

A Detection System of Pests and Diseases for Corn Plant Using Certainty Factor and Fuzzy Sugeno Methods

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Abstract— Corn is one of the leading food that produces carbohydrates in Indonesia. It can grow well in hot and cold areas with sufficient rainfall and irrigation. However, each part of the corn is sensitive to several diseases, and it can reduce the quantity and quality of the corn result production. Damage of corn plant that is caused by the disease can be conducted by the disturbing process into the plant and make the plant died. The diseases can undermine corn plants by disrupting the processes inside the plant and make the plant died. Therefore, this study aims to design a system for detecting diseases and pests in corn plants using Certainty Factor and Fuzzy Sugeno methods. The Fuzzy Sugeno method is employed to identify diseases and pests in corn plants based on the degree of trust in the diseases of the corn plants. The degree of confidence in the disease can be obtained from the certainty level of the base system built by the Certainty Factor and Fuzzy Sugeno methods. Therefore, the detection system can work effectively and efficiently as well as minimize the amount of damaged corn production. We collected 15 diseases or pests and 48 symptoms, and the experiment results have obtained an accuracy of 85.16%.

Keywords— Corn Plant, Detection System, Pest and Diseases, Fuzzy Sugeno, Certainty Factor.

1. Introduction

Corn is a cultivated plant that needs to be developed in Indonesia to meet food and industrial needs[1]. However, there are some obstacles to improve the quantity and quality of corn production, i.e., pests and diseases. Furthermore, some microorganisms cause diseases in corn plants, i.e., fungi, bacteria, and viruses[2]. Moreover, the types of diseases caused by viruses include dwarf mosaics, chlorotic dwarfs, corn mosaics, scratches, and sugarcane mosaics. Additionally, there are several types of pests in corn plants, such as soil caterpillars (Agrotis), grasshopper (Locusta), powder beetle (Sitophilus zeamais Motsch), seed flies (Atherigona), grayworm (Spodoptera), cob borer of corn (Heliotis armigera), stem borer (Ostrinia fumacalis), aphids (Mysus persicae)[3]. Several researchers have conducted a lot of research to provide optimal solutions in detecting diseases and pests in a plant[4]. Numerous expert system methods have been carried out for testing these things, such as Bayes and Dempster Shafer methods. However, these methods are not efficient in solving decision-making problems involving uncertain data [5]. Some previous researches show that fuzzy methods are the study of uncertainty and able to map an input space into an output space correctly[6]. The Fuzzy system consists of four stages, i.e., Firstly, fuzzification as the process of converting firm numbers into Fuzzy numbers. Secondly, the formation of a base rule or known as a Fuzzy rule basis. Thirdly, inference, or Fuzzy reasoning. Fourthly, defuzzification (the process of changing Fuzzy numbers results from a Fuzzy inference system into firm numbers)[7]. The Fuzzy method has infections caused in the fuzzy IF-THEN rule; there is a Weighted Average Value to calculate the weight of each data[8][9]. The advantages of Fuzzy Sugeno compared to other methods are having a membership function that can make objective observations of subjective values. Also, the Fuzzy Sugeno method can translate a quantity expressed using language (linguistic)[10]. In addition, there are some limitations of the Fuzzy Sugeno approach, such as unable to provide a natural framework to represent human knowledge in fact[11]. Therefore, this research uses the Certainty Factor (CF) method for the formation of a natural framework that represents knowledge. This method can measure certainty against a fact or rule[12]. Also, the CF can measure something certain or uncertain in making decisions in the expert system of disease detection in plants. There are some research related to plant detection system, i.e., [13] captured the Internet of Things (IoT) for monitoring plant diseases and insect pest, [14] examined an expert system for the diagnosis of pests, diseases, and disorders in Indian Mango, [15] pointed out a hybrid multi-criteria decision-making technique for diagnosing plant diseases, [16] studied watermelon diseases and treatment using rule based system[17], examined an expert system for diagnosing oyster mushroom diseases, [18] captured detection and classification system for plant diseases using digital image processing, [19] applied decision support system for classification of plant diseases, [20] employed an expert system for diseases diagnosis in Soybean, [21] captured an expert system for rice plant diseases, [22] examined crop diseases using machine learning, [23] applied deep convolutional neural networks for crop diseases classification using mobile system, [24] captured vegeTable diseases and insect pest recognition method using mobile smart devices, [25] examined a decision support system for agricultural and farming. Based on the literature review, there is still limited research about the combination of Fuzzy Sugeno and Certainty Factor methods for corn pests and disease detection systems. Therefore, this research aims to develop a detection system of pests and diseases for corn plants using Certainty Factor and Fuzzy Sugeno methods. Furthermore, the novelty of this research is utilizing the combination of Certainty Factor and Fuzzy Sugeno Methods for the detection system of pests and diseases in the corn plant. Therefore, this research makes contribution by providing a detection system of pests and diseases for corn plant using certainty factor and fuzzy sugeno methods.

2. Research Method

This research employed the Certainty Factor and Fuzzy Sugeno method. The certainty Factor method is a method to accommodate the uncertainty reasoning of the expert[26]. Every rule in the certainty factor method has value belief, not only the premises that have belief factor. It also points out the uncertainty size to a fact or rule[27]. This method is employed to determine the type of disease corn plants were based on the certainty level. This level was obtained from the calculation of the CF method in the knowledge framework. Moreover, Fuzzy sugeno has two main part, i.e., fuzzy conclusion withdraw and input fuzzyfikasi process[28]. In this research, The Fuzzy Sugeno method was utilized to calculate the damage level of the disease with certain symptoms. The input data in this experiment are 15 disease data and 48 symptoms data. The data were collected from the unit of food crop and horticulture protection at the Department of agriculture and food security in Pamekasan, Madura. The symptoms list is shown in Table 1, whereas the diseases list is in Table 2.

Table 1. Data of Symptoms And Diseases For Com Frant		
Symptom Code	Symptom	
S1	There are holes in young leaves	
S2	There is a long tunnel to the base of the stem	
S 3	Young corn plants are short and small	
S 4	There is a short tunnel to the base of the stem	
S5	There is a tunnel to the base of the stem	
S 6	There is a small hole in the leaf	
S 7	Male stems and flowers are easily broken	
S 8	There is an attack that occurs at the age of 20-70	
	weeks	
S 9	There are long bite marks	

Table 1. Data of Symptoms And Diseases For Corn Plant



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010	
S10	There are big holes / broken leaves
S11	The attack of corn plants in the generative phase or
610	the filling phase of the stem bark
S12	Cob damage occurred
S13	There are bite marks on the stem
S14	There are footprints
S15	There are still active holes
S16	There are brownish peacock points like rust
S17	Brown leaf surface
S18	There are brownish-yellow powder under the leaves
S19	There are holes / broken leaves
S20	There are yellow lines that are wide in size and
	covered by white flour
S21	The sick corn leaves are whitish-yellow or greenish-
	yellow, stiff and shortened stems
S22	Young plants with stunted growth
S23	The inside of the lump is dark
S24	Every piece of corn stalk is damaged
S25	A small lump grows around 5 centimeters
S26	All the cob on the plant is infected with burnt disease
	if the male flowers are infected
S27	Disruption has occurred when the plant age between
	45 and 56 weeks
S28	There is a pupa on the cob
S29	The root is damaged because of the caterpillar bite
S30	The plant withers
S30	Caterpillars sometimes attack the roots
S32	The plant can fall or die
S32 S33	Eaten until finished
S34	The attack of young corn plants at night
S35	There are bite marks that attack the stem of young
555	
S36	corn plants Spots spread on the leaves
S30	
S38	The midrib is red and gray
	The presence of white granules
S39	There are bite marks on the leaves like teeth
S40	Broken leaves
S41	Leaves become transparent
S42	There is a hole that separates the bones of the leaves
S43	Mango suction leaves of young corn plants
S44	The stool feels sweet, so it invites ants and has the
	potential to cause secondary attacks, namely sooty
	fungus
S45	The leaves of the plant turn black
S46	The wrapper is broken
S47	Swollen corn seeds are black
S48	Some swollen corn seeds popped out

Table 2. Diseases and the Symptoms

No	Category	Name of Diseases	Types of Symptoms
1	Pest	Atherigona	S1, S3, S6, 10, S19, S21, S40
2	Pest	Ostrinia fumacalis	S2, S4, S5, S6, S7, S8, S11, S13, S35

3	Pest	Sitophilus zeamais Motsch	S6, S9, S10, S21, S40
4	Pest	Rat	S4, S11, S12, S13, S14, S15, S32,
			\$33, 46
5	Diseases	Puccinia polysora	S16, S17, S18, S36, S40, S46
6	Diseases	Peronosclerospora	S3, S19, S20, S21, S22, S30
7	Diseases	Ostrinia fumacalis	S11, S12, S23, S24, S25, S26,
			S27, S46, S47, S48
8	Pest	Heliotis armigera	S12, S13, S27, S28, S46
9	Pest	Mysus persicae	S29, S30, S31, S32
10	Pest	Sitophilus zeamais	S11, S12, S33, S46
		Motscha	
11	Pest	Agrotis	S34, S35
12	Pest	Helmithosporium	S10, S16, S36, S37, S38, S40
		turcicum	
13	Pest	Locusta	S10, S39
14	Pest	Spodoptera	S10, S41, S42
15	Pest	Aphis Glines	S8, S40, S43, S44, S45

Input data should be processed to be a knowledge that shows certainty measurement about a fact or a rule. Based on observation and interview result, CF rule value which is obtained from the expert and users. It will be changed into CF values, as shown in Table 3.

Table 3. CF Rule Values			
No	Confidence Level	Value	
1	Not	-1	
2	Almost Certainly not	-0.8	
3	Probably not	-0.6	
4	Maybe not	-0.4	
5	Unknown	-0.2 to 0.2	
6	Maybe /Not sure	0.4	
7	Probably/ sure	0.6	
8	Very sure	0.8	
9	Definitely	1	

The next step is to count parallel CF from some premises in a rule. First, the calculation of premises and operators that support the CF parallel must be conducted. Each premise and operator can be seen in equations 1, 2, 3, and 4.

$$CF(x \text{ and } y) = \min(CF(x), CF(y)$$
(1)

$$CF(x \text{ and } y) = max \left(CF(x), CF(y) \right)$$
(2)

$$CF(\neg x) = \sim CF(x) \tag{3}$$

$$CF(x, y) = CF(x) * CF(y)$$
(4)

Where CF(x) is the sequential CF of each premise, CF(y) is CF from the experts, and CF(x,y) is parallel CF. After that, the CF combination of each disease will be calculated based on parallel CF values. CF Combination calculation will produce a list of corn disease possibilities, as shown in equation 5. CF combination is the last CF to determine expert confidence level from a rule to the problem.

$$CF(CF1, CF2) = CF + CF2(1 - CF1)$$
 (5)



The next stage is to determine the damage level using the Fuzzy Sugeno method. Fuzzy logic can be utilized to change the data interval into a value from 0 to 1. The overlap interval is obtained by widening the range of the interval. Based on the CF rule results and the application of fuzzy logic, the overlap interval range is divided into three categories: little/light, middle (medium), and heavy (many. The last step of Fuzzy Sugeno is the defuzzification process. The center average method is a defuzzification process using the middle value of each fuzzy set of attacks.

$$b = \frac{\sum a \text{ to } z}{n} \tag{12}$$

Equation 12 shows the calculation to determine the middle value of each attack weight category (b), where *a* to *z* is the range interval, and *n* is the number of damage levels. As a result, the middle value of each damage level is shown in Table 4 and Figure 1.

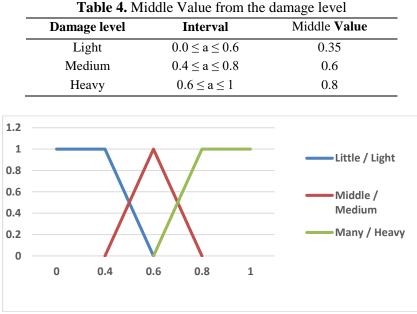


Figure 1. Fuzzy Variable Representation of Damage Levels

3. Results and Discussions

We conducted 20 times experiments. In each experiment, we input some symptoms, and the system showed the pests and diseases rank that might infect the corn plant and the damage level of the attack. Furthermore, two experts analyzed the pests and diseases that attacked the plant based on the input symptoms. We captured the agreement level from the expert analysis with the percentage of detected pests and diseases rank results using equation 12. Furthermore, the testing result can be seen in Table 5.

$$A = \frac{\sum CF(CF1, CF2)_{True}}{\sum CF(CF1, CF2)} \times 100\%$$
(13)

	Table 5. Testing result					
Experiments	Symptoms	Diagnose Result	Damage Level	The First Expert (%)	The Second Expert (%)	
1	S22 (Not sure)		Light	100	100	

	S13 (Not sure)	Peronosclerospora	Light		
	S20 (Not sure)	maydis (56.8%)	Light		
	520 (1107 5410)	Ostrinia fumacalis	Digit		
		(40%)			
		Atherigona			
		(36.64%)			
2	S1 (Not Sure)	Atherigona	Light	100	100
	S2 (sure)	(42.4%)	Mediu		
	S22 (sure)	Ostrinia fumacalis	Heavy		
	× ,	(60%)	2		
		Peronosclerospora			
		maydis (40%)			
3	S12 (Not	Ostrinia fumacalis	Light	75,87	75,87
	Sure)	(88.032 %)			
	S13 (Very	Rat (28%)	Light		
	sure)				
	S7 (Not sure)				
4	S44 (Not sure)	Rhizoctonia	Light	100	100
	S47 (sure)	solani (76%)	Light		
	S48 (Not sure)	Mysus persicae			
		(40%)			
5	S10/S19 (Not	Rat (40%)	Light	100	88
	sure)	Puccinia polysora			
	S6 (Sure)	(92%)	Medium		
	S17 (Very	Helmithosporium	Light		
	sure)	turcicum (18%)			
6	S20 (Not sure)	Atherigona	Light	88.9	88.9
	S21 (Not sure)	(26.08%)	Light		
	S22 (Not sure)	Peronosclerospora	Light		
		maydis (70.62%)			
		Sitophilus			
		zeamais Motsch			
	629 (Sum)	zeamais Motsch (12%)	Licht	100	100
7	S28 (Sure)	zeamais Motsch (12%) Gibberella	Light	100	100
7	S7 (Not Sure)	zeamais Motsch (12%) Gibberella roseum (78.65%)	Light Medium	100	100
7		zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera	-	100	100
	S7 (Not Sure) S27 (Sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%)	Medium		
7	S7 (Not Sure) S27 (Sure) S36 (Sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%)	Medium Light	100	100
	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus	Medium		
	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%)	Medium Light		
8	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%)	Medium Light Medium	100	100
	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure) S45 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%) Rat (40%)	Medium Light Medium Light		
8	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure) S45 (Not sure) S46 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%) Rat (40%) Puccinia polysora	Medium Light Medium Light Light	100	100
8	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure) S45 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%) Rat (40%) Puccinia polysora (8%)	Medium Light Medium Light Light Medium	100	100
8	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure) S45 (Not sure) S46 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%) Rat (40%) Puccinia polysora (8%) Bipolaris maydis	Medium Light Medium Light Light	100	100
8	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure) S45 (Not sure) S46 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%) Rat (40%) Puccinia polysora (8%) Bipolaris maydis (76%)	Medium Light Medium Light Light Medium	100	100
8	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure) S45 (Not sure) S46 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%) Rat (40%) Puccinia polysora (8%) Bipolaris maydis (76%) Puccinia polysora	Medium Light Medium Light Light Medium	100	100
9	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure) S45 (Not sure) S46 (Not sure) S47 (Sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%) Rat (40%) Puccinia polysora (8%) Bipolaris maydis (76%) Puccinia polysora (8%)	Medium Light Medium Light Light Light Light	100	100
8	S7 (Not Sure) S27 (Sure) S36 (Sure) S1 (not sure) S44 (Not sure) S45 (Not sure) S45 (Not sure) S46 (Not sure)	zeamais Motsch (12%) Gibberella roseum (78.65%) Heliotis armigera (60%) Spodoptera (40%) Mysus persicae(85.6%) Rat (40%) Puccinia polysora (8%) Bipolaris maydis (76%) Puccinia polysora	Medium Light Medium Light Light Medium	100	100



		Sitophilus			
		zeamais			
		Motsch(8%)			
		Agrotis (60%)			
11	S35 (sure)	Rat (90.67%)	Light	78.02	55.19
	S11 (Not sure)	Heliotis armigera	Light		
	S12 (Not sure)	(64%)	Light		
	S13 (Not sure)	Ostrinia fumacalis	Light		
	S14 (Not	(61.6%)			
	Sure)				
12	S10 (Not sure)	Rat (40%)	Light	100	61.58
	S31 (not sure)	Puccinia polysora	Light		
	S30 (not sure)	(80.12%)	Light		
	S31 (sure)	Mosaik (9%)			
13	S32 (not sure)	Mosaik (70.62%)	Light	88.96	100
	S20 (not sure)	Atherigona	Light		
	S20 (not sure)	(26.08%)	Light		
		Sitophilus			
		zeamais Motsch			
		(12%)			
14	S21 (Not sure)	Puccinia polysora	Light	61.54	81.66
	S16 (Not sure)	(85.6%)	Medium		
	S17 (not sure)	Mosaik (28%)	Light		
	S18 (sure)	Atherigona (12%)	Light		
		Helmithosporium turcicum (13.5%)			
15	S20 (not sure)	Rhizoctonia	Light	84.85	84.85
13	S31 (not sure)	solani (44.8%)	Light	04.05	04.05
	SST (not sure)	Peronosclerospora	Light		
		maydis (8%)			
16	S30 (not sure)	Helmithosporium	Light	39.22	39.23
	S18 (not sure)	turcicum	Light		
	S37 (not sure)	(61.98%)	Light		
	20. (Puccinia polysora	8		
		(40%)			
17	S38 (not sure)	Bipolaris maydis	Light	100	100
	S45 (not sure)	(64%)	Light		
	S47 (not sure)	Mysus persicae	Light		
		(40%)	_		
18	S48 (not sure)	Peronosclerospora	Light	82.31	82.31
	S20 (Very	maydis (93.76%)	Medium		
	Sure)	Atherigona (24%)			
	S21 (sure)	Sitophilus	Light		
		zeamais Motsch			
10		(18%)	T • 1.	07.5	07 5
19	S22 (not sure)	Agrotis (84%)	Light	87.5	87.5
	S34 (sure)	Ostrinia fumacalis	Medium		
	C 25 ()	(12%)	I date	100	100
20	S35 (sure)	Helmithosporium	Light	100	100
	S27 (not sure)	turcicum (28%)	Medium		

Heliotis armigera		
(58%)		
Average	86.21	84.11
	85.	.16

Table 6 capture that there are 13 experiments points out that the results of the first expert mostly have the same results with the second expert. Some of the results have 100% of the same results between two experts. Furthermore, some others have various percentage, such as 75.87%, 88.9%, 84.95%, 37.25%, 82.31, and 87.5%. Moreover, there are four experiments that the results of the second expert better than the results of the first one as follows: the second expert analyzed 100%, and the first expert evaluated 88.96%, the second expert assessed 81.66% and the first one analyzed 61.54%, as well as the second expert, evaluated 39.23% and the first one assessed 39.22%. Additionally, there are three experiments show the results of the first expert evaluated 88%, the first expert assessed 78.02% and the second expert evaluated 55.19%, as well as the first expert assessed 100% and the second one analyzed 61.58%. Furthermore, there are various symptoms in all experiments and produced numerous diagnose results and percentages as well. The experiment result has generated 85.16% of accuracy. This result has been compared with other research[26]. As a result, the comparison shows our experimental result has produced higher accuracy than [26]. Actually, the level of accuracy not only depends on the method but also is greatly influenced by the accurate of the disease criteria and symptoms.

4. Conclusion

This study has been able to resolve the detection of pests and diseases in corn plants using the Certainty Factor and Fuzzy Sugeno methods. It makes the farmers easier to handle quickly and minimize the amount of damaged corn production. Additionally, the comparison results of the system accuracy and detection carried out by experts with the Certainty Factor and Fuzzy Sugeno method have reached an optimal solution at 85.16% of 15 diseases and 48 symptoms. We will employ forward chaining and Certainty Factor for the detection system of corn pests and diseases in future research. This research has some implications for theory and practice. For theory, it extends the body of knowledge of the intelligent system, expert system, computer science, Certainty Factor, Fuzzy Sugeno, pests, diseases, and cornfields. For practice, the system can be used by farmers and other practitioners to reduce pests and diseases in the corn plant.

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