Crop Disease Prediction with Convolution Neural Network (CNN) Augmented With Cellular Automata

Kiran Sree Pokkuluri
Department of Computer Science and Engineering,
Shri Vishnu Engineering College for Women (A),
Bhimavaram
drkiransree@gmail.com

SSSN Usha Devi Nedunuri
Department of Computer Science and Engineering,
University College of Engineering-Jawaharlal Nehru
Technological University, Kakinada
ushaucek@gmail.com

Abstract: *Food security is the primary concern of any country, and crop diseases are the major threats to this. Each stage of the crop will be affected by various diseases starting from seeding to ripeness. The spread of the crop diseases is very rapid, and identification of this is challenging as the infrastructure is very less to monitor the same. After a thorough literature survey, we understood there are several ways of predicting the disease and yield prediction. We have developed two new and robust classifiers, one which processes images to predict the crop's diseases, and the second one uses the weather data to predict the same. Both classifiers use deep-learning technique Convolution Neural Networks (CNN) augmented with six neighborhood cellular automata to predict the crop disease and yield. This work will be first of its kind to develop two classifiers for six crop disease prediction. The average time to compute the yield of a particular crop is less than 0.5 nanoseconds. The first classifier is named as CNN-CA-I, which was trained/tested to process 245 different crop species and 132 diseases associated with these crops where image segmentation is done with higher accuracy, thus strengthening the disease recognition system. We gave collected public datasets of 12, 45,678 images diseases and leaves of healthy plants taken in ideal conditions. This model reports an accuracy of 92.6% on a tested standard dataset for disease and yield prediction. The second classifier is CNN-CA-W that predicts crop disease trained and tested with environment data.8,52.624 datasets are collected from ECMWF for processing the weather data to predict the crop's condition and thus reporting the yield of the crop. This model reports an accuracy of 90.1% on a tested standard dataset.*

Keywords: *CNN, cellular automata, disease prediction, image segmentation, weather prediction*.

Received May 6, 2020; accepted November 24, 2020
https://doi.org/10.34028/iajit/19/5/8

1. Introduction

The growth and development of any nation depend on agriculture growth. The productivity of the crop depends on the various crop-related diseases. Diseases may affect the entire plant or affect various parts of plants such as root, stem, seed, flower, and foliage, etc. Many researchers have proposed different systems pertaining to diseases, but the research focus is either theoretical or considering the leaves (image processing) or considering the weather parameters. The disease and crop predictions must consider both of these to build an accurate prediction. We propose a mechanism that considers both these and predicts both yields and disease pertaining to crops. The datasets collected by us are pertaining to the prominent crops of India, i.e., rice, wheat, barley, sugarcane, cotton, and oilseeds. This work is the first of its kind to predict the disease pertaining to six prominent crops by processing various images and the weather datasets.

Deep Learning is productive when massive data is available for training, and these models have solvedmany complicated, dynamic real-time problems with higher accuracy with time.

Convolution Neural Networks (CNN) is a unique class of neural networks [3] that processes known data, which has grid topology. CNN has many applications, and it operates on a mathematical operator, which is called convolution. It uses many linear operators, represented in matrix form, and then extracts the features of the samples. We propose a distinctive architecture that processes both weather data, plant images and operates directly and uses simple pooling operations & convolutions, which is termed as CNN augmented with the cellular automata rules to identify these diseases. The main challenge in this research is mapping of the disease characteristics to CNN and proceed to train /test the classifier. This paper is organized in the following way, section 1 depicts the introduction to the problem, section 2 provides the extensive literature survey, section 3 gives the design and methodology used in our work, section 4 provides the results and comparisons to the existing work and section 5 provides the conclusion to our work.

2. Literature Survey

Maji and Chaudhuri [13] has explored the use of CA in design grouping with certain esteemed information. A genetic algorithm is used to implement Fuzzy Cellular Automata, which is a special class of CA. Maji and Chaudhuri [15] has proposed a hypothesis and utilization of CA for design arrangement. A genetic algorithm is used to develop fuzzy MACA. Maji *et al*. [14] have additionally proposed the mistake rectifying the ability of cell automata dependent on cooperative memory. The ideal CA [19, 20, 27] is advanced with the definition of a re-enacted toughening program, which can be helpful in VLSI innovation**.** We have reviewed various types of CA [15, 28] that can be applied for this technique.

Kendal *et al.* [9] have reviewed various disease prediction systems based on weather. Authors have compared various works developed on Multiple Regression (MR), and Support Vector Machine (SVM), Backpropagation Neural Network (BPNN), Generalized Regression Neural Network *(*GRNN*).* The authors have considered various parameters to measure the performance of the system, i.e., % Mean Absolute Error (MAE) wrt average correlation coefficient(r). After a series of experiments, authors have concluded that SVM [22, 26] performance is better compared to the existing literature. Chakraborty *et al.* [6] have proposed an Artificial Neural Network (ANN) to predict various crop diseases based on the variations of weather conditions. Authors have considered different attributes of weather like rainfall, wind speed, temperature, sunshine hours, etc. The performance of ANN [23, 24] is compared with Regression methods with %error in various types. Royer *et al.* [21] have studied the impact on the weather on the crop yield based on the mesoscale.

Priyanka *et al.* [17] has processed various satellite images using ANN methods. Newlands *et al.* [16] has developed a mechanism that processed the weather parameters like temperature, humidity, and integrated this approach with data pertaining to the satellite. Bourke [2] have developed a mechanism that processes various weather parameters, particularly with respect to temperature variations. Kurtah *et al.* [11] has developed a novel disease propagation detection system using ANN, and the developed classifier is trained and tested with various measures. Crane-Droesch, *et al.* [4] has studied the impact of crop yield changes with the weather change.

Khamparia *et al.* [10], have used a combination of autoencoders with CNN to process various crop images to predict the diseases. Authors have tested their classifiers with few images of leaves into eight classes. The accuracy of the system was reported with precision and recall. Ayub and Moqurrab [1] have developed a system that uses various data mining techniques to predict crop diseases. The developed classifier performance is measured by mean accuracy [7, 25, 27], F1score, precision, and recall. This work is compared with Random Forest, SVM, Decision Tree, Neural Networks (NN), K-Means Neighbors (KNN). Mohanty *et al.* [12] have developed an image-based crop detection system using deep learning. You *et al.* [29] have applied a Gaussian process on remote sensing data to predict crop diseases.

After the literature survey on various DL methods and CA types, we understood that CNN, with an embedding layer augmented with eight neighborhood CA [8], would be a better classifier to address the problem of crop disease and yield prediction. After the survey of various crop prediction systems that process weather data, the parameters for testing the accuracy is MAE wrt to r (Average Coefficient) [5] and the methods which process images of leaves should be tested for accuracy, precision, recall, and F1score.

3. The Design and Methodology

3.1. Architecture of CNN-CA-I (Convolution Neural Network-Cellular Automata-Image)

We have proposed a novel and robust CNN augmented with CN to address this problem after a through feasibility study. It was developed in the combination of CA encoding and CNN to process the features is shown in Figure 2 where CA possesses the innate capacity of handling numerical data. The CA encoding takes an image and generates a good quality image in dimensionally, and these features are summarized at various levels. Convolution function is used to take a feature map that will summarize the identified features with the help of a filter. The image segmentation happens at the convolution layer.

Initial convolution layers will process general characteristics, and when the iterations happen deeper go, they will process more complex features very easity. CA strengthens the filters we used during training and testing-batch normalization aim at improving the stability, speed, the performance of CNN. Activation functions augmented with CA rules are used to induce non-linearity into the system, and these are located in dense layers.

Table 1. Data set description.

Class	Disease	Crop
Class 0	Rice Blast	Rice
Class 1	Brown Spot	Rice
Class 2	Barley Yellow Dwarf	Wheat
Class 3	Black Chaff	Wheat
Class 4	Spot blotch	Barley
Class 5	Net blotch	Barley
Class 6	Red rot disease	Sugarcane
Class 7	Smut	Sugarcane
Class 8	Alternaria leaf spot	Cotton
Class 9	Asochyta blight	Cotton
Class 10	Alternaria Black Spot	Oil Seeds
Class 11	Blackleg	Oil Seeds
Class 12	Healthy	All(Six Crops)
Class 13	Un Healthy	All(Six Crops)

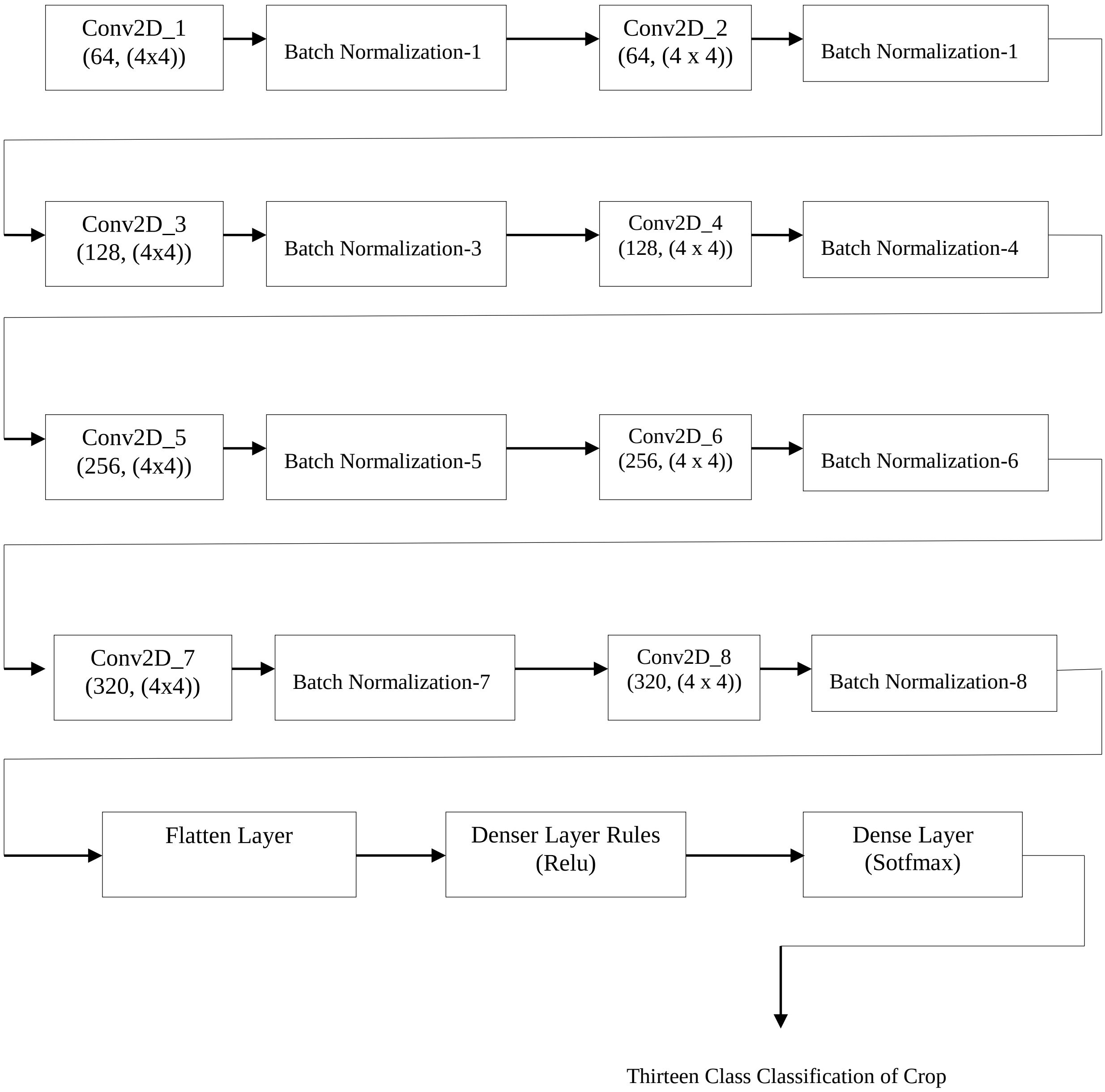

Figure 1. Architecture of CNN-CA-I.

- **Procedure to Create CNN:**

The working of CNN augmented with CA

1. Initialize the weights to zero
2. Analysis of the observation one as Input
3. Start propagating from left to right in forward direction
4. Continue the propagation using activation till we have the predicted values/result
5. Evaluate the actual output with the predicted.
6. Computer the error generated
7. Propagate the error computed from right to left(back propagation)
8. Measure the generated error by comparing the actual and predicted value. The error has to be back propagated from right to left.
9. Synchronize the corresponding weights through updation.
10. Repeat the steps from 1 to 6 for each batch of observations

3.2. Architecture of CNN-CA-W(Convolution Neural Network-Cellular Automata-Weather)

The methodology remains the same for this classifier as reported in 2.1 also, but the input is various parameters which process weather parameters like temperature, atmospheric pressure, humidity, precipitation, rainfall, and wind speed of the particular location, as shown in Figure 2. The minimum, mean and maximum values of the above parameters are extracted from the dataset and processed them for the prediction.

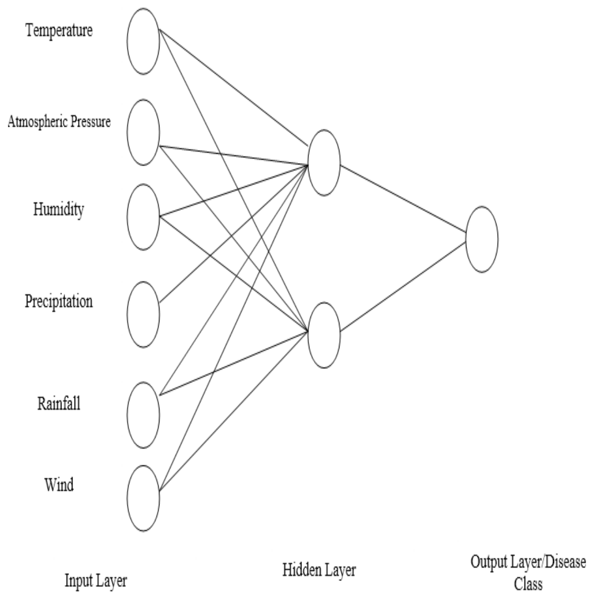

Figure 2. General architecture of CNN-W.

Each convolution uses 4X4 kernel, followed by 3X3, Followed by 2X2. After processing the weather datasets collected from ECMWF, we will get any one of the four classes. The six classes identified are Thunder Strom, Rain, Heavy Rain, Marginal Rain, Dry, Marginally Dry. The entire classifier uses eight pooling/convolution layers, succeeded by five connected layers, as discussed in the earlier section, the dataset description is shown in Table 2.

Table 2. Data set description for the second classifier.

Class	Disease_General	Weather Class
Class 1	Rice_D	Thunder Strom
Class 2	Wheat_D	Heavy Rain
Class 3	Barley_D	Rain
Class 4	Sugarcane_D	Marginal Rain
Class 5	Cotton_D	Marginally Dry
Class 6	Oil Seeds_D	Dry
Class	Disease_General	Weather Class

4. Results and Discussion

The results and discussion section is organized as follows. Section 3.1 completely discusses the design of CNN-CA-I, performance evaluation, and comparison of the existing classifiers. Section 3.2 completely discusses the design of CNN-CA-W, performance evaluation, and comparison of the existing classifiers. Finally, the yield of the crop is computed from the values reported in these two classifiers.

4.1. CNN-CA-W Classifier for Crop Disease Prediction

We gave collected public datasets [18] of 12, 45, 678 of leaves of healthy and infected crops in ideal conditions pertaining to 245 different crop species and 132 diseases. The collected leaves are pertaining to rice, wheat, barley, sugarcane, cotton, and oilseeds. The raw data as initially pre-processed by using fuzzy multiple attractor cellular automat and finally we have made 2683 data pertaining to rice, 67389 data pertaining to wheat, 30129 data pertaining to barley,59423 data pertaining to sugarcane, 296423 pertaining to cotton and 45789 pertaining to oilseeds. We have identified two prominent diseases for each crop and built a classifier that can predict thirteen different types of classes, as shown in Table 1. We have taken 65% of thee datasets for training and 35% for testing the classifier.

The dataset is pre-processed to apply the transformation to minimize the dimension of the images. Transformations will enable the images to undergo any changes possible. The process was depicted in Figure 1. The input is fed to two convolution layers with 64 filters of size 3X3. The activation function is applied to the layer internally. Normalization is applied paralleley so that the training size minimizes considerably. Then the input is fed to another two convolution layers of sizes 4X4 with 64 filters.

Table 7 represents testing and training accuracy for different sizes of epochs and corresponding filter size for a batch of 64. The model reports a training accuracy of 96.8% and testing accuracy of 83.6%.

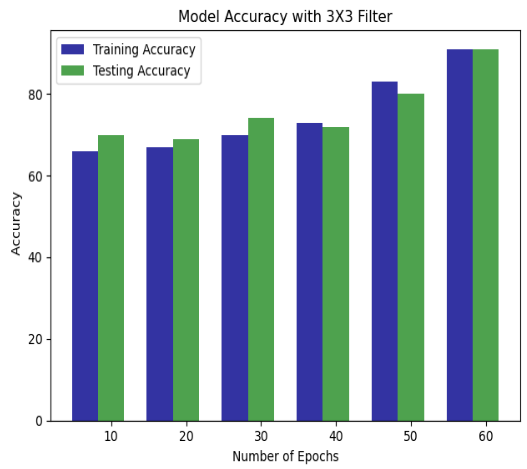

Figure 3. Model % accuracy with 3x3 filter.

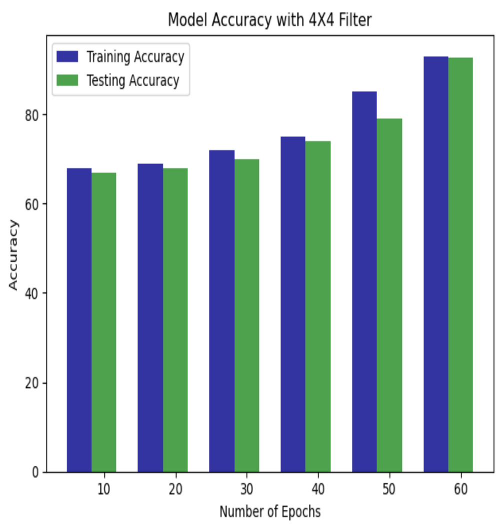

Figure 4. Model % accuracy with 4x4 filter.

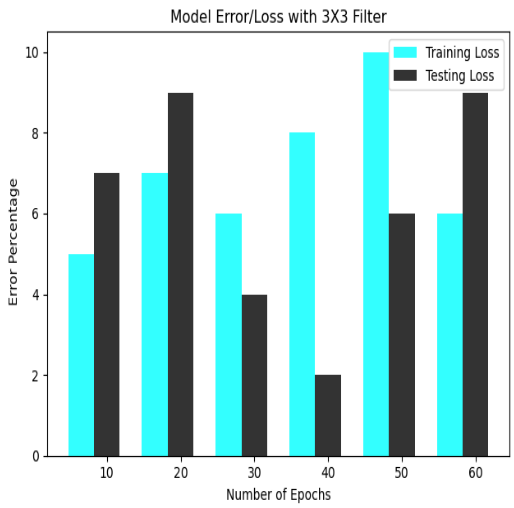

Figure 5. Model-error % with 3x3 filter.

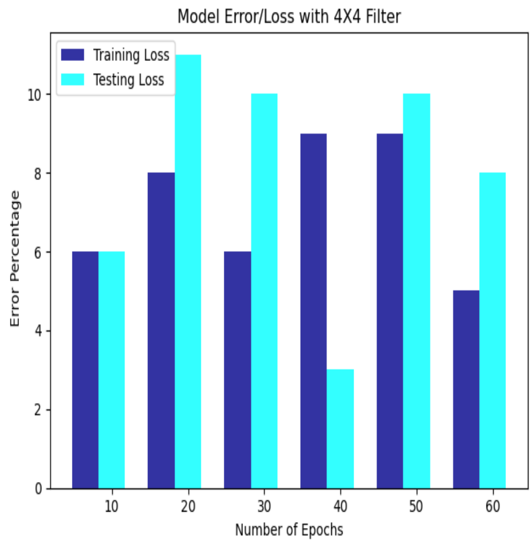

Figure 6. Model-error % with 4x4 filter.

Table 3. Accuracy computation for with variable epochs and filters.

Epochs	Filter size	Size of Batch	Accuracy (Training)	Accuracy (Testing)
10	4X4	64	94.1	81.3
20	3X3	64	93.6	83.2
30	4X4	64	92.8	86.9
40	4X4	64	100	84.6
50	4X4	64	100	86.8
60	3X3	64	96.8	87.6

Table 4. Recall and Precision computation for 4×4(F).

Class Label	Precession	Reported Recall	F1Score	Support
Class 0	0.85	0.79	0.79	55
Class 1	0.89	0.84	0.85	56
Class 2	0.92	0.80	0.80	60
Class 3	0.90	0.81	0.76	54
Class 4	0.92	0.80	0.80	60
Class 5	0.91	0.73	0.75	52
Class 6	0.94	0.72	0.83	52
Class 7	0.85	0.71	0.86	55
Class 8	0.88	0.76	0.78	51
Class 9	0.87	0.72	0.82	50
Class 10	0.79	0.71	0.85	56
Class 11	0.82	0.75	0.84	54
Class 12	0.83	0.79	0.83	53
Class 13	0.88	0.76	0.82	56
Average	**0.87154**	**0.75769**	**0.81385**	**54.1538**

Figures 3 and 4 reports the training and testing accuracies when the classifiers have used 3X3 and 4X4 filter, respectively. The accuracies reported are considerably better, and Figures 5 and 6 shows the training & testing error percentage when the classifiers have used 3X3 and 4X4 filters.

We have identified precision, recall, f1score, and support as the parameters to evaluate our developed classifier, as shown in Figure 7. As Class 0, 1 is pertaining to rice crop, the average accuracy reported was 0.89, which is considerably more than the existing literature. Class 2, 3 represents the crop wheat, and the average precision reported is 0.87, which is best among the cited literature. Class 4, 5 represents barley cop, and the average procession reported is more than 0.91. Class 6, 7 are pertaining to sugarcane; the average accuracy reported was 0.87, which is considerably more than the existing literature. Class 8, 9, are related to cotton crop; the average accuracy reported was 0.90, which is considerable. Class 10, 11 are of oilseed crop; the average accuracy reported was 0.87, which is better than the existing literature. CNN-CA-I performance when compared with standard methods

REG, BNN, GNN, and SVM. The precision, Recall, F1 Score values were better, and the competitor next to CNN-CA-I is identified as SVM as shown in Table 4.

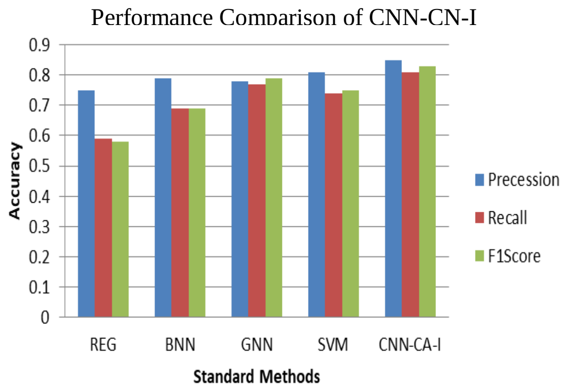

Figure 7. Performance comparison of CNN-CA-I with existing literature.

4.2. CNN-CA-W Classifier for Crop Disease Prediction

We have collected 8, 52, 624 datasets of environment data, which is obtained from ECMWF to train and test CNN-CA-W, as discussed earlier. We have considered 70% datasets for training and 30% datasets for testing the classifier. The number of classes for CNN-CA-W prediction is six i.e., Rain, Strom, Heavy Rain, Marginal Rain, Dry, and Marginally Dry. We have employed the same mechanism as reported above to test our classifier for accuracy.

Figures 8, and 9 reports the training and testing accuracies when the classifiers have used 3X3 and 4X4 filter, respectively. The accuracies reported are considerably better, and Figures 10, and 11 shows the training and testing error percentage when the classifiers have used 3X3 and 4X4 filters.

Table 5 shows the accuracy of CNN-CA-W with respect to the filter size, epochs, and batch size. Our classifier has reported an average training accuracy of 93.5 and average testing accuracy of 92.1.

Table 5. Accuracy computation for with variable epochs and filters (CNN-CA-W)

Epochs	Filter size	Size of Batch	Accuracy (Training)	Accuracy (Testing)
10	4X4	64	92.5	91.3
20	3X3	64	91.2	90.3
30	4X4	64	91.6	90.6
40	4X4	64	96.3	90.6
50	4X4	64	94.3	92.6
60	3X3	64	95.7	92.4

Tables 8, 9, and 10, reports the performance of CNN-CA-W with respect to the used filters 3X3 and 4X4 with precision, recall, and F1 Score as parameters. Class 1 represents crop rice, the average precision, recall and F1 score reported are 0.899, 0.92, and 0.91, respectively. Class 2 represents crop wheat, the average precision, recall, and F1 score reported are 0.91, 0.91 and 0.90, respectively.

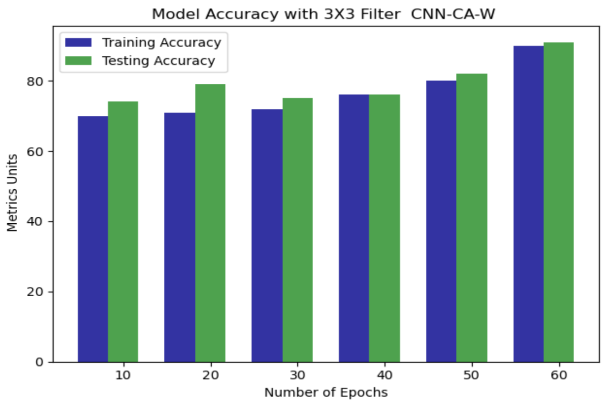

Figure 8. Model % accuracy with 3x3 filter.

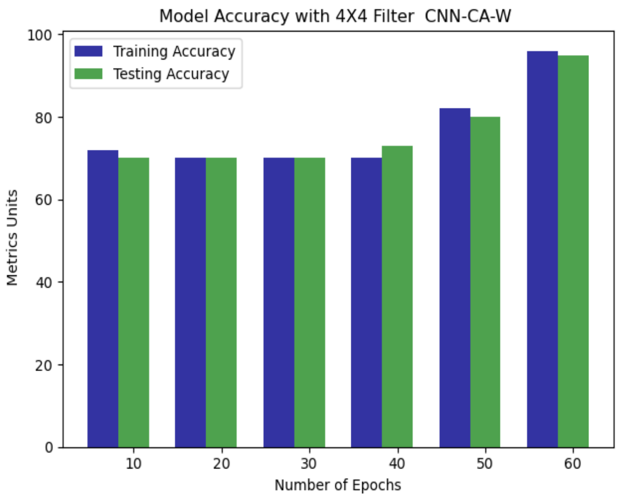

Figure 9. Model % accuracy with 4x4 filter.

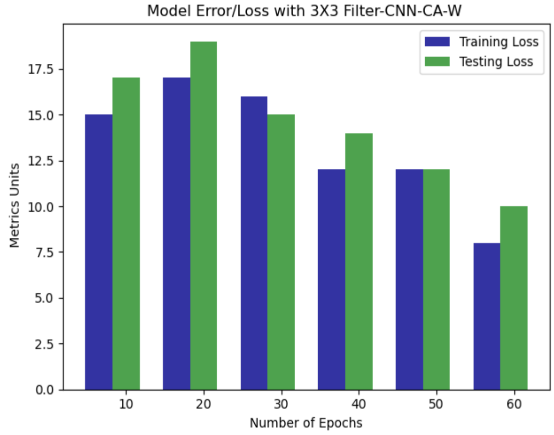

Figure 10. Model-error % with 3x3 filter.

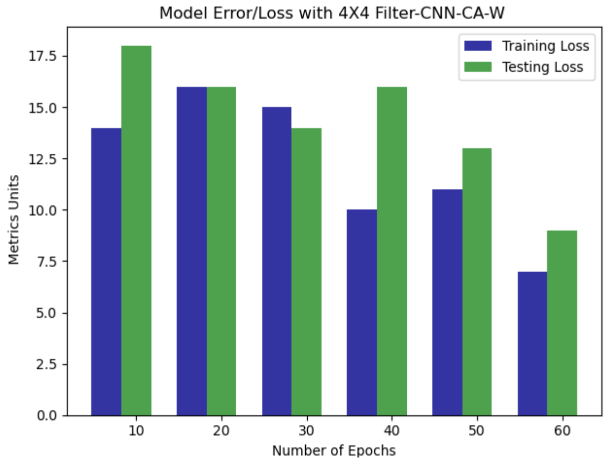

Figure 11. Model-error % with 4x4 filter.

Class 3 represents crop Barley, the average precision, recall, and F1 score reported are 0.89, 0.91 and 0.87, respectively. Class 4 represents crop sugarcane, the average precision, recall, and F1 score reported are 0.91, 0.93 and 0.86, respectively. Class 5 represents crop cotton, the average precision, recall, and F1 score reported are 0.94, 0.95 and 0.88, respectively. Class 6 represents crop oilseeds, the average precision, recall, and F1 score reported are 0.92, 0.89 and 0.93, respectively. As per the discussion, this classifier CNN-CA-W was reported as one of the best for Rice, Barley, and Sugarcane.

We have used an additional parameter MAE as stated in the literature, and the performance of the classifier was found better, as shown in Table 6. CNN-CA-W reports a very less mean absolute error compared to the existing literature, i.e., 30.25. The precision reported is also considerably high compared to the SVM also, reported as 0.88.

The yield prediction of the crop can be predicted with the precision, recall values reported by CNN-CA-W and CNN-CA-I, as shown in Figure 12. Sixty percentages of CNN-CA-I values and forty percentage of CNN-CA-W values will finally compute the yield of the corresponding crop.

Table 6. Performance evaluation of CNN-CA-W.

Model	MAE	Precision	Recall	F1Score	Support	Accuracy
REG	65.24	0.71	0.60	0.56	34	74.5
BNN	51.4	0.81	0.67	0.68	41	70.6
GNN	45.9	0.70	0.76	0.79	46	69.6
SVM	43.9	0.84	0.75	0.75	50	82.65
CNN-CA-W	30.25	0.88	0.81	0.83	58	90.1

Table 7. Recall and precision computation for 3×3 convolution filter.

Class Label	Precession	Reported Recall	F1Score	Support
Class 0	0.85	0.79	0.79	55
Class 1	0.89	0.84	0.85	56
Class 2	0.92	0.80	0.80	60
Class 3	0.90	0.81	0.76	54
Class 4	0.92	0.80	0.80	60
Class 5	0.91	0.73	0.75	52
Class 6	0.94	0.72	0.83	52
Class 7	0.85	0.71	0.86	55
Class 8	0.88	0.76	0.78	51
Class 9	0.87	0.72	0.82	50
Class 10	0.79	0.71	0.85	56
Class 11	0.82	0.75	0.84	54
Class 12	0.83	0.79	0.83	53
Class 13	0.88	0.76	0.82	56
Average	**0.87154**	**0.75769**	**0.81385**	**54.1538**

Table 8. Accuracy computation for with variable epochs and filters (CNN-CA-W).

Epochs	Filter size	Size of Batch	Accuracy (Training)	Accuracy (Testing)
10	4X4	64	92.5	91.3
20	3X3	64	91.2	90.3
30	4X4	64	91.6	90.6
40	4X4	64	96.3	90.6
50	4X4	64	94.3	92.6
60	3X3	64	95.7	92.4

Table 9. Recall and Precision computation for 4×4 convolution filter (CNN-CA-W).

Class	Precession	Recall	F1 Score	Support
Class 1	0.89	0.91	0.91	54
Class 2	0.87	0.90	0.90	56
Class 3	0.89	0.90	0.88	59
Class 4	0.92	0.92	0.92	58
Class 5	0.95	0.91	0.91	59
Class 6	0.89	0.89	0.93	59

Table 10. Recall and Precision computation for 3×3 convolution filter (CNN-CA-W).

Class	Precession	Recall	F1 Score	Support
Class 1	0.89	0.91	0.91	54
Class 2	0.87	0.90	0.90	56
Class 3	0.89	0.90	0.88	59
Class 4	0.92	0.92	0.92	58
Class 5	0.95	0.91	0.91	59
Class 6	0.89	0.89	0.93	59

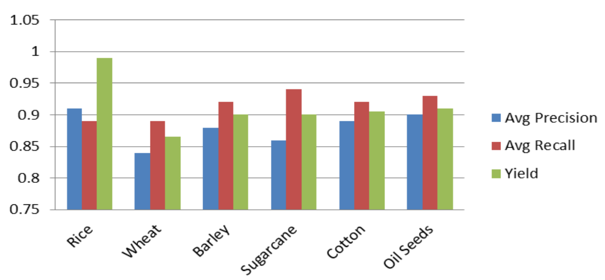

Figure 12. Yield computation.

5. Conclusions

We have successfully developed two classifiers CNN-CA-W and CNN-CA-I to predict the crop diseases in rice, wheat, barley, sugarcane, cotton, and oilseeds, thus predicting the yield of the crop. Two versatile classifiers CNN-CA-I has processed various images pertaining to the crops, and CNN-CA-W has processed environmental data to predict the diseases of the crops. CNN-CA-I trained and tested to predict 13 classes with an average accuracy of 92.6, and CNN-CA-W is trained and tested to predict five classes with an average accuracy of 90.1. Both classifiers are evaluated based on precision, recall, F1score, and MAE. These two classifiers are robust, and the results found very promising. In the future, we try to extend this work for various crops grown in India. This will be the first set of classifiers which predicts the crop diseases of six crops with an average time of 0.5nano seconds.

References

[1] Ayub U. and Moqurrab S., "Predicting Crop Diseases Using Data Mining Approaches: Classification," *in Proceedings of 1st International Conference on Power, Energy and Smart Grid (Icpesg)*, Mirpur Azad Kashmir, pp. 1-6, 2018.

[2] Bourke P., "Use of Weather Information in the Prediction of Plant Disease Epiphytotics," *Annual Review of Phytopathology*, vol. 8, no. 1, pp. 345-370, 1970.

[3] Bhatt P., Sarangi S., and Pappula S., "Comparison of CNN Models for Application in Crop Health Assessment with Participatory Sensing," *in Proceedings of IEEE Global Humanitarian Technology Conference (GHTC)*, San Jose, pp. 1-7, 2017.

[4] Crane-Droesch A., "Machine Learning Methods for Crop Yield Prediction and Climate Change Impact Assessment in Agriculture," *Environmental Research Letters*, vol.13, no. 11, pp. 114003, 2018.

[5] Chlingaryan A., Sukkarieh S., and Whelan B., "Machine Learning Approaches for Crop Yield Prediction and Nitrogen Status Estimation in Precision Agriculture: A Review," *Computers and Electronics in Agriculture*, vol. 151, pp. 61-69, 2018.

[6] Chakraborty S., Ghosh R., Ghosh M., Fernandes C., Charchar M., and Kelemu S., "Weather-Based Prediction of Anthracnose Severity Using Artificial Neural Network Models," *Plant Pathology*, vol. 53, no. 4, pp. 375-386, 2004.

[7] Dahikar S. and Rode S., "Agricultural Crop Yield Prediction Using Artificial Neural Network

Approach," *International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering*, vol. 2, no. 1, pp. 683-686, 2014.

[8] González Sánchez A., Frausto-Solís J., and Ojeda-Bustamante W., "Predictive Ability of Machine Learning Methods for Massive Crop Yield Prediction," *Spanish Journal of Agricultural Research*, vol. 12, no. 2, pp. 313-328, 2014.

[9] Kendal R., Kapoor A., and Raghava G., "Machine Learning Techniques in Disease Forecasting: A Case Study on Rice Blast Prediction," *BMC bioinformatics*, vol. 7, no. 1, 485, 2006.

[10] Khamparia A., Saini G., Gupta D., Khanna A., Tiwari S., and De Albuquerque V., "Seasonal Crops Disease Prediction and Classification Using Deep Convolutional Encoder Network," *Circuits, Systems, and Signal Processing*, vol. 39, no. 2, pp. 818-836, 2020.

[11] Kurtah P., Takun Y., and Nagowah L., "Disease Propagation Prediction using Machine Learning for Crowdsourcing Mobile Applications," *in Proceedings of 7th International Conference on Information and Communication Technology*, Kuala Lumpur, pp. 1- 6, 2019.

[12] Mohanty S., Hughes D., and Salathé M. "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in Plant Science*, vol. 7, pp. 1419, 2016.

[13] Maji P. and Chaudhuri P., "Fuzzy Cellular Automata for Modeling Pattern Classifier," *IEICE Transactions on Information and Systems*, vol. 88, vol. 4, pp. 691-702, 2005.

[14] Maji P., Shaw C., Ganguly N., Sikdar B., and Chaudhuri P., "Theory and Application of Cellular Automata for Pattern Classification," *Fundamental Informaticae*, vol. 58, no. 3, pp. 321-354, 2003.

[15] Maji P. and Chaudhuri P., "FMACA: A Fuzzy Cellular Automata Based Pattern Classifier," *in Proceedings of International Conference on Database Systems for Advanced Applications*, Jeju Island, pp. 494-505, 2004.

[16] Newlands N., "Model-Based Forecasting of Agricultural Crop Disease Risk At The Regional Scale, Integrating Airborne Inoculum, Environmental, and Satellite-Based Monitoring Data," *Frontiers in Environmental Science*, vol. 6, pp. 63, 2018.

[17] Priyanka T., Soni P., and Malathy C., "Agricultural Crop Yield Prediction Using Artificial Intelligence and Satellite Imagery," *Eurasian Journal of Analytical Chemistry*, vol. 13, pp. 6-12, 2019.

[18] Prasad A., Chai L., Singh R., and Kafatos M., "Crop Yield Estimation Model for Iowa Using Remote Sensing and Surface Parameters," *International Journal of Applied Earth Observation and Geoinformation*, vol. 8, no. 1, pp. 26-33, 2006.

[19] Pokkuluri K. and Nedunuri S., "A Novel Cellular Automata Classifier for Covid-19 Prediction," *Journal of Health Sciences*, vol. 10, no.1, pp. 34-38, 2020.

[20] Panda S., Ames D., and Suranjan Panigrahi S., "Application of Vegetation Indices for Agricultural Crop yield Prediction Using Neural Network Techniques," *Remote Sensing*, vol. 2, no. 3, pp. 673-696, 2010.

[21] Royer M., Russo J., and Kelley J., "Plant Disease Prediction Using A Mesoscale Weather Forecasting Technique," *Plant Disease*, vol. 73, no. 8, pp. 618-624, 1989.

[22] Ramesh D. and Vardhan B., "Analysis of Crop Yield Prediction Using Data Mining Techniques," *International Journal of Research in Engineering and Technology*, vol. 4, no. 1, pp. 470-473, 2015.

[23] Sree K. and Babu R., "Identification of Promoter Region in Genomic DNA Using Cellular Automata Based Text Clustering," *The International Arab Journal of Information Technology*, vol. 7, no. 1, pp. 75-78, 2010.

[24] Sree P. and Babu I., "Identification of Protein Coding Regions in Genomic DNA Using Unsupervised FMACA Based Pattern Classifier," *International Journal of Computer Science and Network Security*, vol. 8 no.1, pp. 305-309, 2008.

[25] Sree P., Babu I., and Devi N., "Investigating an Artificial Immune System to Strengthen Protein Structure Prediction and Protein Coding Region Identification Using the Cellular Automata Classifier," *International Journal of Bioinformatics Research and Applications*, vol. 5, no. 6, pp. 647-662, 2009.

[26] Sree P., Babu I., and Nedunuri S., "AIS-INMACA: A Novel Integrated MACA Based Clonal Classifier for Protein Coding and Promoter Region Prediction," *arXiv preprint arXiv: 1403.5933*, 2014.

[27] Stuart L. and Watkins G., APSNet. 2019. Resources for Plant Diseases. https://www.apsnet.org/edcenter/resources/commonnames/Pages/default.aspx. Last Visited, 2020.

[28] Van der Linden and Mitchell 2009; https://ensemblesrt3.dmi.dk/) Last Visited, 2020.

[29] You J., Li X., Low M., Lobell D., and Ermon S., "Deep Gaussian Process for Crop Yield Prediction Based on Remote Sensing Data," *in Proceedings of in 31st AAAI Conference on Artificial Intelligence(IAAIC)*, San Francisco, pp. 4559-4565, 2017.

Pokkuluri Kiran Sree has received his B.Tech and M.E in Computer Science and Engineering from JNTU and Anna University, respectively. He has obtained his Ph.D. degree in the area of Artificial Intelligence from JNTU-Hyderabad. He has authored Six textbooks for UG and PG students of engineering in AI and published more than 96 research articles in various international journals and conferences. He has filed and published six patents in the area of Deep Learning. His biography was listed in Marquis Who's Who in the World, 29th Edition (2012), USA. Prof Kiran is the Recipient of Bharat Excellence Award from Dr. G.V. Krishna Murthy, Former Election Commissioner of India for two times and recipient of Rashtrya Ratan Award. He was the BOS member of CSE&IT in some universities and autonomous colleges. He also worked as Principal of the N.B.K.R.Institute of Science & Technology (Second Oldest Private Engg College), Vidyanagar, for two years. He has got 18+ years of teaching experience and working as Head & Professor in the department of CSE at Shri Vishnu Engineering College for Women(A), Bhimavaram. He has delivered many technical talks on Deep Learning and AI in various International Conferences, FDP'S, Webinars. His research interests include Deep Learning, Big Data Analytics, Bioinformatics, and Cloud Computing. He is associated with various journals& conferences in various capacities as Editor in Chief, Editorial Member, and Reviewer. His the Global Vice President of WSA: World Statistical Data Analysis Research Association.

SSSN Usha Devi Nedunuri has received her B.Tech degree from JNTU Hyderabad and M.Tech from JNTU Kakinada. She is pursuing her Ph.D from National Institue of Technology, Trichy in the area of Deep Learning. She has published 52 papers in various journals and conferences. She has filed a patent on Deep Learning integrated with IOT. She has acted as resource person for many AICTE sponsored FDP'S and Conferences.