https://doi.org/10.17221/70/2020-AGRICECON

Finite automata model for leaf disease classification

Krishnaprasath V.T.[1]*, *Preethi J.*[2]

[1]*Department of Computer Science and Engineering, Nehru Institute of Engineering and Technology, Anna University, Tamilnadu, India*
[2]*Department of Computer Science and Engineering, Anna University Regional Campus, Coimbatore, Tamilnadu, India*

**Corresponding author: prasathkriss@gmail.com*

Citation: Krishnaprasath V.T., Preethi J. (2021): Finite automata model for leaf disease classification. Agric. Econ. – Czech, 67: 220–226.

Abstract: In this modern era, the detection of plant disease plays a vital role in the sustainability of agricultural ecosystem. Today, India being second in farming, well-timed information related to crop is still questioning. Indian Government's farmer portal is available for pesticides, fertilisers, and farm machinery. To alleviate this problem, the paper describes a model to validate the leaf image, predicting leaf disease and notifying the farmer in an effective way on the harvest failure to stabilise farming income. For specific consideration on the validation, a data set library with predefined, uniformly scaled, regular image patterns of leaf disease, is maintained. The research suggests that farmers utilising the model can predict the breakout of leaf disease predominantly acquiring 100% yield.

Keywords: agriculture; automata model; image processing; plant disease; segmentation

India, the region of the largest economy in Asia having a population of 1.3 billion, almost eighty per cent of the population, relies on agriculture. The productivity of farming goods depends on the quality, and agriculture is a key contributor to the country's economy (Hoang 2018). Farming is a risky business; diseases affect crop yields making the production life cycle vulnerable, leading to harvest failure, and affecting farmers' livelihood (Kung 2018). Generally, the rapid prognosis and accurate prediction of leaf disease play a vital role in controlling plant disorders (Das et al. 2017). Globally plant diseases are a threat to farmers whose livelihood depends on healthy crops (Mohanty et al. 2016). Leaf shape supports plant visualisation; it is crucial to categorise leaves in agricultural industries. Leaves exhibit taxonomic characteristics surviving long term in plants compared to flowers and fruits. Leaves are classified based on colour, texture, and shape (Steiner 1990; Palanivel et al. 2017). A computer model Maryblyt predicts specific infection in pears and apples during fire blight epidemics. For an efficient disease predicting model, a strong mathematical base and statistical observation are required. The research aims to model a finite automaton accepting regular leaf images, the results validated using the data set library with 54 306 images for 14 species categorising 26 diseases considered from the PlantVillage project (Mohanty et al. 2016). The identification of affected leaf disease (Smita and Niket 2013) is stored in the finite-state system. In addition to finite-state validation, the machine incorporates techniques like virtual image processing, plant pathology, mathematical foundations of finite automaton, and other relevant fields. The contribution of this paper is to provide an analytical approach to identify specific leaf disease characteristics, assisting the farmers in plant treatment (Gusavac et al. 2019), planning and decreasing the loss that occurred on it. It will help the farmers, in monitoring crop health and disease diagnosis in the early stages, on a massive global scale (Anand and Ashwin Patil 2012). The model intimates farmer quickly on the existence of the leaf disease, proving an automata technique addressing user-friendly solutions for societal issues. From this description, the objective of our research influences

https://doi.org/10.17221/70/2020-AGRICECON

farmer's decision and analyses the impact on farming income and complementing by insurance (Yanuarti et al. 2019) in the world agricultural market.

Literature review on identification of plant disease. Research by Landge et al. (2013) have developed a programming technique addressing the issues faced by Indian ranchers. A technique developed a computationally demanding gadget, recording and sending SMS to ranchers on plant masking notifications, upgrading agriculture productiveness by reducing time and cost. Haiguang et al. (2012) points out a model to identify infections in grapes plant by applying image editing, pressure, and picture denoising to plant specimens and the results were limited to character the ailments. Dhaygude and Kumbhar (2013) specifically described the complementarity concept of how morphological regenerative structure recognised microscopic cell genetic disorders. The infections related to protein and genetic sold were the specific area overlooked, and the molecules were negligible. Alex and Kanavalli (2019) focussed on a big data analytics model to examine soil nutrients of precision agriculture crops in specific consideration to drumstick, papaya, and banana. The plant health hazards on excessive use of fertilisers were reported. Rao and Kulkarni (2020) point out the structured framework for shading investigations in grape leaves, grouping the plant sickness into three frameworks: rust infection, scab illness, and no malady for its broad usage in rural regions. Jayme and Barbedo (2013) proposed a visible spectrum-based image processing method for detecting plant disease and the survey was not dealt in depth.

MODEL FORMULATION

Finite automata, the abstract mathematical machine with finite memory, adopted for tasks reminiscent of matching regular expression, text parsing, protocol analysis, and speech recognition. The finiteness limitation forbid to redesign a software model solving the task assigned in a consistent manner by transforming it to the regular pattern of those accepted by the model. Complications exist only on understanding the problem in depth.

Source model description (MD). Finite automaton defined as a five-tuple system. For a machine:

$$M = (K, \Sigma, \delta, q_0, F)$$

where: K – finite non-empty set of states; Σ – finite non-empty set of input alphabets; δ – the transition function, δ: $K \times \Sigma \rightarrow K$; q_0 – the initial state, $q_0 \in K$; F – the set of final states, $F \subseteq K$.

Figure 1. signifies a deterministic finite automaton (DFA) model for the identification and classification of leaf disease. The model composed of finite control (FC), the FC and an input tape to accept the input images of size 256 × 256 pixels, in case of difference, the image pixel will be resized. The reading head reads one input image at a time, advancing the input tape one unit to the right.

The model, on its primary phase, accepts or rejects an image of a minimum from 1 to infinite numbers and processing one image at a time comparing with the set of images in the data set library, signifying "validation

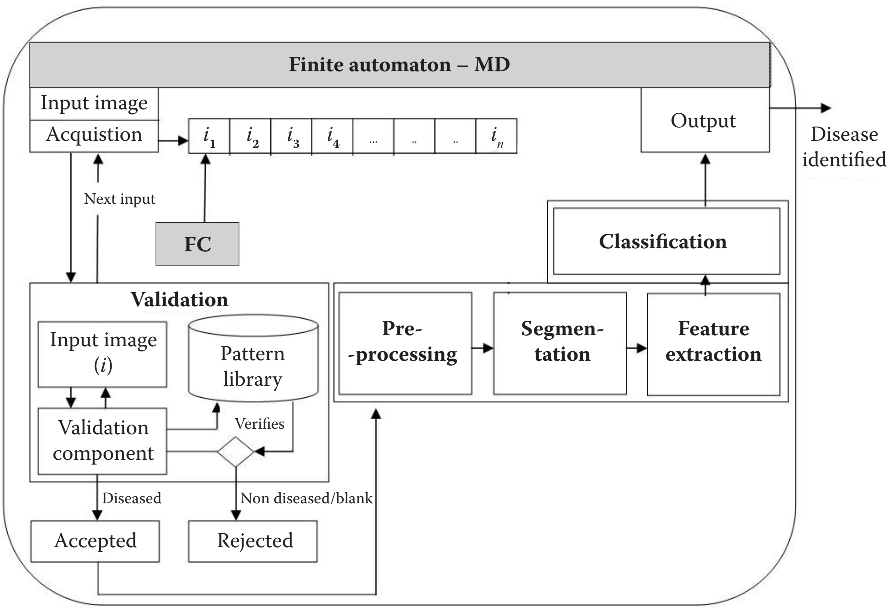

Figure 1. Redesigned finite automaton

MD – model description; FC – finite control; i – input symbol

Source: Author's composition based on the source MD

https://doi.org/10.17221/70/2020-AGRICECON

state". The model is intact on the concept of internal states and transitions at discrete time intervals. Pattern library comprises diseased images and their identification rules (Haiguang et al. 2012). The research model significance was analysed using the specimen images categorised and reported in the PlantVillage project (Mohanty et al. 2016). On positive validation, the machine model description (MD) has definite acceptance for non-diseased leaf or irrelevant image; the machine rejects at its instigation, avoiding unnecessary processing. On disease assured image, the machine performs subsequent phases of pre-processing, segmentation, feature extraction, and classification for classifying the disease type.

The finite automata tuples for the redesigned model is defined as follows:

for a machine MD = (Q, X, δ, q_0, Y)

where: Q – finite non-empty set of states; X – finite non-empty set of input alphabets; δ – transition function, δ: $Q \times X \rightarrow Q$; q_0 – the initial state, $q_0 \in Q$; Y – set of final states, $Y \subseteq Q$.

States and representations of redesigned finite automata model is given in Table 1.

The associated set of states for the model, $Q = \{q_0, q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8\}$ are described in Table 1.

The other new variables used in the model are defined as below:

$X = \{i, a, b, r\}$, the set of input images

Considered assumption: a – diseased image; b – non-diseased/blank/irrelevant image, i – fixed input image for the state q_0; r – fixed result image for the state q_8; δ: $Q \times X \rightarrow Q$, the transition function for state $q \in Q$ in the i^{th} moment of discrete time d_t, $q(i)$ and the image $x_i \in X$ expressed in Equation (1).

$$q\ (i + 1) = \delta\ (q(i), x_i) \qquad (1)$$

For the state $q \in Q$ and $x \in X$, the transition function $\delta\ (q(i), x)$, if not defined, the finite machine stops the task.

q_0 initial/image acquisition state, fixed to accept the only preliminary input image i.

$Y = \{q_8\}$, the final state, fixed to display the result only on accepting the image r. The research considered PlantVillage project (Mohanty et al. 2016) use a support vector machine (SVM) classification method for the identification of leaf disease, the dataset utilised perfectly matches with the constraints of the finite automata model.

Table 1. States and representations of redesigned finite automata model

States	Representations	Remarks
q_0	initial state/image acquisition state	d_t = 0, zero moment discrete time
q_1	validation state	accepts/rejects image
q_2	diseased state	validation acceptance
q_3	rejection state- -non-diseased/blank	machine, model description (MD) rejection
q_4	pre-processing state	–
q_5	segmentation state	–
q_6	feature extraction state	–
q_7	classification state	–
q_8	result state	displays results

Source: Authors

The machine MD having transition function δ, the sequence of state transitions, is described in Figure 2.

Transition diagram for the model:

$q_0 \in Q \rightarrow$ initial state
$\delta\ (q_0, i) = q_1$
$\delta\ (q_1, a) = q_2$
$\delta\ (q_1, b) = q_3$
$\delta\ (q_2, a) = q_4$
$\delta\ (q_2, b) = q_3$
$\delta\ (q_3, a) = q_3$
$\delta\ (q_3, b) = q_3$
$\delta\ (q_4, a) = q_5$
$\delta\ (q_4, b) = q_3$
$\delta\ (q_5, a) = q_6$
$\delta\ (q_5, b) = q_3$
$\delta\ (q_6, a) = q_7$
$\delta\ (q_6, b) = q_3$
$\delta\ (q_7, r) = q_8$
$q_8 \in Q \rightarrow$ displays result

Table 2. describes the transition of each state specified in Figure 2.

Procedure of a finite control (FC). The finite automata (FA) model for identification and classification of leaf diseases goes through a number of states:

1. The initial state – q_0, fixed to accept the only input image i, signifies as "image acquisition stage".
2. The state q_0 on receiving i, the image transformed to a regular pattern. Subsequently, the transition moves to the next state, the "validation state":

$\delta\ (q_0, i) = q_1$

https://doi.org/10.17221/70/2020-AGRICECON

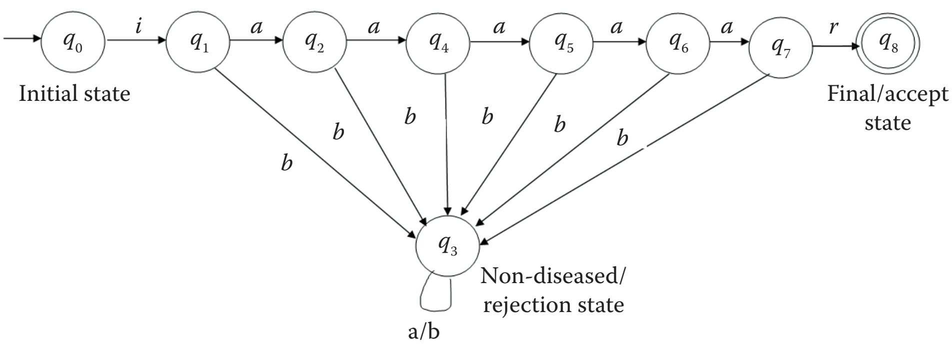

Figure 2. Transition diagram for the model

$q_0, q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8$ – states; i, a, b, r – input symbols

Source: Author's composition

3. The validation state q_1, a significant stage of the model. On comparing the image with the data set library, the output is either diseased or non-diseased/ blank/irrelevant image. The validation is diseased, the transition moves from q_1 to q_2. On non-diseased/ blank/irrelevant, the transition moves to q_3, the rejection state. Here the machine rejects the image avoiding unnecessary computations, reducing processing time:

$\delta\ (q_1, a) = q_2$
$\delta\ (q_1, b) = q_3$

4. On successful validation of the diseased image from q_1 to q_2, the image is ready for subsequent operations like pre-processing (q_4 state), segmentation (q_5 state), feature extraction (q_6 state) and classification (q_7 state). In states q_4, q_5, q_6, and q_7 the transition occurs stage by stage only if the image is eligible for further processing. In the case of non-eligibility, the transition moves directly to q_3 state, where the machine terminates/stops. The state transitions are described as below:

$\delta\ (q_2, a) = q_4$
$\delta\ (q_4, a) = q_5$
$\delta\ (q_5, a) = q_6$
$\delta\ (q_6, a) = q_7$

5. q_3, the rejection state. Here the machine terminates/ stops due to the following reasons:
   i) When the input runs out of tape.
   ii) Image is non-diseased/blank/irrelevant.
   iii) Image not eligible for further processing.

$\delta\ (q_2, b) = q_3$
$\delta\ (q_3, a) = q_3$
$\delta\ (q_3, b) = q_3$
$\delta\ (q_4, b) = q_3$
$\delta\ (q_5, b) = q_3$
$\delta\ (q_6, b) = q_3$

6. On successful completion of the subsequent phases, the image moved to the disease classification state q_7. q_7, on reading the classified result image r, the transition moves to the final state q_8. The state q_8 fixed only for displaying the result. Thus, q_8 considered to be the final state for the finite automaton model, which displays the classified disease type:

$\delta\ (q_7, r) = q_8$
$q_0 \rightarrow q_1 \rightarrow q_2 \rightarrow q_4 \rightarrow q_5 \rightarrow q_6 \rightarrow q_7 \rightarrow q_8 \in Q$, MD accepts
$q_0 \rightarrow q_1 \rightarrow q_3 \in Q$, MD rejects

7. Also, the machine MD stops if the state transitions are non-defined. The non-defined states given below:

$\delta\ (q_0, a)$, $\delta\ (q_0, b)$, $\delta\ (q_0, r)$
$\delta\ (q_1, i)$, $\delta\ (q_2, i)$, $\delta\ (q_3, i)$, $\delta\ (q_4, i)$, $\delta\ (q_5, i)$, $\delta\ (q_6, i)$, $\delta\ (q_7, i)$
$\delta\ (q_8, i)$, $\delta\ (q_8, a)$, $\delta\ (q_8, b)$

Table 2 Transition table

State	Input			
	i	*a*	*b*	*r*
q_0	q_1	Φ	Φ	Φ
q_1	Φ	q_2	q_3	Φ
q_2	Φ	q_4	q_3	Φ
q_3	Φ	q_3	q_3	Φ
q_4	Φ	q_5	q_3	Φ
q_5	Φ	q_6	q_3	Φ
q_6	Φ	q_7	q_3	Φ
q_7	Φ	Φ	Φ	q_8
q_8	Φ	Φ	Φ	displays result

Φ – no transition; $q_0, q_1, q_2, q_3, q_4, q_5, q_6, q_7, q_8$ – states; i, a, b, r – input symbols

Source: Author's own calculations from the source model

https://doi.org/10.17221/70/2020-AGRICECON

$\delta(q_1, r)$, $\delta(q_2, r)$, $\delta(q_3, r)$, $\delta(q_4, r)$, $\delta(q_5, r)$, $\delta(q_6, r)$

Acceptance definition: For the DFA, MD = (Q, X, δ, q_0, Y), L(MD) = $\{ia^n\ r$, where $n \geq 5\}$, the language accepted by the finite automaton.

Rejection definition: For the DFA, MD = (Q, X, δ, q_0, Y), L(MD) = $\{iba^n\ r$, where $n \geq 1\}$ or L(MD) = $\{ia^n\ br$, where $n \geq 1\}$ the machine MD terminates/stops.

The model undergoes subsequent classification of the leaf disease (Ghaiwat and Arora 2014) are described as below: image acquisition reads the input image and resizes for validation. The pre-processing removes noise using bilateral filtering (Kornprobst et al. 2008). Followed by segmentation, Otsu's threshold-based segmentation and finally, the feature extraction and classification by applying SVM classifier.

Bilateral filtering. Bilateral filtering (Durand and Paris 2006) preserves the image edges, is a simple non-iterative to smoothen the dissimilar edges, expressed in Equation (2). At σ process using Gaussian filter G each pixel, the weighted average of neighbouring pixels considered for the calculation of the intensity value.

$$G\sigma(x) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left(\frac{-x^2}{2\sigma^2}\right) \tag{2}$$

The filter measure σ, the series connection of pixel x with y shown in Equation (3).

$$\mathrm{sim}(u) = \| u(x) - u(y) \|^2 \tag{3}$$

Equation (4) express the sub. of Equation (2) in (1).

$$G\sigma(sim(u)) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left(\frac{-\| u(x) - u(y) \|^2}{2\sigma^2}\right) \tag{4}$$

Equation (5) expresses the similarity contrast.

$$\mathrm{Contr}(u) = 1 - \mathrm{sim}(u) = 1 - \| u(x) - u(y) \|^2 \tag{5}$$

Equation (6) describes the contrast quantity of pixel x having neighbour y.

$$G\sigma(\mathrm{contr}(u)) = \frac{1}{\sigma\sqrt{2\pi}}\exp\left(-\frac{1 - \| u(x) - u(y) \|^2}{2\sigma^2}\right) \tag{6}$$

Equation (7) express the calculation for bilateral filter $B(u)$.

$$B(u) = \frac{1}{Wx}\sum_{y\in s} G\sigma x(\| x - y \| G\sigma r(\mathrm{sim}(u))u(y) \tag{7}$$

Equation (8) express the substitution of sim(u) in Equation (7).

$$B(u) = \frac{1}{Wx}\sum_{y\in s} G\sigma x(\|x - y\|)\, G\sigma r\,(\|x - y\|)\, u(y) \tag{8}$$

Finally, the normalised weight, Wx, with spatial (σ s) and intensity (σ r) filter scales is expressed in Equation (9).

$$Wx(x) = \sum_{y\in s} G\sigma s(\|x - y\|)\, G\sigma r(\|u(x) - u(y)\|) \tag{9}$$

The next phase forwards to Otsu's threshold, the finest method to threshold the background leaf objects and categorise based on dual periods. The possibility incidence of grey level (Padmavathi and Thangadurai 2016) is expressed in Equation (10).

$$P = \frac{ni}{n} \tag{10}$$

where: P – possible incidents of grey level; ni – current input image; n – total number of images in the data set.

The last phase of feature extraction and SVM classification, finished based on colour variation, border structure, and asymmetrical diameter. The SVM classifier trains the data holding enormous feature spaces. Equation (11) express the *Accuracy* calculation of the SVM classifier.

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \times 100\% \tag{11}$$

RESULTS

The comparison result of the input image with the data set images as discussed in the model formulation section, the proposed system identifies the leaf disease is as follows.

The system performs the disease identification process by accepting the input image and perform validation process discussed in the model formulation section to return the state of the leaf as diseased with classification or healthy as an output. Based on the output, the attention given to the diseased plant to get the maximum yield.

The following Figure (3) depicts the input image and the corresponding output after validating with the proposed model.

The researched finite automaton model validates the resized input leaf image with patterns in the data set library consisting of 39 221 images for 26 species. The validation resulted for a diseased image, the ma-

https://doi.org/10.17221/70/2020-AGRICECON

Input image

Validation result

Disease classification

Figure 3. Disease classification stages of the model

Source: Output from developed model

chine MD accepted the image for subsequent processing and finally identifying the disease as *Cercospora* leaf spot, as shown in Figure 3. The limitation in paper, is the study area not expanded much on the image processing techniques. Further, studies need to be carried out in this field on the possibility of applying other image processing techniques with some modifications. The model claim guarantees to reduce the production risk of farmers having a positive impact on farmer's income to facilitate the welfare of the agriculture economy.

CONCLUSION

Harvest failure has a significant effect on the farmers' income and livelihood. To reduce the production risk, they can be encouraged on the usage of such models in farming. The researched model predicts the leaf diseases on its preliminary stage of validation further undergoing subsequent image processing techniques to classify the disease type. The existence of the validation phase reduces the processing time, avoiding the verification of unnecessary inputs those not accepted by the machine. This study guarantees an agricultural complementary model; farmer's willingness in such deployments will ensure more benefit on finding a better place in the regional markets for their qualified products. In order to make the model farmer-friendly to the global scale the level of disease (low, medium, critical) with warning messages could be predicted, along with the output can be considered for future work.

Acknowledgement: We thank the editors and reviewers for their valuable support.

REFERENCES

Anand H.K., Ashwin Patil R.K. (2012): Applying image processing technique to detect plant diseases. International Journal of Modern Engineering Research (IJMER), 2: 3661–3664.

Gusavac B.A., Stanojevic M., Cangalovic M. (2019): Optimal treatment of agricultural land – Special multi-depot vehicle routing problem. Agricultural Economics – Czech, 65: 569–578.

Rao A., Kulkarni S.B. (2020): A hybrid approach for plant leaf disease detection and classification using digital image processing methods. International Journal of Electrical Engineering and Education (IJEEE): 1–19.

Ghaiwat S.N., Arora P. (2014): Detection and classification of plant leaf diseases using image processing techniques: A review. International Journal of Recent Advances in Engineering and Technology, 2: 2347–2812.

Das R., Pooja V., Kanchana V. (2017): Identification of plant leaf diseases using image processing techniques. In: Proceedings of the 2017 IEEE Technological Innovations in ICT for Agriculture and Rural Development (TIAR), Chennai, Tamil Nadu, India, April 7–8, 2017: 130–133.

Durand F., Paris S. (2006): A fast approximation of the bilateral filter using a signal processing approach. In: 9th European Conference on Computer Vision, Graz, Austria, May 7–13, 2006: 568–580.

Haiguang W., Guanlin L., Zhanhong M., Xiaolong L. (2012): Image recognition of plant diseases based on back propagation networks. In: 5th International Congress on Image and Signal Processing (CISP), Chongqing, China, Oct 16–18, 2012: 894–900.

Hoang V. (2018): Assessing the agricultural trade complementarity of the Association of Southeast Asian Nations countries. Agricultural Economics – Czech, 64: 464–475.

Jayme G., Barbedo A. (2013): Digital image processing techniques for detecting, quantifying and classifying plant diseases. SpringerPlus, 2: 1–12.

Padmavathi K., Thangadurai K. (2016): Implementation of RGB and grayscale images in plant leaves disease detection – Comparative study. Indian Journal of Science and Technology, 9: 1–6.

https://doi.org/10.17221/70/2020-AGRICECON

Kornprobst P., Tumblin J., Paris S., Durand F. (2008): Bilateral filtering: Theory and applications. Computer Graphics and Vision, 4: 1–73.

Kung Ch.-Ch. (2018): A dynamic framework of sustainable development in agriculture and bioenergy. Agricultural Economics – Czech, 64: 445–455.

Palanivel N., Lavanya S., Devapriya E., Vinitha M. (2017): PCA and RF: An automatic plant leaf disease detection using texture, shape and color features. International Journal of Engineering Applied Sciences and Technology, 2: 120–125.

Steiner P.W. (1990): Predicting apple blossom infections by *Erwinia amylovora* using the maryblyt model. Acta Horticulturae, 273: 139–148.

Landge P.S., Patil S.A., Khot D.S., Otari O.D., Malavkar U.G. (2013): Automatic detection and classification of plant disease through image processing. International Journal of Advanced Research in Computer Science and Software Engineering, 3: 798–801.

Dhaygude S.B., Kumbhar N.P. (2013): Agricultural plant leaf disease detection using image processing. International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering, 2: 598–602.

Mohanty S.P., Hughes D.P., Salathé M. (2016): Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7: 1–10.

Alex S.A., Kanavalli A. (2019): Intelligent computational techniques for crops yield prediction and fertilizer management over big data environment. International Journal of Innovative Technology and Exploring Engineering (IJITEE), 8: 3521–3526.

Smita N., Niket A. (2013): Advances in image processing for detection of plant disease. International Journal of Application or Innovation in Engineering & Management, 2: 168–175.

Yanuarti R., Aji J.M.M., Rondhi M. (2019): Risk aversion level influence on farmer's decision to participate in crop insurance: A review. Agricultural Economics – Czech, 65: 481–489.

Received: February 17, 2020
Accepted: April 14, 2021