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Application of Extreme Learning Machine and Modified Simulated Annealing for Jatropha Curcas Disease Identification

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Abstract

Jatropha Curcas is a plant that has many functions and uses for everyday purposes such as biodiesel and beauty tools, but this plant can not can also be separated from the disease. Expert systems can be applied in identifying so as to help both farmers and extension workers to identify disease. The method that can be used one of them is the method of Extreme Learning Machine. Extreme Learning Machine has been done and the results of accuracy given still need improvement. Optimizing the value of weight on Extreme Learning Machine can improve the accuracy value. Optimization done using Simulated Annealing and using decision tree gives better result than before, with best accuracy average 90%,95% and maximum accuracy equal to 94%,74%.

Keywords: *Jatropha Curcas, Extreme Learning Machine, Simulated Annealing, Decision Tree, Identification.*

1 Introduction

Jatropha is a plant that can survive in dry conditions so it can live in conditions of low rainfall. Jatropha is commonly found in Southern and Central Africa, South India and Southeast Asia [1]. Jatropha curcas can be used as a substitute for diesel fuel [2]. Jatropha curcas can be used also on the seeds of oil for candles, soaps, cosmetics and detergents. The oil content in castor plants is 63% more than soybean oil, sunflower and palm oil.

Regardless of the results given from Jatropha curcas, this plant can still get sick. Diseases that attack these plants can have an impact on parts of plants such as leaves, stems, roots and fruit. The number of diseases that attack jatropha become a problem because it can decrease the quality of the crop [3]. The lack of expertise as well as the lack of knowledge of farmers on Jatropha is a major influence on Jatropha curcas [1].

The development of information technology and zama can now be an advantage for the community. Systems that can connect directly with users make users feel comfortable in doing things. The availability of an online system can provide benefits for the community in making it easier to serve the community in particular.

This problem can be solved by incorporating existing expert knowledge into an intelligent system [4]. The intelligent system processes the knowledge that has been entered and then issues a decision based on the algorithm used. Based on the results of the decision that can be compared with the decision of an expert how good the algorithm we use [5].

Neural Network is a computation method that can be used in identifying [6]. Neural Network is commonly used in classification methods with such high dimensions [7]. Some identifiable Neural Network methods such as Extreme Learning Machine [8] - [10], Fuzzy Neural Network [6], [11] and Multi Layer Perceptron [7]. The Extreme Learning Machine method is often used as a method of performing identification performed by the system and delivering better results at such a high dimension [12] - [14].

Previous work has been done using several method. Previous research using Dempster-Shafer and optimize belief value using Genetic Algorithm has been done that giving accuracy 87.1% [15]. Other previous research has been done using Fuzzy Neural Network that give accuracy 11.2% [16] and using Simulated Annealing for optimize weight value on neuron give accuracy 19.5% [17].

Weight value on Neural Network still uses random value. The value of random weight can allow the work of Neural Network is not maximal so as to enable neural network does not give maximum results of identification. The problem of weight assignment on Neural Network can be solved using Simulated Annealing [18]. Simulated Annealing works optimize based on nearest neighbor search [18] - [20]. Simulated Annealing has faster computation time compared to other optimization methods [20].

Based on previous research, Simulated Annealing is used for optimization in the case of Deep Learning and provides a lower error value than without using Simulated Annealing optimization [21]. Simulated Annealing can be used to optimize the value of weight on Neural Network. The optimization of weighted values on Neural Network aims to increase the accuracy value performed by

Neural Network. Therefore, the researcher wants to use Simulated Annealing method for weight value optimization.

Based on the problems that have been described, researchers tried to use the modification Simulated Annealing-Extreme Learning Machine on the identification of Jatropha diseases. Modifications are used to provide a good optimum solution. Using this algorithm can provide optimum solutions that are better than ever and provide valid identification.

2 Jatropha Curcas Disease

The cause of jatropha diseases is pathogen [22]. There are many kinds of pathogenic fungi that attack the Jatropha plant, *Helminthosporium tetramera* causes leaf blight, *Pestalotiopsis paraguarIensis* causes leaf spot, *Cercospora jatrophaecurces* cause cercospora leaf spot, *Phutophthora* spp. cause of dieback, *Fusarium* spp. causes of fusarium wilt, *Colletotrichum* sp. causes of leaf spot, *Oidium* sp. cause of powdery mildew, *Alternaria* sp. causes of altenaria leaf spot [23], *Armillaria tabescens* causes dieback and bacteria *Xanthomonas* sp. causes of bacterial blight[24].

3 Extreme Learning Machine

The Extreme Learning Machine (ELM) is one algorithm that serves to classify, clarify, and manage features that have one or more hidden layers that work in one iteration [12], [25], [26]. The advantages of this ELM method are thousands of times faster than other Neural Network methods that use the concept of backpropogation learning [12]. The architecture of the ELM can be seen in Figure 1.

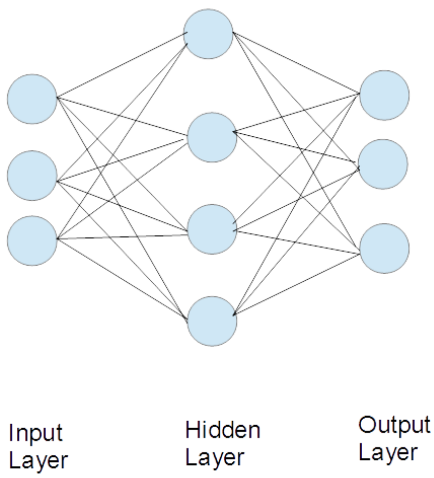

Figure 1 Architecture Extreme Learning Machine [27]

Extreme Learning Machine is widely used in identification cases. This method is often used because the computation time is very fast also gives good results. Here is an explanation of the flow method of Extreme Learning Machine.

1. Input on this process is the data train, test data, and optimization results of the weighting value of Simulated Annealing.
2. Conduct ELM training on training data.
3. Obtain the result β output weight matrix from the ELM training to be processed into the test.
4. Conduct ELM testing based on weight matrix already obtained from ELM training for test data.
5. The result of this method is a value of accuracy on this system.

4 Simulated Annealing

Simulated Annealing (SA) is an algorithm that works to optimize using statistical thermodynamic principles [28]. SA works based on an analogy of the process of cooling and freezing a metal into a crystalline structure using a minimum energy called annealing process [29].

The SA algorithm has advantages over other metaheuristic algorithms such as Genetic Algorithms and Evolution Strategies. The excess SA is less time consuming in computing and less memory is used [30]. The SA algorithm allows the current solution to be replaced by the worst neighboring solution with very little possibility to avoid getting stuck on a local optimum solution [31]. The weakness in SA is that there is no guarantee to get the optimum solution, the solution obtained for each iteration can not be reproduced and different every process because it is stochastic and is relatively slow in calculation compared with direct search algorithm [32]. Direct search is a method used to solve optimization problems that do not require information about the gradient of the destination function.

The stages in Simulated Annealing are as follows [33]:

1. Generating initial solution (S), initial temperature T0, final temperature Tt, maximum iteration, temperature drop rate □ (usually 0.9 or 0.95), initial energy E, best solution Sbest = S, and best energy Ebest = E.
2. Generating a neighboring solution (Sn) and enumerating En's energy.
3. If value is En <E, go to step 7. If not, go to step 4.
4. Calculating energy changes ΔE = En- E.
5. Generating your uniform random values between 0 and 1.

6. If u value $u < e^{\left(\frac{-\Delta E}{T}\right)}$, go to step 7. If not, go to step 10.
7. Accepting the Sn solution as S and En energy as E.
8. If the value is En <Ebest, go to step 9. If not, go to step 10.
9. Accepting new solution as best solution, Sbest = Sn and Ebest = En.
10. If the maximum number of iterations for the current temperature is reached, go to step 11. If not, go to step 2.
11. Reduced temperature $T = T_0 \times \alpha$ where α is the rate of temperature drop.
12. If the minimum temperature has been reached, go to step 13. If not, go to step 2.
13. Process completed, solution found

5 METHODOLOGY

The mechanism of the method to be done is first started from the process of Simulated Annealing (SA). In the SA process will be optimized for weight assignment on Neural Network neurons. In SA there is a process modification to the permutation representation. In the process of permutation representation using a new method that has the first process of cutting two long points, both points are determined randomly. After cutting and then exchanging the position of the two points, then one of the cutting points will be done randomize the new position at the cut point.

To find out how well the optimization results from SA then used Extreme Learning Machine (ELM) to identify disease. The amount of data used is as much as 80% training data and 20% test data from a total of 166 cases of jatropha diseases. Once obtained the best trust value then it will be saved as the latest generation for the next iteration process. This SA and ELM process continues until a predetermined number of iterations from the start.

Here is a plot of the proposed method

1. Data is the number of neuron weights used and disease case data as initial input for processing.
2. Optimize the weighting value using Simulated Annealing.
3. The result of Simulated Annealing is the value of neuron weight.
4. Conducting disease classification process using Extreme Learning Machine based on disease case data.
5. Getting the type of disease based on the results of the classification process

Optimizing the value of neuron weight on Extreme Learning Machine using Simulated Annealing aims to give the best weight value in the process of Extreme Learning Machine. In Simulated Annealing there is a solution repository which is the solution to this problem. Representation of established solutions can be seen in table 1.

The length of the value for a solution repository is the number of neurons used. Each value in each representation of a solution is representative of each weight of a neuron. Table 1 is an example of a solution representation if there are nine neurons. The first to ninth grades represent the first to ninth weight of a neuron.

Table 1 Example of representation solution

(x_1)	(x_2)	(x_3)	(x_4)	(x_5)	(x_6)	(x_7)	(x_8)	(x_9)
0,5	**0,4**	**0,1**	**-0,1**	**0**	**-0,3**	**0,2**	**0,45**	**-0,3**

The method of mutation used in this study is the modified mutation proposed in this study. This method works by exchanging points of value and shifting positions for each selected value group. The mutation process is illustrated with the following steps:

1. Input on this process is the repository of the main solution.
2. Generate the iteration by setting j = j + 1.
3. Choose 2 groups of values to be exchanged for position. The length of each value group should be the same.
4. Exchange the two positions of the value group.
5. One group randomizes the position of the value to get a new position.
6. Perform the calculation of fitness values on the repository of solutions that have been formed by finding the value of accuracy using the Extreme Learning Machine method.
7. Repeat steps 2 through 7 as many neighbors as you want to search.
8. Store one fitness value repre- sentation of the best solution as best energy.
9. Output of this process is the best solution along with the best energy.

6 Results and Discussion

In the previous test on Extreme Learning Machine obtained the best number of neurons as much as 19 with the best average accuracy of 60.61%. The parameters of the best number of neurons are then used as the initial parameters of this test.

In this test is done to see how well the Extreme Learning Machine (ELM) which weight value on neuron has been optimized with Simulated Annealing (SA) which have been modified. The modification process in SA is on the proposed new permutation representation to search for nearest neighbors to find the best solution. This test uses temperature and cooling factor parameters. In Figure 2 is the result of temperature testing.

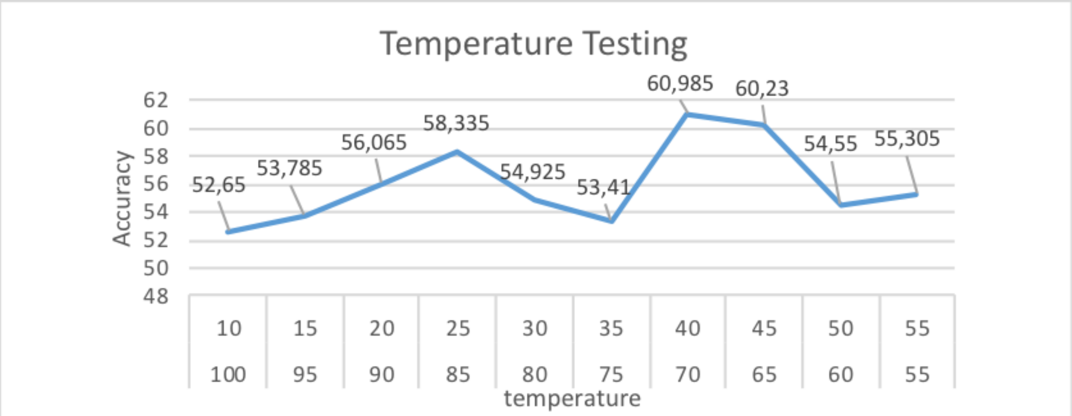

Figure 2 Temperature Testing Chart

In Figure 2 is a graph of temperature testing results. This testing used 19 neuron parameters based on ELM's best test result parameters and cooling factor of 0.9. At the temperature test, a combination of the initial temperature of 70 and the end of 40 with the best average accuracy of 60.985%.

The last test is testing the cooling factor. This test aims to see the great cooling factor that gives the best solution. The results of the cooling factor test can be seen in Figure 3.

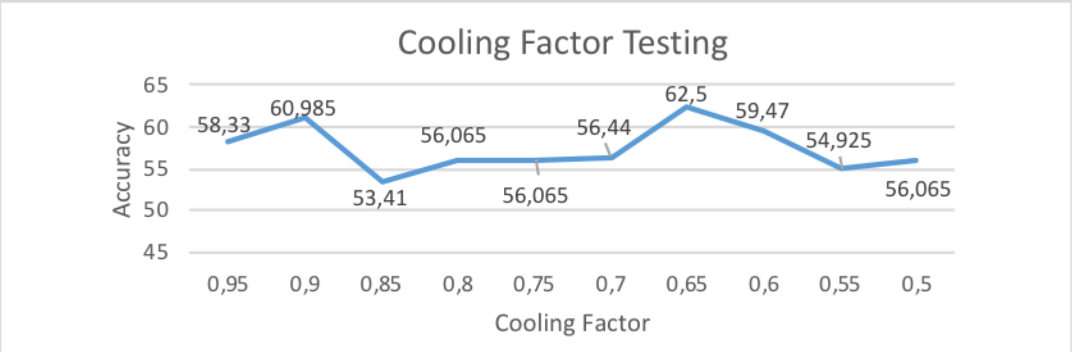

Figure 3 Cooling Factor Testing Graph

In Figure 3 is the result of cooling factor testing. The parameters used in this testing are 19 as the neurons based on the best parameters in the ELM test and the combination of the initial temperature 70 and the end of 40. The best average accuracy is 62.5% with the cooling factor of 0.65. Maximum accuracy is obtained that is equal to 69.7% which means an increase compared without optimizing the value of weight.

After that then added a decision tree for the determination of jatropha seed disease. Decision tree aims to facilitate the system to make decisions based on expert knowledge. The rules in Table 2 are based on expert knowledge in which there is a symptom of only one disease, so that it can facilitate the decision making of disease identification if one specific symptom emerges. In Table 2 is an example of the rules of jatropha curcas disease.

Table 2 Table Decision Trees Against Disease Symptoms

Number	Rules
R-1	IF G01 OR G27 THEN P1
R-2	IF G05 THEN P3
R-3	IF G11 OR G19 OR G20 THEN P4
R-4	IF G12 OR G16 OR G18 THEN P5
R-5	IF G09 OR G26 OR G28 THEN P6
R-6	IF G04 OR G10 THEN P7
R-7	IF G24 THEN P8
R-8	IF G15 OR G21 THEN P9

Based on these rules then it can be tested to embed the parameters in accordance with the previous best parameters. The results of the examination can be seen in Table 3

Table 3 Test Results Using Tree Decision Additions

	1	2	3	4	5	6	7	8	9	10
Training data	87,22	94,74	88,72	84,21	90,23	87,97	88,72	84,21	87,97	87,22
Testing data	84,85	84,85	78,79	84,85	81,82	90,91	84,85	84,85	93,94	84,85
Average Accuracy	86,035	89,795	83,755	84,53	86,025	89,44	86,785	84,53	90,955	86,035

After all the testing methods done, it can be seen in Table 4 comparison between methods.

Table 4 Comparison of Inter-Method Results

Method	Best Average Accuracy	Best Accuracy
FNN [2]	11,2%	30%
SA-FNN [3]	19.5%	32.5%
MLP	9,1%	12,12%

ELM	60,61%	66,67%
Modified SA and ELM	62,5%	69,7%
Modified SA and ELM + Tree Decision	90,955%	94,74%

Based on the results of comparison between the methods shown in Table 4 shows that the proposed method of modification of SA and ELM gives the best results in the identification of jatropha diseases. This is evidenced by having the best results on the best average accuracy of 90,955% and best accuracy of 94,74%.

7 Conclusion

The best average accuracy in the Simulation Annealing and Extreme Learning Machine modulation algorithm is 90,955% with the best accuracy of 94,74% by adding the decision tree inside. This proves the proposed method gives a good enough identification result and becomes the best compared to other comparative methods based on table 4.

The higher the accuracy the better the results of the identification of the method used. For further research it may be possible to perform real-coded representations for optimizing weight values in neurons using Simulated Annealing to provide better accuracy results. The use of modification of Extreme Learning Machine is also expected to provide better results than ever before. The addition of decision tree automation for the identification of Jatropha curcas is necessary so that if symptoms appear to be typical of a disease it can provide better decisions

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