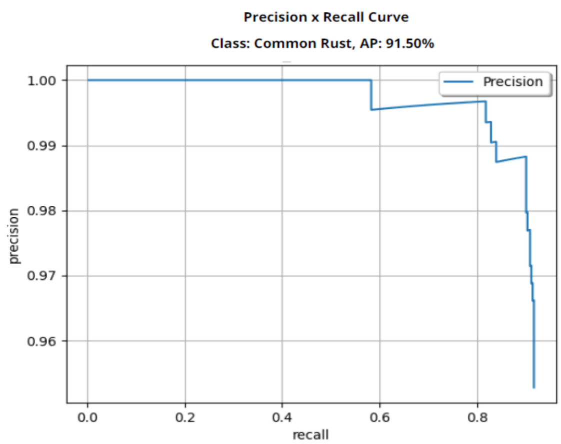
Figure 1. Total loss curve of our proposed system

Table 1. Proposed system results achieved for maize diseases

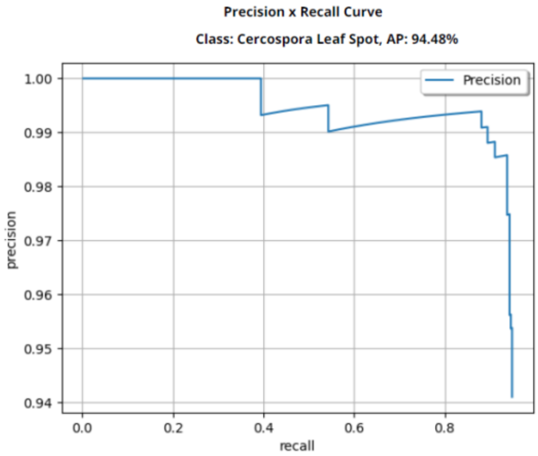
Class	ResNet50
Northern Leaf Blight	96.22%
Common Rust	91.50%
Bacterial Spot	94.48%
Total mean AP	**94.06%**



(a)

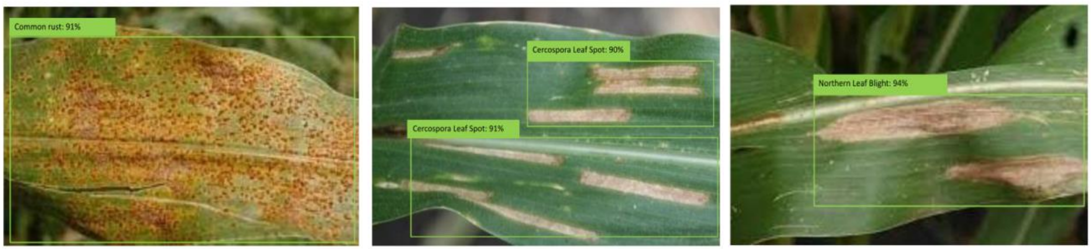


(b)



(c)

Figure 2. Precision x Recall curve for (a) Northern Leaf Blight (b) Common rust (c) Cercospora Leaf Spot



(a) (b) (c)

Figure 3. Qualitative results achieved by the proposed system (a) Common rust (b) Cercospora Leaf Spot (c) Northern Leaf Blight

Conclusion

The purpose of this study is to develop an automated detection model that uses a combination of image processing and deep learning techniques to analyze real-time images captured by the simple camera and detect and classify the three common maize plant diseases: Common Rust, Northern Leaf Blight, and Cercospora Leaf Spot. Maize dataset contains data like, various resolutions images (48MP, 12MP), medium, last and early infection status of maize leaves, complex background (e.g soil), images where the desired object (disease) is partially obscured, overlapped with something else (leaves, stems), or only halfway in the image. The proposed system (Faster R-CNN+ResNet-50) successfully detects three common maize diseases and achieved 91% accuracy with an error-rate less than 0.1. Currently the proposed system detects maize diseases, further work can be extended to detect other plant diseases by training the proposed system with other disease dataset.

References

Arjun, Kekane Maruti. "Indian agriculture-status, importance and role in Indian economy." *International Journal of Agriculture and Food Science Technology* 4.4 (2013): 343-346.

https://farmer.gov.in/m_cropstaticsmaize.aspx

Natarajan, V. Anantha, Ms Macha Babitha, and M. Sunil Kumar. "Detection of disease in tomato plant using Deep Learning Techniques." *International Journal of Modern Agriculture* 9.4 (2020): 525-540.

Brahimi, Mohammed, Kamel Boukhalfa, and Abdelouahab Moussaoui. "Deep learning for tomato diseases: classification and symptoms visualization." *Applied Artificial Intelligence* 31.4 (2017): 299-315.

Natarajan, V.A., Kumar, M.S., Patan, R., Kallam, S. and Mohamed, M.Y.N., 2020, September. Segmentation of Nuclei in Histopathology images using Fully Convolutional Deep Neural Architecture. *In 2020 International Conference on Computing and Information Technology (ICCIT-1441)* (pp. 1-7). IEEE.

Shijie, Jia, Jia Peiyi, and Hu Siping. "Automatic detection of tomato diseases and pests based on leaf images." *2017 Chinese automation congress (CAC)*. IEEE, 2017.

Malchi, S.K., Kallam, S., Al-Turjman, F. and Patan, R., 2021. A trust-based fuzzy neural network for smart data fusion in internet of things. *Computers & Electrical Engineering*, 89, p.106901.

Fuentes, Alvaro, et al. "A robust deep-learning-based detector for real-time tomato plant diseases and pests recognition." *Sensors* 17.9 (2017): 2022.

Kumar, M. S, and D. Harshitha. "Process innovation methods on business process Reengineering." *Int. J. Innov. Technol. Explor. Eng* (2019).

Khan, Saiqa, and Meera Narvekar. "Disorder Detection in Tomato Plant Using Deep Learning." *Advanced Computing Technologies and Applications*. Springer, Singapore, 2020. 187-197.

Sushama, C., Kumar, M.S. and Neelima, P., 2021. Privacy and security issues in the future: A social media. *Materials Today: Proceedings*.

Gampala, V., Kumar, M.S., Sushama, C. and Raj, E.F.I., 2020. Deep learning based image processing approaches for image deblurring. *Materials Today: Proceedings*.

Balaji, K., Kiran, P.S. and Kumar, M.S., 2021. An energy efficient load balancing on cloud computing using adaptive cat swarm optimization. *Materials Today: Proceedings*.

Hasan, Mosin, Bhavesh Tanawala, and Krina J. Patel. "Deep learning precision farming: Tomato leaf disease detection by transfer learning." *Proceedings of 2nd International Conference on Advanced Computing and Software Engineering (ICACSE)*. 2019.

Sangamithra, B., Swamy, B.M. and Kumar, M.S., 2021. A comparative study on a privacy protection in personalized web search. *Materials Today: Proceedings*.

Sreedhar, B., BE, M.S. and Kumar, M.S., 2020, October. A Comparative Study of Melanoma Skin Cancer Detection in Traditional and Current Image Processing Techniques. *In 2020 Fourth International Conference on I-SMAC (IoT in Social, Mobile, Analytics and Cloud) (I-SMAC)* (pp. 654-658). IEEE.

DeChant, Chad, et al. "Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning." *Phytopathology* 107.11 (2017): 1426-1432.

Peneti, S., Kumar, M.S., Kallam, S., Patan, R., Bhaskar, V. and Ramachandran, M., 2021. BDN-GWMNN: Internet of Things (IoT) Enabled Secure Smart City Applications. *Wireless Personal Communications,* pp.1-17.

Davanam G, T. Pavan Kumar, and M. S Kumar. "A Dynamic and adaptive learning mechanism to reduce cross layer attacks in cogntive networks." *Materials Today: Proceedings* (2020).

Chauhan, Ms Deepika. "Detection of Maize Disease Using Random Forest Classification Algorithm." *Turkish Journal of Computer and Mathematics Education (TURCOMAT)* 12.9 (2021): 715-720.

Kumar, M. Sunil, and K. Jyothi Prakash. "Internet of things: IETF protocols, algorithms and applications." *Int. J. Innov. Technol. Explor. Eng.*, 8, no. 11 (2019): 2853-2857.

Everingham, Mark, et al. "The pascal visual object classes (voc) challenge." *International journal of computer vision* 88.2 (2010): 303-338.

Abadi, Martín, et al. "Tensorflow: A system for large-scale machine learning." *12th {USENIX} symposium on operating systems design and implementation ({OSDI} 16)*. 2016.