International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

COPY RIGHT

2024 IJIEMR. Personal use of this material is permitted. Permission from IJIEMR must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating newcollective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works. No Reprint should be done to this paper; all copy right is authenticated to Paper Authors

IJIEMR Transactions, online available on 31st August 2024. Link

https://ijiemr.org/downloads.php?vol=Volume-13&issue=issue08

DOI:10.48047/IJIEMR/V13/ISSUE08/25

Title: "PREDICTING THE ACCURACY AND PERFORMANCE OF CORN DISEASE USING CONVOLUTION NEURAL NETWORK"

Volume 13, ISSUE 08, Pages: 181- 191

Paper Authors
Kartik Kumar, Sumika Jain, Varun Bansal

USE THIS BARCODE TO ACCESS YOUR ONLINE PAPER

To Secure Your Paper as Per UGC Guidelines We Are Providing A ElectronicBar code

International Journal for Innovative Engineering and Management Research
PEER REVIEWED OPEN ACCESS INTERNATIONAL JOURNAL
www.ijiemr.org

PREDICTING THE ACCURACY AND PERFORMANCE OF CORNDISEASE USING CONVOLUTION NEURAL NETWORK

[1]Kartik Kumar, [2]Sumika Jain, [3]Varun Bansal

[1]Research Scholar, M. Tech (CSE)Shobhit University, Gangoh
[2]Assistant Professor, Department of CSEShobhit University, Gangoh
[3]Professor, Department of CSEShobhit University, Gangoh

ktkkmr1998@gmail.com, sumika.jain@shobhituniversity.ac.in, varun.bansal@shobhituniversity.ac.in

Abstract— For agricultural output to continue rising, crop leaf diseases must be accurately and promptly detected. In order to detect illnesses of the maize leaf, recent research focus on utilizing deep learning (DL), machine learning (ML), and image processing approaches. Plant disease classification typically uses deep learning techniques. Those based on convolutional neural networks (CNN) are being employed more and more. This article evaluates the effectiveness and performance of the CNN architecture for image classification tasks. When it comes to identifying maize leaf disease, modified DL techniques outperform conventional ML techniques in terms of performance. The paper also presents the comparison with the reported work showing the accuracy of CNN model used in this work.

Keywords— CNN Model, Skip-Connected Convolutional Neural Network, Image Classification, Corn Disease.

I. INTRODUCTION

Maize (Zea mays L) is one of the most significant cereal crop that is cultivated in a variety of environmental circumstances throughout the world [1]. India is ranked fourth among the 170 countries that grow maize, but seventh in terms of production. It contributes roughly 4.6% and 2.4% of the world's total acreage and production respectively [2].

The majority of India's maize-growing regions are plagued by several common diseases, including Maydis Leaf Blight (MLB)/Southern Corn Leaf Blight (SCLB), Turcicum Leaf Blight (TLB)/Northern Corn Leaf Blight (NCLB), and Banded Leaf and Sheath Blight (BLSB). NCLB, also known as Turcicum Leaf Blight TLB, is the most serious and widespread disease infecting maize leaves worldwide, especially in India. NCLB is a fungal disease of maize or corn and is caused by a fungus called Exserohilum turcicum [3]. The fungus is active and grows well in cold to moderate temperatures and high relative humidity. This disease initially affects lower leaves in favourable environmental conditions before progressing upthe plant.

Southern Corn Leaf Blight also known as Maydis Leaf Blight is a fungal disease that the plant pathogen causes that affects maize. This disease is caused by the fungus Cochliobolus heterostrophus (formerly known as Helminthosporium maydis). Tan to brown lesions is typical initial sign of SCLB, which often begins at the lower leaves and moves upward. The lesions may be shaped like a typical rectangle, and in the right circumstances, they may combine to cause significant harm. It grows in humid, warm environments around the

world [4, 5]. It can significantly reduce yield and quality of grains if left uncontrolled.

Banded leaf and sheath blight is caused by maize pathogen named basidiomycete fungus Rhizoctonia solani, which is mostly prevalent in China, South Asia, and South East Asia. It is thought to be an emerging disease that causes anything from small losses to total crop elimination. Additionally, diseased leaves dry out and die more quickly, and young tillers may be lost.

Common Rust is caused by the fungus Puccinia Sorghi. Late-onset infections have very little effect on yield. These are easily recognized and distinguished from other diseases because they create dark, reddish-brown pustules (uredinia) on both the upper and bottom surfaces of the corn leaves [5, 6, 7].

Considering the damage caused due to leaf diseases, accurate and timely diagnosis may be essential for improving the yield and reducing the losses. Existing traditional disease detection methods often rely on manual observation, which may lack the requisite speed and precision required for large-scale farming operations. Moreover, inexperienced growers frequently misjudge diseases, leading to improper pesticide usage, thereby negatively impacting corn yield, quality, and the environment. A possible answer to these problems has been offered recently by deep learning (DL), a subfield of artificial intelligence. A highly accurate and effective solution for early detection is provided by the automated diagnosis of crop leaf diseases using deep learning models specifically designed for corn disease classification, which takes advantage of developments in deep learning techniques and digital image processing technologies. Specifically, convolutional neural networks (CNNs) have shown impressive performance in image-based tasks, which makes them a good fit for deciphering the complex visual patterns linked to different corn illnesses. If this deep learning strategy is successful, it might greatly increase global food security concerns, advance sustainability, and boost total agricultural production [8]. Keeping the challenges in mind, we have designed a CNN based model for the detection of maize leaf.

The diseases focused in this work are Blight and Common Rust, which are most prevalent in India [9] based on the literatures survey done. The general aim of this paper is to introduce CNN approaches into classifying various types of maize leaf diseases (GLS, CR and LB), and to predict the severities of the same. A CNN model has been designed to predict the severities of the maize leaf diseases.

II. LITERATURE SURVEY

A lot of study has been done for predicting the diseases in the corn leaf. Deep learning which is a branch of machine learning has been used in most of the prediction techniques [10, 11]. Several deep learning techniques exist in the literature, out of which, Convolutional Neural Networks (CNNs) were most often utilized.

The use of EfficientNet deep learning model for the classification of leaf diseases in maize was proposed by M. Çakmak [12]. The model was trained using the maize leaf disease dataset. 4188 images were used for the original dataset and 6176 images for the augmented dataset. The diseases studied were common rust, gray leaf spot, and leaf blight. The proposed

model was then compared with ResNet50, Dense-Net121, VGG19 and Inception V3 models based on their accuracy, sensitivity, F1-Score and precision values. The EfficientNet B6 model achieved 98.10% accuracy on the original dataset, while on theaugmented dataset, the EfficientNet B3 model achieved thehighest accuracy of 99.66%.

Another study by Rai and Phuja [13] investigated a real- time method for segmentation and identification of NLB illnesses using a deep learning-based Attention U-Net model. Data augmentation was done to improve the model'sefficacy following image annotation. After the model was trained for a maximum of 50 epochs with Adam serving as the optimizer and an initial learning rate of 0.0001, its performance was assessed on the test dataset. With corresponding Intersection over Union (IoU) values of 72.41%, 70.91%, and 51.95%, the Attention U-Net model outperformed the Res U-Net and Plain U-Net image segmentation algorithms, according to the study. Pixel by pixel, the proposed model achieves an average F1 score of85.23%.

In one such study, the diagnosis of illnesses in maize plants was done using deep convolutional neural networks [14]. The three distinct but prevalent types of maize diseases—leaf blight, common rust, and gray leaf spot— were captured in 4,988 images by the authors. Thirteen different pre-trained CNN models (Xception, Shuf-flenet, Resnet-18, Resnet-50, Resnet-101, Alexnet, Densenet201,Googlenet, Incep-tionresnetV2, InceptionV3, MobilenetV2, VGG-16, VGG-19, and Resnet-18) were used to test and train all of these photos. The models were evaluated based on sever-al metrics, including MCC, Kappa, F1 Score, accuracy, specificity, precision, and False Positive Rate. Comparing the models for the diseases listed, the results show that Densenet201 has the highest accuracy and the lowest False Positive Rate (FPR) whereas VGG-19 has the highest.

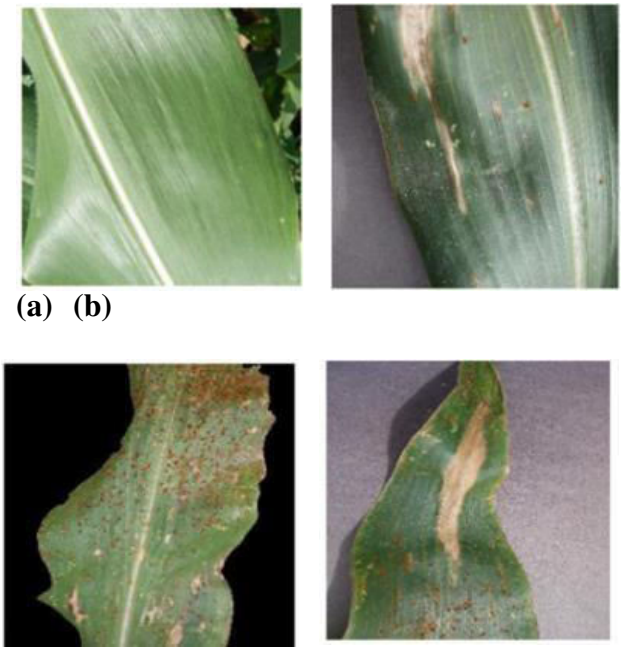
A multi-model network including multi-contextual networks was created by Rashid et al. [15] and is automatically exploited with CNN methods in many variation forms. In terms of accuracy, MMFNet using fused features outperformed MMFNet without fused feature approach. It was possible to achieve an overall accuracy of 99.23% since the datasets used for training were varied.

Utilizing a collection of corn leaf photos from farmers' fields in the Madura Region, the authors developed a classification system utilizing the CNN method with four target classes: healthy, gray leaf spot, blight, and common rust. Several CNN architectural models, including SqueezeNet, AlexNet, ResNet-101, ResNet-50, and ResNet-18, were used for testing. The parameters included a data distribution of 70% for training data and 30% for testing data, five epochs with 100 iterations, and a learning rate of 0.0001 utilizing Adam optimization. A very good accuracy rating of 95.59% is obtained in the test results for categorizing corn photos using the Convolutional Neural Network approach with the ResNet-50 architecture [16].

For the detection of corn leaf disease, Ashwini and Sellam [17] proposed a hybrid model named Whale Optimization Algorithm with Joint Search Mechanisms (JSWOA) optimized hybrid 3DCNN-RNN model. For enhancing the identification of 3-Dimensional images, 3DCNN includes Four MaxPooling3D layers and six 3D convolutional layers. Two datasets used were Maize_in_field, and KaraAgro AI. According to the results of the simulation, the

suggested hybrid model predicts dif- ferent classes of maize leaves on both datasets with a performance level above 90%.

Olayiwola and Adejoju [18] used a deep learning model called Keras on TensorFlow based on a CNN to classify three common diseases of maize leaves: leaf spot, common rust, and leaf blight. All the four classes were precisely identified and the accuracy was 98.56%.to reduce overfitting. This promotes feature redundancyand improves model generalization.



(a) (b)

(c) (d)

Fig. 1: Corn leaf images (a) Healthy (b) Gray Leaf Spot (c)Common rust (d) Blight.

III. DATASET

At every stage of object recognition research, from the training phase to assessing the effectiveness of recognition algorithms, a suitable dataset is necessary. A total of 4188 Images have been gathered from various sources. Which are separated into four groups. There are four categories: one for healthy leaves and the others for blight, grey leaf spot, and common rust.

IV. IMPLEMENTATION

A. CNN

A simple CNN design often starts with an input layer that represents raw data, such as photographs, and each pixel functions as a neuron. It is followed by convolutional layers made up of numerous filters or kernels, each of which performs convolutions on limited portions of the input data to extract certain features. The receptive field of feature maps and activation functions like ReLU introduce non-linearity to enable complex feature representations, while weight sharing and parameter sharing ensurecomputational efficiency

and enable the network to learn spatial hierarchies of features, followed by pooling layers, such as max pooling or average pooling. This involves systematically down sampling feature maps to reduce spatial dimensions, capturing essential information while reducing computational load and improving translation invariance. It is frequently combined with techniques such as batch normalization to stabilize learning by normalizing activations within each minibatch. Dropout layers deactivate a fraction of neurons randomly during training The architecture also incorporates fully integrated connected layers that flatten high-dimensional feature maps into vectors and provide predictions by performing computations with weights and bias. The output layer typically consists of a softmax function for multi-class classification problems, offering probability distributions over class labels, or a sigmoid function for binary classification tasks, generating probabilities of belonging to each class. It is supported by optimization algorithms such as stochastic gradient descent (SGD) variants, Adam, or RMS prop, which iteratively update network parameters based on gradients computed through backpropagation. Hyperparameters such as learning rate, momentum, and weight decay are refined using methods such as grid search or random search to optimize model performance and convergence, and architectural variations include deeper networks with increased depth and width. By enabling tasks like autonomous driving, facial recognition, and disease diagnosis, this forms the foundation for a plethora of advanced architectures that are customized for particular tasks and domains, ranging from image classification and object detection to natural language processing and medical imaging. This highlights the profound significance and continuous evolution of CNNs within the field of machine learning and artificial intelligence [19].

Algorithm:

Inputs:-

num_classes: Number of classes/categories in the dataset. input_shape: Shape of the input images (height, width,channels).
data_path: Path to the dataset containing all classes. batch_size: Number of images to be processed in a single batch.
img_size: Target size to which images are resized (height,width).
num_epochs: Number of epochs for training. learning_rate: Learning rate for the optimizer.
random_state: Seed for random number generators to ensure reproducibility.
train_size: Proportion of the dataset used for training. val_size: Proportion of the remaining dataset used for validation.
callbacks: Custom callback function to monitor training and apply certain actions (e.g., early stopping).

Output:
Trained CNN model
Plot of training and validation metrics Validation loss and accuracy
Test loss and accuracy.
Confusion matrix and Classification report.

Step 1: Data PreprocessingLoad and organize dataset

Split dataset into training, validation, and test sets. Initialize data generators: Create data generators fortraining, validation, and testing without data augmentation.

Step 2: Model Architecture
Construct a Sequential model with the following layers: Convolutional layer with 32 filters, 3x3 kernel size, ReLUactivation, and input shape.
MaxPooling layer with 2x2 pool size. Repeat the above layers with 64 filter size.
Flatten layer to convert 2D matrix data to a vector.
Fully connected Dense layer with 64 neurons and ReLUactivation.
Output Dense layer with softmax activation having thenumber of neurons equal to num_classes.

Step 3: Model Compilation and Training
- Compile the model using the Adamax optimizer andcategorical crossentropy loss.
- Train the model for a maximum of 4 epochs with earlystopping based on validation accuracy.

Step 4: Plot Training and Validation Metrics
- Plot training and validation loss and accuracy over epochswith annotations for the best epoch.

Step 5: Model Evaluation on Test Set
- Evaluate the model on the test set to compute test loss,accuracy, and additional metrics.

Step 6: Create Confusion Matrix and Classification Report:
- Generate the confusion matrix and classification reportusing the model's predictions on the test set.

Step 7: End.

The loss and accuracy have been calculated through somestandard formulas listed below process was conducted to determine the optimal number ofdense units, dropout rates, and learning rates.

The provided TensorFlow code implements a CNN architecture for image classification tasks, with hyperparameters including num_classes set to 4 for the number of classes in the dataset, input_shape defining the dimensions of input images (256x256 pixels with 3 color channels), and learning rate assigned as 0.01 for the Adamoptimizer. The CNN architecture comprises four convolutional layers with filter sizes 32, 64, 64, and 64, each followed by ReLU activation functions. After each convolutional layer, max pooling layers with a pool size of(2, 2) are applied for downsampling. Following the convolutional layers, the flattened output is passed through a fully connected dense layer consisting of 64 units with ReLU

activation, and a dropout layer to prevent overfitting. Finally, the output layer with num_classes units and softmax activation is employed for multi-class classification.

The experiments were conducted for 4 epochs using Anaconda and Jupyter Notebook on an Intel Core i3 CPU operating at 1.80 GHz. The evaluation focused on precision, recall, F1-scores, and overall model correctness.

Table 1 presents the performance metrics for the CNN architecture. Additionally, Fig. 2 and 3 illustrates the training and validation loss and accuracy graph for the CNN model respectively. Fig. 4 displays the confusion matrix for the CNN model.

Table 1. Performance Parameters for CNN Model

1. $Accuracy = \frac{Tp+Tn}{Tp+Tn+Fp+Fn}$

2. $Recall = \frac{Tp}{Tp+Fn}$

3. $Precision = \frac{Tp}{Tp+Fp}$

4. $F1\ Score = \frac{2\times Precision\times Recall}{Precision+Recall}$

	Precision rate	Recall	F1 score	Support
Blight	0.80	0.77	0.78	86
Common rust	0.94	0.91	0.92	98
Grey Leaf Spot	0.58	0.67	0.62	43
Healthy	0.98	0.97	0.97	88
Accuracy			0.85	315
Macro avg	0.82	0.83	0.82	315
Weighted avg	0.86	0.85	0.86	315

where T_p is true positive, T_n is true negative, F_p is false positive, and F_n is false negative.

V. RESULTS AND ANALYSIS

The advancement of deep learning techniques has significantly improved image classification tasks, leading to substantial gains in accuracy and efficiency. To optimize the performance of the models, an extensive optimization

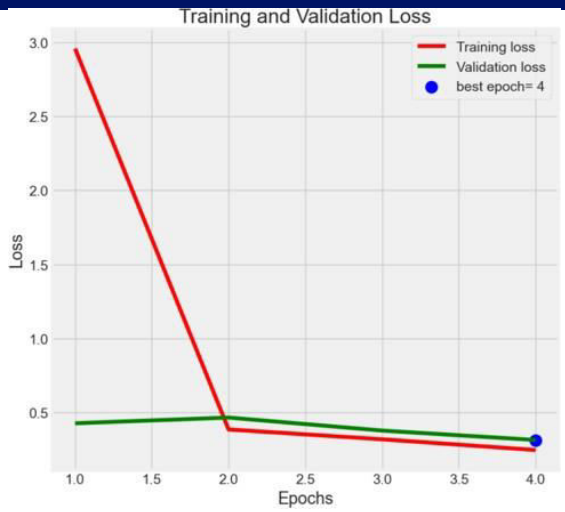


Fig. 2. CNN Model Loss Graph for Training and Validation data

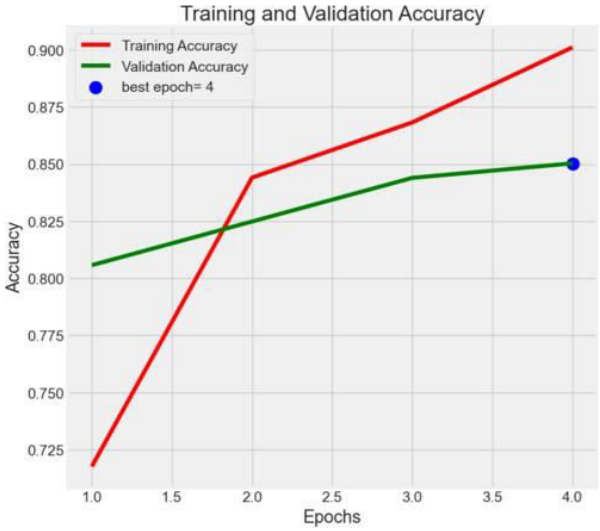


Fig. 3. CNN Model Accuracy Graph for Training and Validation data

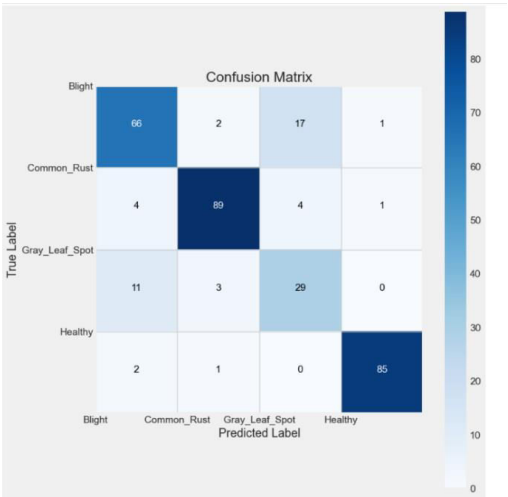


Fig. 4. Confusion Matrix for CNN Model

Diseases diagnosed	Dataset	No. of images	ML/DL Techniques used	Accuracy obtained
Maydis Leaf Blight, Turcicum Leaf Blight, Banded Leaf and Sheath Blight, &Healthy leaves	ICAR-IIMR, Ludhiana	5939	Inception-v3_flattenfc	95.42% [2]
Healthy Leaf, Cercospora, Northern leaf blight, Common rust	Mohanty plant village	200	AlexNet	93.5% [5]
Healthy leaf, Common rust, Northern leaf blight	Plant village, Corn plantations in the Raebareli	4382	Model based on realtime deep learning	88.46% [7]
Healthy, Gray Leaf Spot, Common rust, Blight (This Work)	Kaggle	4188	CNN	95.23% (Common Rust) 88.89% (Gray Leaf Spot) 88.23% (Blight)

Table 2. Comparison of our CNN Model with previous work

From Table 1, it can be observed that the precision rate is more for Common Rust compared to leaf blight and grey leaf spot using the CNN model. F1 score is also high in case of Common rust disease. Table 2. shows the comparison of our CNN Model with previous work. From the table it can be observed that the CNN model outperforms other reported model having almost same number of datasets and diseases as in our work.

VI. CONCLUSION

Considering the agricultural benefits of maize and its use as a main source of food, we have developed a CNN model for predicting the common diseases in maize plant. The diseases studied include grey leaf spot, common rust and blight. This is necessary as the diseases results in lower productivity of the crop resulting in food shortage also. We have calculated the performance of the model using several parameters including accuracy, precision, F1 score and loss. The proposed model shows better accuracy compared to model using approximately same number of datasets. Future work may include comparing the model with more diseases increasing the number of datasets.

REFERENCE

[1] Kaur, H., Kumar, S., Hooda, K.S., Gogoi, R., Bagaria, P., Singh, R.P., Mehra, R. and Kumar, A., 2020. Leaf stripping: an alternative strategy to manage banded leaf and sheath blight of maize. Indian Phytopathology, 73, pp.203-211.

[2] Haque, M.A., Marwaha, S., Deb, C.K., Nigam, S., Arora, A., Hooda, K.S., Soujanya, P.L., Aggarwal, S.K., Lall, B., Kumar, M. and Islam, S., 2022. Deep learning-based approach for identification of diseases of maize crop. Scientific reports, 12(1), p.6334.

[3] Jackson-Ziems, T.A., 2016. Northern Corn Leaf Blight.

[4] Haque, M.A., Marwaha, S., Arora, A., Paul, R.K., Hooda, K.S., Sharma, A. and Grover, M., 2021. Image-based identification of maydis leaf blight disease of maize (Zea mays) using deep learning.

[5] Syarief, M. and Setiawan, W., 2020. Convolutional neural network for maize leaf disease image classification. Telkomnika (Telecommunication Computing Electronics and Control), 18(3), pp.1376-1381.

[6] Sibiya, M. and Sumbwanyambe, M., 2019. A computational procedure for the recognition and classification of maize leaf diseases out of healthy leaves using convolutional neural networks. AgriEngineering, 1(1), pp.119-131.

[7] Mishra, S., Sachan, R. and Rajpal, D., 2020. Deep convolutional neural network based detection system for real-time corn plant disease recognition. Procedia Computer Science, 167, pp.2003-2010.

[8] Panigrahi, Kshyanaprava Panda, Himansu Das, Abhaya Kumar Sahoo, and Suresh Chandra Moharana. "Maize leaf disease detection and classification using machine learning algorithms." In Progress in Computing, Analytics and Networking: Proceedings of ICCAN 2019, pp. 659-669. Springer Singapore, 2020.

[9] https://iimr.icar.gov.in/?page_id=2136.

[10] Amin, Hassan, Ashraf Darwish, Aboul Ella Hassanien, and Mona Soliman. "End-to-end deep learning model for corn leaf disease classification." IEEE Access 10 (2022): 31103-31115.

[11] Baliyan, Anupam, Vinay Kukreja, Vikas Salonki, and Kuldeep Singh Kaswan. "Detection of corn gray leaf spot severity levels using deep learning approach." In 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions) (ICRITO), pp. 1-5. IEEE, 2021.

[12] Çakmak, M., 2024. Automatic Maize Leaf Disease Recognition Using Deep Learning. Sakarya University Journal of Computer and Information Sciences, 7(1), pp.61-76.

[13] Rai, C.K. and Pahuja, R., 2024. Northern maize leaf blight disease detection and segmentation using deep convolution neural networks. Multimedia Tools and Applications, 83(7), pp.19415-19432.

[14] Dash, A. and Sethy, P.K., 2024. Statistical analysis and comparison of deep convolutional neural network models for the identification and classification of maize leaf diseases. Multimedia Tools and Applications, pp.1-14.

[15] Rashid, R., Aslam, W. and Aziz, R., 2024. An Early and Smart Detection of Corn Plant Leaf Diseases Using IoT and Deep Learning Multi-Models. IEEE Access.

[16] Rachmad, A., Fuad, M. and Rochman, E.M.S., 2023. Convolutional Neural Network-Based Classification Model of Corn Leaf Disease. Mathematical Modelling of Engineering Problems, 10(2).

[17] Ashwini, C. and Sellam, V., 2024. An optimal model for identification and classification of corn leaf disease using hybrid 3D- CNN and LSTM. Biomedical Signal Processing and Control, 92, p.106089.

[18] Olayiwola, J.O. and Adejoju, J.A., 2023, June. Maize (Corn) leaf disease detection system using convolutional neural network (CNN). In International Conference on Computational Science and Its Applications (pp. 309-321). Cham: Springer Nature Switzerland.

[19] Ghose, S., 2020, November. Corn or maize leaf disease dataset. Kaggle. https://www.kaggle.com/datasets/smaranjitghose/corn-or- maize-leaf-disease-dataset.