Indonesian Journal of Electrical Engineering and Computer Science
Vol. 32, No. 3, December 2023, pp. 1795~1804
ISSN: 2502-4752, DOI: 10.11591/ijeecs.v32.i3.pp1795-1804

Optimization deep learning with rough set approach model classification Otitis

Irzal Arief Wisky[1], Teri Ade Putra[2]
[1]Department of Information Systems, Faculty of Computer Science, Universitas Putra Indonesia YPTK, Padang, Indonesia
[2]Department of Informatics Engineering, Faculty of Computer Science, Universitas Putra Indonesia YPTK, Padang, Indonesia

Article Info

Article history:

Received Sep 12, 2023
Revised Sep 25, 2023
Accepted Oct 5, 2023

Keywords:

Classification analysis
Deep learning
Knowledge pattern
Otitis disease
Preprocessing

ABSTRACT

Otitis is a disease that occurs in the middle ear in the form of inflammation. This research aims to develop an analysis model for the classification of Otitis disease based on knowledge patterns based on symptoms and type of disease. The analysis methods used include the performance of the certainty factor (CF), rough set (RS), artificial neural network (ANN), and decision tree (DT) methods. CF and RS performance can be used to generate classification rule patterns. These rule patterns become new knowledge in the classification analysis process using the concept of deep learning (DL). DL analysis with ANN and DT performance can work optimally in exploring and discovering hidden knowledge. Based on the results of performance testing, the combination of CF and RS in preprocessing can present a classification pattern of 106 rules. The output of DL analysis results is proven to produce precise and accurate classification results with an accuracy of 89%. Based on these results, the analytical model developed was proven to be effective in classifying Otitis disease. Not only that, this research is also able to contribute to updating the knowledge-based system in the classification process.

Corresponding Author:

Irzal Arief Wisky
Department of Information Systems, Faculty of Computer Science, Universitas Putra Indonesia YPTK
Padang, 25145, Indonesia
Email: irzal.arief12@gmail.com

1. INTRODUCTION

Otitis disease can attack any part of the human body [1]. This disease is an infectious disease with symptoms that often look like fluid in the middle ear and is characterized by pain and even causes a high fever [2]. These are some of the early signs or symptoms that are felt [3]. If this is allowed to continue it will result in loss of hearing function [4]. Basically, Otitis disease has several types of levels based on the symptoms felt by the sufferer [5]. Therefore, a classification analysis process is needed that can produce information and knowledge related to Otitis disease.

Visualization analysis classification of the type of Otitis media carried out using the concept of deep learning (DL) gave results with an accuracy rate of 97.45% [6]. The visualization model with the concept of machine learning (ML) was developed to perform of the classification of Otitis media and presents quite good results [7]. In a different concept, using an extraction system method based on red, green, and blue (RGB) colors is also able to present fairly accurate classification results [8]. Analysis using classification algorithms can also provide significant results in presenting the classification process based on images of Otitis disease [9]. Based on several previous explanations, it can be seen that the classification analysis is still focused on one type of Otitis disease. The process presented is also still unable to provide a level of certainty so that the results provided are only limited to the classification process. Furthermore, the analysis process presented has not carried out the initial pre-processing stage to get better analysis results. For this reason, this study presents a different analysis process by applying pre-processing in the early stages of analysis.

The methods used in the pre-processing analysis include the certainty factor (CF) and rough set (RS) methods. This method will be used to carry out the pre-processing process in order to provide an appropriate classification rule in Otitis disease. CF is able to provide a level of certainty in the rules of classification [10]. CF can also be developed in a model to provide hypothetical conclusions [11]. Conceptually, CF works to provide solutions to the problem of uncertainty in identification [12]. The RS method can be developed in a classification model to present the stored knowledge of data [13]. RS can also provide support for the development of a classification model to get maximum results [14]. Hospital performance has been proven in many classification models presenting the effectiveness of the analysis process which is seen based on the output of the analysis [15].

The concept of analytical learning in this study uses DL. DL is a technique used in classifying by training network weights on a large amount of data and can produce perfect weights [16]. In general, DL has made a major contribution to the mining process for big data [17]. DL also has a pretty good performance based on the level of positivity, precision, F1 scores, and accuracy values [18]. Thus, the concept of DL is used in the classification of Otitis disease. Artificial neural network (ANN) is a popular method in the concept of DL and is used in solving problems by doing learning in the network [19]. ANN gives results by presenting a fairly high level of accuracy [20]. ANN is also used in problem-solving analysis to produce a better classification model [21]. In addition to the ANN method in classification analysis, the decision tree (DT) method is also used to provide an overview of the results of the classification analysis in the form of a DT [22]. The results of the DT analysis can be used in making decisions based on the resulting knowledge base [23]. DT performance can be developed in a structured classification model to provide optimal analysis results [24].

Based on the previous explanation, this research provides a new analytical model. The novelty of this research is presented in the optimized DL performance with the RS approach. This novelty is presented in the pre-processing analysis process to obtain precise and accurate classification rules. The resulting classification rule is also equipped with a certainty level CF value based on facts and knowledge of symptom data for the type of Otitis disease. The analysis output using the DL concept is expected to provide optimal results in classification. Overall, this study will present a much better analytical model than previous models for classifying Otitis disease. With this research, the analysis results obtained can provide new knowledge in the form of a knowledge-based system that can be used as a basis for decision-making.

2. RESEARCH METHOD

The classification process for Otitis is carried out in several stages to get the right classification results. These stages can be described in the form of a research framework. The research framework in conducting the classification process for Otitis disease can be seen in Figure 1.

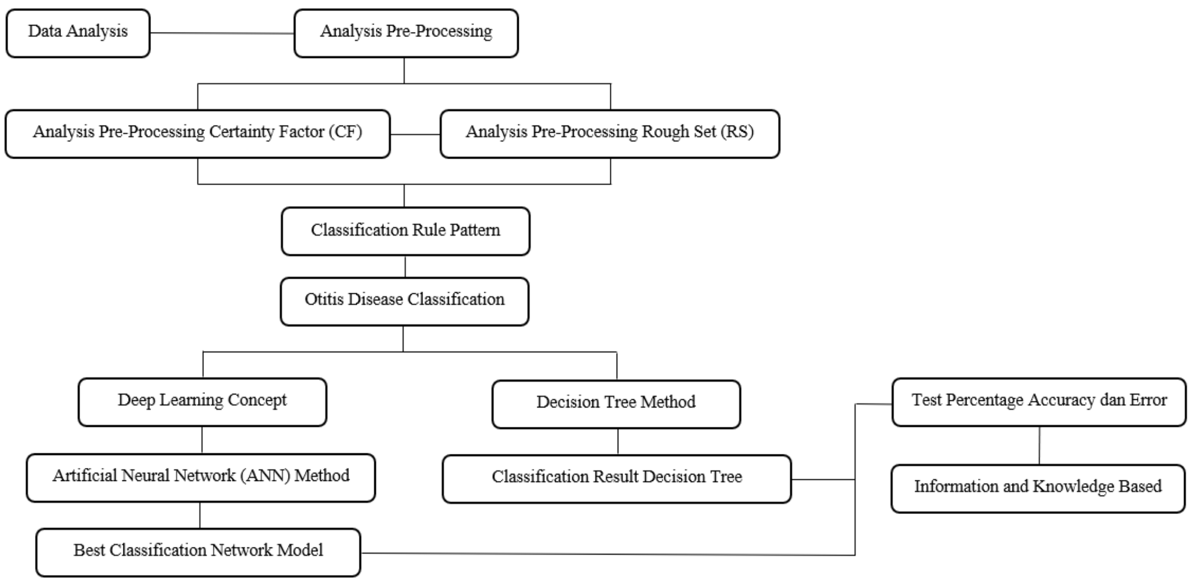


Figure 1. Research framework

Figure 1 is an interpretation visual of the stages carried out in the analysis of the classification of Otitis disease. These stages start from: i) data analysis which aims to see the indicators used in the classification process; ii) pre-processing analysis used to generate classification rule patterns using the concept CF and the rough set RS method; iii) the classification process uses the concept of DL and DT; and iv) the final process to measure the percentage level of accuracy and error obtained. So that the final result of this study will provide an information and knowledge base in the process of classifying Otitis disease.

2.1. Certainty factor

CF is a method of presenting solutions by providing certainty in an ambiguous relationship between cause and effect [25]. CF is used to analyze the correlation between factors and the results obtained with the value of the confidence level [26]. The CF method can be seen in (1) [27].

$$\begin{aligned} \mathrm{CF\ ij} &= \frac{f_{ij}-f}{f_{ij}(1-f)} \text{ if f ij } \geq \text{ f} \\ & \frac{f_{ij}-f}{f_{ij}(1-f)} \text{ if f ij } < \text{ f} \end{aligned} \tag{1}$$

According to (1) is the concept used to present the value for each variable. The concept is presented in a mathematical calculation where CFij is the certainty factor contained in classes i and j. fij is a class i probability value of the variable j.

2.2. Rough set

The rough set method is a concept used in problem-solving to eliminate ambiguity in the data [28]. This method can be called an unsupervised method that can process data in the form of numeric or nominal attributes [29]. This method works with U; K; F as a knowledge expression system to classify objects. U={x1, x2, x3......xn} is a domain consisting of xi as objects that represent data. A={a1, a2, a3....an} is a set of attributes ai (Xj) in attribute a. Existing elements refer to the input parameters. an (x) is the appropriate data for each impact factor. K is a description of the range of values of the attribute set A. f is also a set of information functions U and A, which represent the mapping U x A → K, giving the information values for each attribute of each object, i.e., A x U, f(x, a) K [30].

2.3. Deep learning

DL is a broad learning concept that has been developed for a specific purpose [31]. DL can represent knowledge with a fairly large data model [32]. This concept is widely used to produce a solution based on learning based on the data used and the results provided provide a fairly minimal error rate [33].

2.4. Artificial neural network

The concept of ANN is implemented in classification analysis by presenting quite good results [34]. Classification analysis was developed with a learning model with precise and accurate results [35]. Learning outcomes are proven to produce the best results based on the results of the training process and network testing [36]. Classification analysis with the concept of ANN adopts learning with a feedforward algorithm to provide optimal results [37]. The network visualization architecture model used in the learning process can be seen in Figure 2 [38].

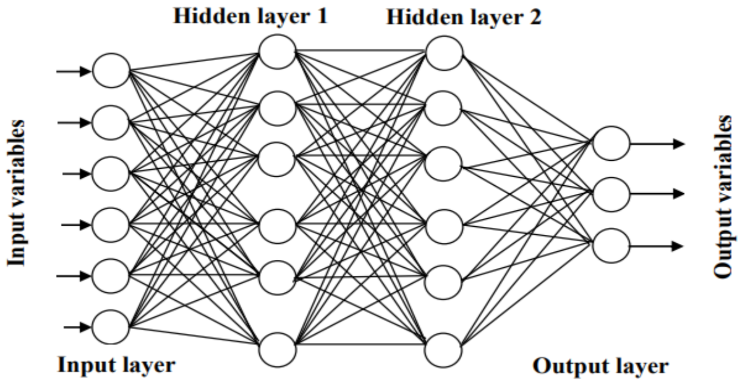


Figure 2. Artificial neural network architecture

Figure 2 explains that the ANN architectural visualization model has 3 layers including the input layer, hidden layer, and output layer. The architectural model can be redeveloped with a multilayer model of the hidden layer used. The concept of ANN is a learning method that adopts human intelligence [39]. With this, the ANN concept can be developed in the case of Otitis disease classification analysis to provide the best results.

2.5. Decision tree

DT is a classification method that performs the process of presenting knowledge in the form of a DT [40]. The resulting decisions are based on the knowledge contained in the data used [41]. The DT method can be seen in (2) [42].

$$\mathrm{Entropy(S)} = -\sum_{i=1}^{c} \mathrm{PS(ci)logPS(ci)} \quad (2)$$

DT is the method used in the classification analysis process. Where used in (2), it can be seen that S is a set, A is a feature, ci is the number of partitions and PS is a proposition to S. On the basis of the concept of a DT, it will describe data in the form of symbols and produce branches in the form of decisions obtained [43]. The results obtained by the decision tree can present new knowledge [44]. This is what underlies the development of the Otitis disease classification analysis process to produce a precise and accurate classification model.

3. RESULTS AND DISCUSSION

3.1. Pre-processing analysis

Analysis of pre-processing data is the most vital stage in the classification process [45]. This is because the process can determine the direction of the problem-solving process [46]. The analysis carried out at the beginning is to determine indicators in the classification process. The indicators are used in the form of data on symptoms and types of Otitis disease. The data was obtained from an expert who served at M. Djamil Hospital, Padang City, West Sumatra, Indonesia. The following data on Otitis disease can be seen in Table 1.

Table 1. Otitis disease data

Code	Disease symptoms	Disease code		
		Acute Otitis (P1)	Otitis effusion (P2)	Chronic Otitis (P3)
G01	Ear pain	√	√	√
G02	Easy to angry	√	√	
G03	Sleep disturbance	√		√
G04	High fever	√	√	√
G05	Loss of balance		√	√
G06	Hearing disorders		√	√
G07	Nauseous			√
G08	Headache	√	√	
G09	Diarrhea	√	√	
G10	Decreased appetite	√	√	

Table 1 explains that Otitis disease consists of 4 types including acute Otitis (P1), effusion Otitis (P2), and chronic Otitis (P3). Based on the disease data and symptoms in Table 1, the pre-processing process can be carried out using the CF concept. CF is a concept used to provide a level of confidence [47]. The CF value can affect the classification process to provide the accuracy of the results given [48]. The results of the pre-processing analysis using CF can be seen in Table 2.

Table 2. Pre-processing analysis using CF

Ear pain	Easy to angry	Sleep disturbance	High fever	Loss of balance	Hearing disorders	Naus eous	Head ache	Diarr hea	Decreased appetite	Disease
Yes	Yes	No	Yes	No	No	No	No	No	No	Acute Otitis = 0.6
No	Yes	Yes	Yes	No	No	No	No	No	Yes	Acute Otitis = 0.8
Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes	Acute Otitis = 1.0
No	Yes	Yes	Yes	No	No	No	No	Yes	No	Otitis effusion (0.6)
Yes	Yes	Yes	Yes	Yes	No	No	No	Yes	Yes	Otitis effusion (0.8)
Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Otitis effusion (1.0)
No	No	No	No	Yes	Yes	No	No	No	No	Chronic Otitis (0.6)
No	No	No	Yes	Yes	Yes	No	No	Yes	No	Chronic Otitis (0.6)
No	Yes	No	Yes	Yes	Yes	No	No	Yes	No	Chronic Otitis (0.8)
No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	Chronic Otitis (1.0)

Table 2 explains that the results of pre-processing using CF provide a confidence level for the type of Otitis disease consisting of 0.6 (probably), 0.8 (almost certain), and 1.0 (definitely). The certainty value is used to generate new knowledge that will be developed at the next pre-processing stage using the RS method. RS can provide a pattern based on the data class grouping used [49]. In other respects, RS is also a concept that is implemented in the case of classification based on information [50]. The results of the presentation of the RS analysis process are a major contribution to the classification process [51]. The sample outputs carried out by the hospital can be seen in Table 3.

Table 3. Results of preprocessing classification analysis with rough set method

Ear pain	Easy to angry	Sleep disturbance	High fever	Loss of balance	Hearing disorders	Naus eous	Head ache	Diarr hea	Decreased appetite	Disease
No	Yes	No	Yes	No	No	No	No	No	No	Acute Otitis (0.6)
No	Yes	No	Yes	No	No	No	No	No	Yes	Acute Otitis (0.8)
No	Yes	No	Yes	No	No	No	No	Yes	Yes	Acute Otitis (1.0)
No	Yes	No	Yes	No	No	No	No	Yes	No	Otitis effusion (0.6)
No	Yes	No	Yes	Yes	No	No	No	Yes	Yes	Otitis effusion (0.8)
No	Yes	No	Yes	Yes	Yes	No	No	Yes	Yes	Otitis effusion (1.0)
No	No	No	Yes	Yes	Yes	No	No	No	No	Chronic Otitis (0.6)
No	No	No	Yes	Yes	Yes	No	No	Yes	No	Chronic Otitis (0.6)
No	Yes	No	Yes	Yes	Yes	No	No	Yes	No	Chronic Otitis (0.8)
No	Yes	No	Yes	Yes	Yes	Yes	No	Yes	No	Chronic Otitis (1.0)
No	Yes	No	Yes	No	No	No	No	No	No	Acute Otitis (0.6)
No	Yes	No	Yes	No	No	No	No	No	Yes	Acute Otitis (0.8)
No	Yes	Yes	Yes	No	No	No	Yes	No	Yes	Acute Otitis (1.0)
No	Yes	Yes	Yes	No	No	No	No	No	No	Otitis effusion (0.6)
No	Yes	Yes	Yes	Yes	No	No	No	No	Yes	Otitis effusion (0.8)
No	Yes	Yes	Yes	Yes	No	No	Yes	No	Yes	Otitis effusion (1.0)
No	No	No	Yes	Yes	No	No	No	No	No	Chronic Otitis (0.6)
No	Yes	No	Yes	Yes	No	No	No	No	No	Chronic Otitis (0.8)
No	Yes	No	Yes	Yes	No	Yes	No	No	No	Chronic Otitis (1.0)

Table 3 is the result of pre-processing produced by the hospital to present the pattern in the classification. In the process, RS provides a classification pattern of 106 rules. This pattern can become new knowledge in the classification process to provide maximum results [52]. With the results of the pattern generated from the pre-processing analysis based on the CF concept and the RS method, it can be used to carry out the classification process for Otitis disease.

3.2. Classification analysis process

The process of classifying Otitis disease will begin by doing learning using the concept of DL. The development of DL has been widely used in case classification to produce good results [53]. In another explanation, DL is also a concept capable of exploiting data based on the learning process [54]. DL can present an appropriate and accurate learning process in solving classification problems [55]. To carry out the learning process, the ANN method can be used in classifying Otitis disease. ANN can solve problems effectively in the classification process [56]. In other cases, ANN is also a method that can allocate data for the classification process [57]. The ANN learning process in the classification process will start from training and testing. The results of the training and testing carried out can be seen in Table 4.

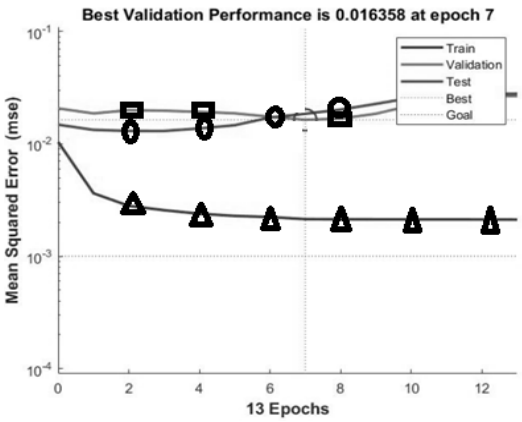
Table 4 explains that the training and testing process uses several network models. From this process the best network model in conducting the classification process is obtained with the 10-10-5-5-2 model. This model consists of 1 input layer with 10 units. 3 hidden layers with 10-5-5 units. and 1 output layer with 2 units. This model provides a fairly good value of accuracy, error, gradient, sensitivity, and validation. The form of visualization of the picture of the learning process can be seen in Figure 3.

Figure 3 presents the results of learning visualization with interpretation based on performance. Figure 3(a) explain the performance graph product, Figure 3(b) explain the validation result, Figure 3(c) explain the histogram graph and Figure 3(b) explain the training and testing output graph. These results show that the DL concept using the ANN method can provide training and testing results with an accuracy of 89%. Visualization of the comparison results of ANN learning output can be seen in Figure 4.

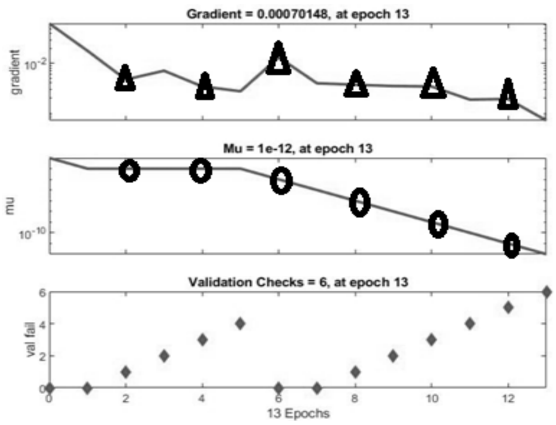
Figure 4 explains that the visible classification visualization results have given the right results. This result can be seen by comparing the output with the classification target. To get a better classification analysis result. the Otitis disease classification process is continued by using the DT method. This method can interpret the output of the classification in the form of a DT [58]. The DT concept provides a problem-solving solution in the classification process [59]. The DT work process performs grouping based on membership in the data [60]. The results of the classification using the DT method are presented with a decision tree which can be seen in Figure 5.

Table 4. ANN training and testing

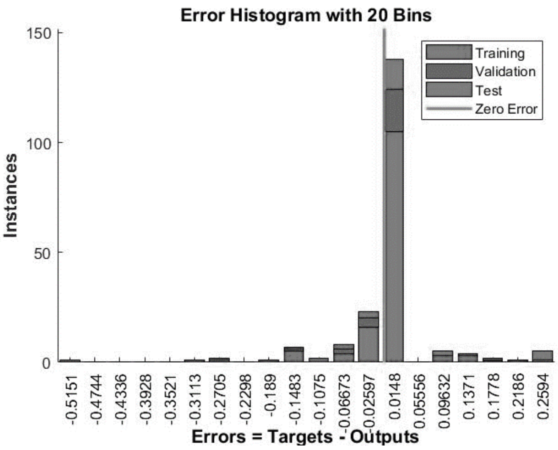
Architecture	Accuracy	MSE	Training Gradient	Sensivity	Validation	Accuracy	MSE	Testing Gradient	Sensivity	Validation
Single hidden layer										
(10-3-1)	99.7037	0.2963	0.0003	0.9654	0.8977	99.9919	0.0081	0.0034	0.9359	0.9655
(10-7-1)	99.9859	0.0141	0.0214	0.9589	0.9263	99.9851	0.0149	0.0006	0.9537	0.9829
(10-13-1)	99.9868	0.0132	0.0004	0.9678	0.7849	99.9841	0.0159	0.0013	0.9743	0.8814
(10-17-1)	99.9756	0.0244	0.0009	0.8320	0.8410	99.9896	0.0104	0.0004	0.9460	0.9417
(10-20-1)	99.9787	0.0213	0.0003	0.9794	0.8759	99.9840	0.0160	0.0001	0.9609	0.9646
Multi hidden layer										
(10-5-5-2)	99.9831	0.0169	0.0114	0.9540	0.8689	99.9948	0.0052	0.0011	0.9632	0.8399
(10-10-5-2)	99.9799	0.0201	0.0006	0.9699	0.8688	99.9958	0.0042	0.0002	0.9768	0.8733
(10-10-10-2)	99.9846	0.0154	0.0008	0.9813	0.9210	99.9890	0.0110	0.0003	0.9634	0.9735
(10-5-5-5-2)	99.9702	0.0298	0.0037	0.8916	0.8484	99.9840	0.0160	0.0112	0.9694	0.8917
(10-10-5-5-2)	**99.9886**	**0.0114**	**0.0017**	**0.9742**	**0.9353**	**99.9948**	**0.0052**	**0.0018**	**0.9532**	**0.9914**
(10-10-10-5-2)	99.9852	0.0148	0.0002	0.9836	0.8126	99.9914	0.0086	0.0005	0.9735	0.9335
(10-5-5-5-5-2)	99.9860	0.0140	0.0124	0.9043	0.8800	99.9925	0.0075	0.0033	0.9749	0.6273
(10-10-10-5-5-2)	99.9749	0.0251	0.0001	0.9629	0.9237	99.9934	0.0066	0.0002	0.9241	0.9543
(10-10-10-10-5-2)	99.9765	0.0235	0.0004	0.9680	0.8373	99.9843	0.0157	0.1123	0.9427	0.8724



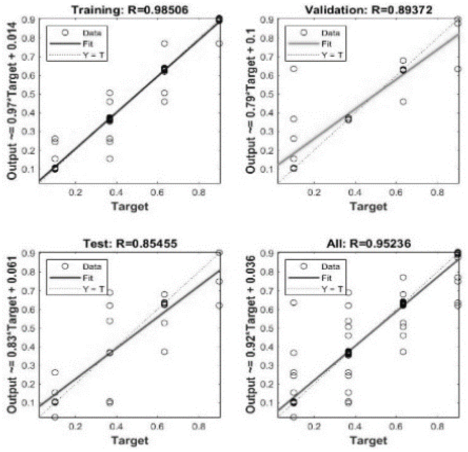
(a)



(b)



(c)



(d)

Figure 3. ANN learning graph: (a) analysis performance can be presented at the resulting error rate of 0.0016358; (b) validation of ANN performance results; (c) histogram graph shows the average ANN analysis process of 0.00148; and (d) ANN learning graph from the training process and testing

Figure 5 is a representation of the results of the classification visualization using the DT method. This DT description is also able to provide good results. The classification pattern obtained in the previous pre-processing can have a positive impact on the classification process for Otitis. Based on the discussion, the results provided provide excellent results from the classification analysis process in Otitis disease.

Based on the discussion, this research contributes to the development of an analysis model for the classification of Otitis disease. This analysis model has been able to provide novelty that can optimize the previous classification process. Optimization of the classification process can be seen based on preprocessing performance in presenting precise and accurate classification rule patterns. The analysis pattern is presented based on the certainty value obtained based on the CF output. The overall analysis results presented are quite effective in carrying out classification analysis. Not only that, this research can also present a knowledge-based system that can be used as a basis for decision-making.

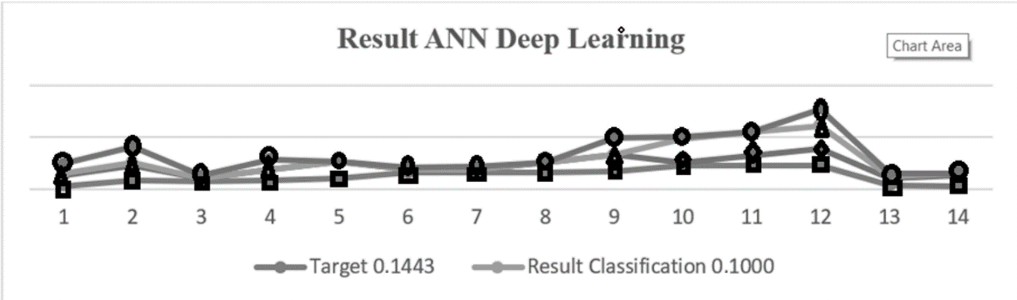


Figure 4. Deep learning classification learning results: the performance of DL classification analysis with a sample target value of 0.1443 presents a result of 0.1000 indicating that DL is suitable for recognizing analysis patterns

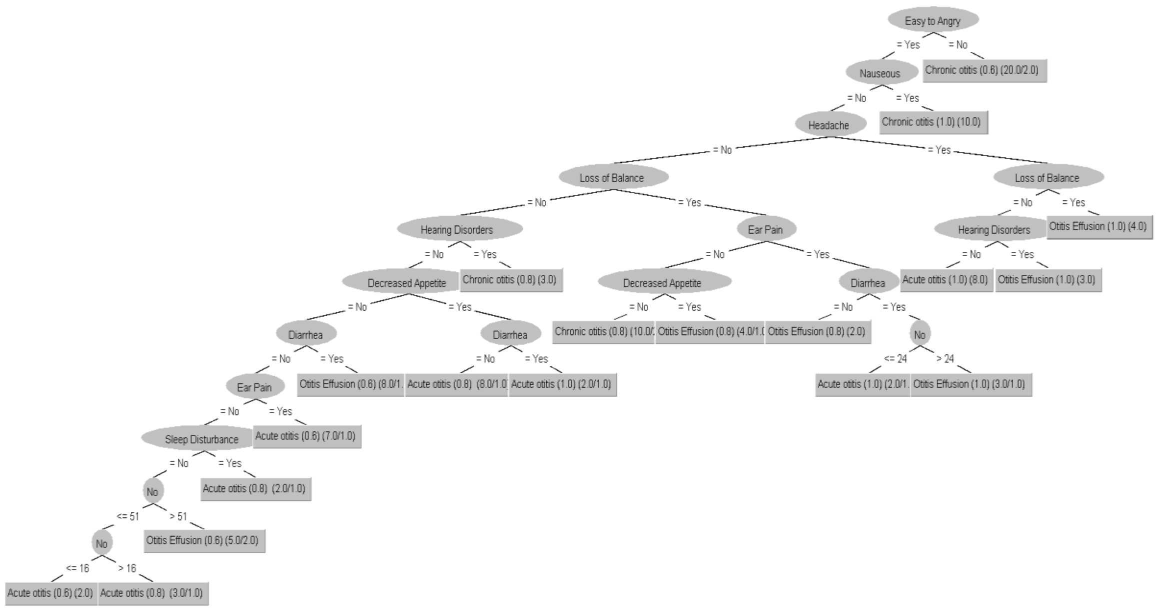


Figure 5. Decision tree in Otitis disease classification

4. CONCLUSION

The classification analysis developed by optimizing the performance of DL using the RS approach has been able to present a new analysis model for the classification of Otitis disease. The novelty of the model is demonstrated quite well in preprocessing with the performance of the CF and RS methods in producing classification pattern rules. The CF method explicitly provides certainty for each classification indicator used. This classification rule pattern will work optimally in DL learning with the performance of the ANN and DT methods. Based on the overall results. the analytical model developed provides maximum results and is better than the previous model. Furthermore, this research can be useful for providing new knowledge in carrying out the classification analysis process for Otitis.

ACKNOWLEDGEMENTS

The author's thanks to Dr. Hj. Zerni Melmusi. SE. MM. Ak. CA. as head of the YPTK Padang Computer College Foundation which has provided the Simlitupi YPTK Padang 4.1 2023 research funding grant as stated in the research contract agreement letter No. 215/UPI-YPTK/LPPM/P/KP/IX/2023.

REFERENCES

[1] J. V. Sundgaard *et al.*, "Deep metric learning for Otitis media classification," *Medical Image Analysis*, vol. 71, p. 102034, Jul. 2021, doi: 10.1016/j.media.2021.102034.

[2] G. van Ingen *et al.*, "Identifying distinct trajectories of acute Otitis media in children: a prospective cohort study," *Clinical Otolaryngology*, vol. 46, no. 4, pp. 788–795, Jul. 2021, doi: 10.1111/coa.13736.

[3] E. Ekinci *et al.*, "Streptococcus pneumoniae serotypes carried by young children and their association with acute Otitis media during the period 2016–2019," *Frontiers in Pediatrics*, vol. 9, Jul. 2021, doi: 10.3389/fped.2021.664083.

[4] A. Shrestha, H. Bhattarai, P. Rayamajhi, and R. B. Pradhananga, "Correlation of status of mastoid with outcomes of myringoplasty with cortical mastoidectomy in mucosal Otitis media with high risk perforation," *Journal of Institute of Medicine Nepal*, vol. 43, no. 1, pp. 25–30, Apr. 2021, doi: 10.3126/jiom.v43i1.37468.

[5] M. Guan, J. Zhang, Y. Jia, Y. Teng, X. Cao, and Y. Li, "Primary bilateral tuberculous Otitis media with peripheral facial paralysis: a case report and literature review.," *International journal of clinical and experimental pathology*, vol. 14, no. 3, pp. 304–313, 2021.

[6] Z. Wu *et al.*, "Deep learning for classification of pediatric Otitis media," *Laryngoscope*, vol. 131, no. 7, pp. E2344–E2351, Jul. 2021, doi: 10.1002/lary.29302.

[7] A. Alhudhaif, Z. Cömert, and K. Polat, "Otitis media detection using tympanic membrane images with a novel multi-class machine learning algorithm," *PeerJ Computer Science*, vol. 7, pp. 1–22, Feb. 2021, doi: 10.7717/PEERJ-CS.405.

[8] E. Resita, R. Sigit, T. Harsono, and R. Rahmawati, "Color RGB and structure glcm method to feature extraction system in endoscope image for the diagnosis support of Otitis media disease," in *IES 2020 - International Electronics Symposium: The Role of Autonomous and Intelligent Systems for Human Life and Comfort*, Sep. 2020, pp. 599–605, doi: 10.1109/IES50839.2020.9231532.

[9] T. T. Tran, T. Y. Fang, V. T. Pham, C. Lin, P. C. Wang, and M. T. Lo, "Development of an automatic diagnostic algorithm for pediatric Otitis media," *Otology and Neurotology*, vol. 39, no. 8, pp. 1060–1065, Sep. 2018, doi: 10.1097/MAO.0000000000001897.

[10] I. W. Sutoyo, A. P. Widodo, and A. F. Rochim, "Decision support system for handling intervention on toddlers stunting cases in Indonesia using the certainty factor method," *Journal of Physics: Conference Series*, vol. 1943, no. 1, p. 012110, Jul. 2021, doi: 10.1088/1742-6596/1943/1/012110.

[11] M. Stawowy, W. Olchowik, A. Rosiński, and T. Daąbrowski, "The analysis and modelling of the quality of information acquired from weather station sensors," *Remote Sensing*, vol. 13, no. 4, pp. 1–20, Feb. 2021, doi: 10.3390/rs13040693.

[12] S. K. Metin, B. Karaoğlan, T. Kışla, and K. Soleymanzadeh, "Certainty factor model in paraphrase detection," *Pamukkale University Journal of Engineering Sciences*, vol. 27, no. 2, pp. 139–150, 2021, doi: 10.5505/pajes.2020.75350.

[13] K. H. Hu, M. F. Hsu, F. H. Chen, and M. Z. Liu, "Identifying the key factors of subsidiary supervision and management using an innovative hybrid architecture in a big data environment," *Financial Innovation*, vol. 7, no. 1, p. 10, Feb. 2021, doi: 10.1186/s40854-020-00219-9.

[14] S. Moslemnejad and J. Hamidzadeh, "Weighted support vector machine using fuzzy rough set theory," *Soft Computing*, vol. 25, no. 13, pp. 8461–8481, Jul. 2021, doi: 10.1007/s00500-021-05773-7.

[15] S. K. Ghosh and A. Ghosh, "Classification of gene expression patterns using a novel type-2 fuzzy multigranulation-based SVM model for the recognition of cancer mediating biomarkers," *Neural Computing and Applications*, vol. 33, no. 9, pp. 4263–4281, May 2021, doi: 10.1007/s00521-020-05241-7.

[16] A. Jaiswal, N. Gianchandani, D. Singh, V. Kumar, and M. Kaur, "Classification of the COVID-19 infected patients using DenseNet201 based deep transfer learning," *Journal of Biomolecular Structure and Dynamics*, vol. 39, no. 15, pp. 5682–5689, Oct. 2021, doi: 10.1080/07391102.2020.1788642.

[17] M. Mahmud, M. S. Kaiser, T. M. McGinnity, and A. Hussain, "Deep learning in mining biological data," *Cognitive Computation*, vol. 13, no. 1, pp. 1–33, Jan. 2021, doi: 10.1007/s12559-020-09773-x.

[18] S. Majumder, Yogita, V. Pal, A. Yadav, and A. Chakrabarty, "Performance analysis of deep learning models for binary classification of cancer gene expression data," *Journal of Healthcare Engineering*, vol. 2022, pp. 1–11, Mar. 2022, doi: 10.1155/2022/1122536.

[19] L. Withington, D. D. P. Vera, C. Guest, C. Mancini, and P. Piwek, "Artificial neural networks for classifying the time series sensor data generated by medical detection dogs," *Expert Systems with Applications*, vol. 184, p. 115564, Dec. 2021, doi: 10.1016/j.eswa.2021.115564.

[20] N. Ali *et al.*, "Deep learning-based classification of blue light cystoscopy imaging during transurethral resection of bladder tumors," *Scientific Reports*, vol. 11, no. 1, p. 11629, Jun. 2021, doi: 10.1038/s41598-021-91081-x.

[21] H. Yu *et al.*, "An evaluation of machine learning classifiers for next-generation, continuous-ethogram smart trackers," *Movement Ecology*, vol. 9, no. 1, p. 15, Dec. 2021, doi: 10.1186/s40462-021-00245-x.

[22] P. Ibba *et al.*, "Supervised binary classification methods for strawberry ripeness discrimination from bioimpedance data," *Scientific Reports*, vol. 11, no. 1, p. 11202, May 2021, doi: 10.1038/s41598-021-90471-5.

[23] F. Yavari Nejad and K. D. Varathan, "Identification of significant climatic risk factors and machine learning models in dengue outbreak prediction," *BMC Medical Informatics and Decision Making*, vol. 21, no. 1, p. 141, Dec. 2021, doi: 10.1186/s12911-021-01493-y.

[24] P. Zhou and Y. Chang, "Automated classification of building structures for urban built environment identification using machine learning," *Journal of Building Engineering*, vol. 43, p. 103008, Nov. 2021, doi: 10.1016/j.jobe.2021.103008.

[25] H. Wang and P. Chen, "Intelligent diagnosis method for rolling element bearing faults using possibility theory and neural network," *Computers and Industrial Engineering*, vol. 60, no. 4, pp. 511–518, May 2011, doi: 10.1016/j.cie.2010.12.004.

[26] W. Chen *et al.*, "Modeling flood susceptibility using data-driven approaches of naïve Bayes tree, alternating decision tree, and random forest methods," *Science of the Total Environment*, vol. 701, p. 134979, Jan. 2020, doi: 10.1016/j.scitotenv.2019.134979.

[27] P. Tsangaratos and I. Ilia, "Landslide susceptibility mapping using a modified decision tree classifier in the Xanthi perfection, Greece," *Landslides*, vol. 13, no. 2, pp. 305–320, Apr. 2016, doi: 10.1016/j.media.2021.102034.

[28] A. Campagner, D. Ciucci, and E. Hüllermeier, "Rough set-based feature selection for weakly labeled data," *International Journal of Approximate Reasoning*, vol. 136, pp. 150–167, Sep. 2021, doi: 10.1016/j.ijar.2021.06.005.

[29] Z. Yuan, H. Chen, T. Li, Z. Yu, B. Sang, and C. Luo, "Unsupervised attribute reduction for mixed data based on fuzzy rough sets," *Information Sciences*, vol. 572, pp. 67–87, Sep. 2021, doi: 10.1016/j.ins.2021.04.083.

[30] R. Abbruzzese, A. Gaeta, V. Loia, L. Lomasto, and F. Orciuoli, "Detecting influential news in online communities: an approach based on hexagons of opposition generated by three-way decisions and probabilistic rough sets," *Information Sciences*, vol. 578, pp. 364–377, Nov. 2021, doi: 10.1016/j.ins.2021.07.014.

[31] J. Zhang and R. X. Gao, "Deep learning-driven data curation and model interpretation for smart manufacturing," *Chinese Journal of Mechanical Engineering (English Edition)*, vol. 34, no. 1, p. 71, Dec. 2021, doi: 10.1186/s10033-021-00587-y.

[32] M. G. Jamil and Z. Bhuiyan, "Deep learning elements in maritime simulation programmes: a pedagogical exploration of learner experiences," *International Journal of Educational Technology in Higher Education*, vol. 18, no. 1, p. 18, Apr. 2021, doi: 10.1186/s41239-021-00255-0.

[33] S. R. Fahim, S. K. Sarker, S. M. Muyeen, S. K. Das, and I. Kamwa, "A deep learning based intelligent approach in detection and classification of transmission line faults," *International Journal of Electrical Power and Energy Systems*, vol. 133, p. 107102, Dec. 2021, doi: 10.1016/j.ijepes.2021.107102.

[34] L. Lei *et al.*, "Identification of different bran-fried Atractylodis Rhizoma and prediction of atractylodin content based on multivariate data mining combined with intelligent color recognition and near-infrared spectroscopy," *Spectrochimica Acta - Part A: Molecular and Biomolecular Spectroscopy*, vol. 262, p. 120119, Dec. 2021, doi: 10.1016/j.saa.2021.120119.

[35] A. A. Pishro, S. Zhang, D. Huang, F. Xiong, W. Y. Li, and Q. Yang, "Application of artificial neural networks and multiple linear regression on local bond stress equation of UHPC and reinforcing steel bars," *Scientific Reports*, vol. 11, no. 1, p. 15061, Jul. 2021, doi: 10.1038/s41598-021-94480-2.

[36] M. Razzaq *et al.*, "An artificial neural network approach integrating plasma proteomics and genetic data identifies PLXNA4 as a new susceptibility locus for pulmonary embolism," *Scientific Reports*, vol. 11, no. 1, p. 14015, Jul. 2021, doi: 10.1038/s41598-021-93390-7.

[37] N. Amor, M. T. Noman, M. Petru, A. Mahmood, and A. Ismail, "Neural network-crow search model for the prediction of functional properties of nano TiO2 coated cotton composites," *Scientific Reports*, vol. 11, no. 1, p. 13649, Jul. 2021, doi: 10.1038/s41598-021-93108-9.

[38] M. A. Mojid and A. B. M. Z. Hossain, "Comparative performance of multiple linear regression and artificial neural network models in estimating solute-transport parameters," *Sains Tanah*, vol. 18, no. 1, pp. 27–35, Jun. 2021, doi: 10.20961/STJSSA.V18I1.49207.

[39] H. Il Suk, "An introduction to neural networks and deep learning," in *Deep Learning for Medical Image Analysis*, Elsevier, 2017, pp. 3–24.

[40] B. Korwisi *et al.*, "Classification algorithm for the International Classification of Diseases-11 chronic pain classification: development and results from a preliminary pilot evaluation," *Pain*, vol. 162, no. 7, pp. 2087–2096, Jul. 2021, doi: 10.1097/j.pain.0000000000002208.

[41] J. M. Chen, "An introduction to machine learning for panel data," *International Advances in Economic Research*, vol. 27, no. 1, pp. 1–16, Feb. 2021, doi: 10.1007/s11294-021-09815-6.

[42] G. Ke *et al.*, "LightGBM: a highly efficient gradient boosting decision tree," *Advances in Neural Information Processing Systems*, vol. 2017-Decem, pp. 3147–3155, 2017.

[43] Priyanka and D. Kumar, "Decision tree classifier: a detailed survey," *International Journal of Information and Decision Sciences*, vol. 12, no. 3, pp. 246–269, 2020, doi: 10.1504/ijids.2020.108141.

[44] N. K. Al-Salihy and T. Ibrikci, "Classifying breast cancer by using decision tree algorithms," in *ACM International Conference Proceeding Series*, Feb. 2017, pp. 144–148, doi: 10.1145/3056662.3056716.

[45] S. K. Lakshmanaprabu, K. Shankar, M. Ilayaraja, A. W. Nasir, V. Vijayakumar, and N. Chilamkurti, "Random forest for big data classification in the internet of things using optimal features," *International Journal of Machine Learning and Cybernetics*, vol. 10, no. 10, pp. 2609–2618, Oct. 2019, doi: 10.1007/s13042-018-00916-z.

[46] K. Makantasis, A. D. Doulamis, N. D. Doulamis, and A. Nikitakis, "Tensor-based classification models for hyperspectral data analysis," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 56, no. 12, pp. 6884–6898, Dec. 2018, doi: 10.1109/TGRS.2018.2845450.

[47] I. Sumatorno, D. Arisandi, A. P. U. Siahaan, and M. Mesran, "Expert system of catfish disease determinants using certainty factor method," *International Journal of Recent Trends in Engineering and Research*, vol. 3, no. 8, pp. 202–209, 2017, doi: 10.23883/ijrter.2017.3405.tcyz2.

[48] B. Ambara, D. Putra, and D. Rusjayanthi, "Fuzzy expert system of dental and oral disease with certainty factor," *International Journal of Computer Science Issues*, vol. 14, no. 3, pp. 22–30, May 2017, doi: 10.20943/01201703.2230.

[49] J. G. Bazan, H. S. Nguyen, S. H. Nguyen, P. Synak, and J. Wróblewski, "Rough set algorithms in classification problem," 2000, pp. 49–88.

[50] K. Selvakumar *et al.*, "Intelligent temporal classification and fuzzy rough set-based feature selection algorithm for intrusion detection system in WSNs," *Information Sciences*, vol. 497, pp. 77–90, Sep. 2019, doi: 10.1016/j.ins.2019.05.040.

[51] F. Pacheco, M. Cerrada, R. V. Sánchez, D. Cabrera, C. Li, and J. V. de Oliveira, "Attribute clustering using rough set theory for feature selection in fault severity classification of rotating machinery," *Expert Systems with Applications*, vol. 71, pp. 69–86, Apr. 2017, doi: 10.1016/j.eswa.2016.11.024.

[52] B. K. Baniya and J. Lee, "Rough set-based approach for automatic emotion classification of music," *Journal of Information Processing Systems*, vol. 13, no. 2, pp. 400–416, 2017, doi: 10.3745/JIPS.04.0032.

[53] S. Jia, S. Jiang, Z. Lin, N. Li, M. Xu, and S. Yu, "A survey: deep learning for hyperspectral image classification with few labeled samples," *Neurocomputing*, vol. 448, pp. 179–204, Aug. 2021, doi: 10.1016/j.neucom.2021.03.035.

[54] A. Al-Saegh, S. A. Dawwd, and J. M. Abdul-Jabbar, "Deep learning for motor imagery EEG-based classification: a review," *Biomedical Signal Processing and Control*, vol. 63, p. 102172, Jan. 2021, doi: 10.1016/j.bspc.2020.102172.

[55] J. Chen, T. Yang, D. Zhang, H. Huang, and Y. Tian, "Deep learning based classification of rock structure of tunnel face," *Geoscience Frontiers*, vol. 12, no. 1, pp. 395–404, Jan. 2021, doi: 10.1016/j.gsf.2020.04.003.

[56] J. Gao, C. Huang, X. Huang, K. Huang, and H. Wang, "Classification of imbalanced fetal health data by PSO based ensemble recursive feature elimination ANN," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, vol. 12690 LNCS, 2021, pp. 300–312.

[57] G. Avila and A. Pacheco-Vega, "ANN-based classification of operating data in humid air-water heat exchangers," in *Proceedings of the 6th World Congress on Momentum, Heat and Mass Transfer*, Jun. 2021, doi: 10.11159/enfht21.lx.302.

[58] G. Blanc, J. Lange, M. Qiao, and L. Y. Tan, "Decision tree heuristics can fail, even in the smoothed setting," *Leibniz International Proceedings in Informatics, LIPIcs*, vol. 207, 2021, doi: 10.4230/LIPIcs-APPROX/RANDOM.2021.45.

[59] B. Liu and B. Ji, "Balance detection system based on the entropy weight method and decision tree classification," *International Conference on Applications and Techniques in Cyber Intelligence. ATCI 2021*, Springer, Cham, pp. 395–400, 2021, doi: 10.1007/978-3-030-79200-8_57.
[60] Çelik, H., & Çinar, A. (2021, October). An application on ensemble learning using KNIME. In *2021 International Conference on Data Analytics for Business and Industry (ICDABI)*, pp. 400-403, Oct. 2021. doi**:** 10.1109/ICDABI53623.2021.9655815

BIOGRAPHIES OF AUTHORS

Irzal Arief Wisky was educational background comes from the information systems study program. Further education for the post-graduate program in Information Technology, Faculty of Computer Science, was completed in 2013. He is a lecturer at Putra Indonesia University YPTK Padang majoring in information systems. The history of research includes decision support systems and expert systems. He can be contacted at email: irzal.arief12@gmail.com.

Teri Ade Putra his educational background comes from the Informatics Engineering study program. Advanced education in the Information Technology graduate program at the Faculty of Computer Science was completed in 2013. He is a lecturer at Putra Indonesia University YPTK Padang majoring in Informatics Engineering. Research history includes business management analysis and software design. He can be contacted at email: teriputra2@gmail.com.