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MEASURING THE ACCURACY OF SEARCH INTERVAL PARAMETERS ON RIDGE POLYNOMIAL NEURAL NETWORK IN EARLY DETECTION OF BRAIN CANCER

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ABSTRACT

Brain cancer is a disease that causes the highest death for men and women at the age of 20-30 years. Epidemiology of brain cancer data in Indonesia to date is inadequate, this is due to suboptimal diagnostic techniques and incomplete case registration problems. One of the factors causing delays in early detection of brain cancer is the high cost and lack of public knowledge about the risk of brain cancer. The purpose of this paper is to develop a method and system that is able to detect brain cancer early using a polynomial neural network ridge algorithm based on Accuracy of Search Interval Parameters. Ridge polynomial neural network is one algorithm with good accuracy results for early detection of brain cancer from artificial neural network methods. This research will use eight input variables including: headaches gradually becoming more frequent and more severe, nausea and vomiting without cause, impaired memory, seizures, tingling and numbness in the arms and legs, visual disturbances such as blurred vision, related problems with the sense of hearing and impaired balance (difficulty in moving). The data will use weights from genetic algorithms arranged in time-series and then trained using artificial neural networks with the polynomial neural network ridge algorithm. The results of early detection of brain cancer will be visualized in patients at Haji Adam Malik General Hospital Medan which was shown in the 427th iteration by achieving an MSE of 0.021844.

Keywords: *RPNN, Search Interval Parameters, MSE, Brain Cancer.*

1. INTRODUCTION

The brain is one of the most important parts in the human body [1]. The brain functions as organizing and coordinating the entire body and human thought [2]. Brain function will be disrupted when the head is injured and there is cancer or tumour in the brain [3]. Brain cancer is a malignant abnormal cell growth (tumour) in the brain. Brain cancer is the second most dangerous disease that causes death in men aged 20-30 and the fifth most dangerous disease that causes death in women aged 20-30 [4]. Brain cancer is a disease in which brain cells grow or develop abnormally [5]. Symptoms of brain cancer depend on several factors including, age, medical history, size, location, and cell size [6]. Common symptoms that appear are headache, numbness, nausea, vomiting, and seizures [7]. One of the causes of the high number of brain cancer cases is the tendency and misunderstanding of early detection, which is quite expensive and does not go to the doctor because of fear in the diagnosis of cancer [8]. This condition causes headaches to gradually become more frequent and severe, nausea and vomiting without cause, impaired memory, convulsions, tingling and numbness in the arms and legs, impaired vision, impaired balance and risk of death.

Thus artificial neural networks can be used to detect early brain cancer based on computed tomography scanning (CT-Scan), magnetic resonance imaging (MRI) and positron emission tomography (PET-Scan) which are diagnostic support tools that have universal applications for examinations organs such as the central nervous system, muscles, bones, throat to the abdominal cavity [9]. Reading CT brain scan results requires high accuracy to be precise in providing therapy to slow the development of brain cancer [10]. Based on the problems mentioned above, researchers want to develop a software application with a method that is able to detect brain cancer sufferers in a detailed and accurate manner so as to reduce the risk of death in men and women due to brain cancer using the polynomial neural network ridge algorithm.

Various applications of neural networks are widely applied in various cancer problems [11]. As stated in Al-Khowarizmi and Suherman [12], they classify skin cancer patients with the SECoS algorithm which results in classification to determine malignant skin cancer and benign skin cancer. Early detection of breast cancer using digital mammograms has also been carried out using SECoS [13]. Joshi [14] carried out the extraction of texture features on the detected tumors was achieved using Gray Level Co-occurrence Matrix (GLCM) to detect early brain cancer where MRI images of cancer patients. Kalas [15] developed an automated cancer detection system that focuses on MRI images by applying neuro fuzzy logic for classification and estimation of cancer effects on a given MRI image. While Ismael [16] explained the high need in the field of Artificial Intelligence for a Computer Assisted Diagnosis (CAD) system to assist in the diagnosis of tumors in brain cancer by evaluating the proposed model on a benchmark data set containing 3064 MRI images of 3 types of brain tumors (Meningioma, Glioma), and pituitary tumors and get the highest accuracy of 99%. In classification or detection, other techniques are available, such as support vector machine (SVM) [17], markov probability, as well as deep convolutional neural network (CNN) [18], KNN [19] and Ridge Polynominal Neural Network (RPNN) [20].

RPNN has been studied by Dillak [21] Cervical cancer is one of the most dangerous cancers among women. Detect cervical cancer early to prevent and prevent the subject from cervical cancer which aims to hybridize the RPNN with the Chaos Algorithm so as to get optimal results in the classifier shown based on sensitivity 95.56%, specificity 96.67% and accuracy 96%. In addition, Al-Jumeily [22] developed a high-order polynomial neural network architecture called Dynamic RPNN which combines the properties of high-order and iterative neural networks for prediction of physical time series with cases used by cancer patients. Various methods have been developed so that the process of early detection in brain cancer is needed by optimizing the Search Interval Parameters on the RPNN.

2. MATERIAL AND METHOD

2.1. Ridge Polynomial Neural Network (RPNN)

Formation of Ridge Polynomial is formed in the presence of Multivariate Polynomial which can be calculated based on equation (1) [23].

$$p(x) = \sum_{j=0}^{k} \sum_{m=1}^{n_j} c_{jm} x^{ijm} \Leftrightarrow p(x) = \sum_{j=i}^{N} \prod_{i=1}^{i} \big((x, w_{ji}) + w_{ji} \big) \quad (1)$$

While in the Ridge Polynomial Network, it is included in the general form of the pi-sigma network which is specifically for the ridge polynomial formulated in equation (2).

For $x = [x_1 \dots x_n]^T$ and $w = [w \dots w_n]^T \in R^n$ given
$$(x, w) = \sum_{i=1}^{N} w_i x_i \quad (2)$$

$w_i x_i$ is defined as an *inner product* between two definitions vector.

Given a set of compact $k \subset \mathbb{R}^d$,all functions are defined on K with the form, $f((.,w)) : K \to R$, where$x \subset \mathbb{R}^d$ and $f(.) : R \to R$ is continuous, called the ridge function. Ridge polynomial can be calculated by the Ridge function as in equation (3).

$$\sum_{i=0}^{N} \sum_{j=0}^{M} a_{ij} (x, w_{ij}) \quad (3)$$
for some $a_{ij} \in \mathbb{R}$ and $(x, w_{ij}) \in \mathbb{R}^d$

From equation (3) shows that the value of the multivariate polynomial can be equated with the value of the ridge polynomial, so that it can be applied to the right polynomial ridge network. The Ridge Polynomial Network is able to map continuous functions that are on a set compact in $\mathbb{R}^d$ can be approximated with the network. Every continuous function in a compact set $\mathbb{R}^d$ can be approximated evenly with a ridge polynomial network. So thar, a function f is defined on a compact set that $k \subset \mathbb{R}^d$ can be approximated with a polynomial ridge network as follows:
$$f(x) \simeq ((x, w_{11}) + w_{11}) + ((x, w_{21}) + w_{21}) + ((x, w_{22}) + w_{22}) + \cdots + ((x, w_{NN}) + w_{NN}) \quad (4)$$

Where each multiplication is obtained as the output of the pi-sigma network with the output units.

2.2. Equation Output of the RPNN

The polynomial ridge network output equation that refers to can be explained as follows [24]:

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$$y = \theta\left(\sum_{j=1}^{N}\prod_{i=1}^{i}\left((x, w_{ij}) + \theta_{ji}\right)\right) \; or \; = f\left(\sum_{j=1}^{N}\prod_{i=1}^{j}\left(\sum_{k=1}^{n} w_{ijk}x_k + \theta_{ji}\right)\right) \quad (5)$$

Where:
j is the number of PSNs from 1 to N,
i is the number of orders on PSN from i to j,
k is the number of inputs from 1 to n,
w_{ijk} is the weight that is updated from the input x_k to the PSN order to-i from PSN to-j.
$f(x)$ is a nonlinear activation function.

For example, of the polynomial ridge network with order $N = 2$, the number of inputs is $n = 5$.

$$y = \left(\sum_{j=1}^{2}\prod_{i=1}^{j}\left(\sum_{k=1}^{3} w_{ijk}x_k + \theta_{ji}\right)\right) \quad (6)$$

And total number of weights is $\frac{N(N+1)(n+1)}{2} = \frac{2(2+1)(5+1)}{2} = 18$. Comparison of the total weights of the three types of polynomial network structures is given in Table 1. The results show that when the network has the same high order level, the weight of the RPNN is significantly less than HONN. In particular, this is very interesting in the improvements offered by RPNN.

Table 1. Number of weights in the polynomial network

Order of Network	Number of Weights					
	Pi–sigma		RPNN		HONN	
N	$n = 5$	$n = 10$	$n = 5$	$n = 10$	$n = 5$	$n = 10$
2	12	22	18	33	21	66
3	18	33	36	66	56	286
4	24	44	60	110	126	90

The RPNN architecture using PSN as the basic block can be seen in Fig. 1.

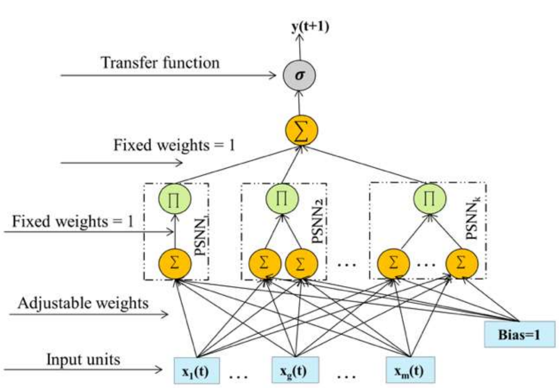

Fig. 1. RPNN network

2.3. Architecture of Training Algorithm of RPNN

Training algorithm of RPNN are consists of five stages on focus this paper:

1. Looking for 1 unit on the first order PSN to get RPNN on the first order
2. Conduct training data by updating weights (w) in each RPNN network
3. If the error of the PSN changes or is below the standard error r, $\left|\frac{\epsilon_c - \epsilon_p}{\epsilon_p}\right| < r$ that is, then Add PSN Value on higher orders. Note that it e_c is MSE for the current iteration and e_p is MSE for the previous iteration.
4. Target error r and learning rate n divided by a decrease factor.
5. The network evolves in the training cycle from steps 2 to 4 with the number of PSN units to be achieved or at the maximum iteration

Training of ridge polynomial ridge neural network:

Step 1: Add pi-sigma networks. If the number of pi-sigma tissue neurons has not been met to the desired level, perform steps 2-10.

Step 2: Initialize weights and bias. Weights and biases are obtained from chaos optimization algorithm calculations that have previously been calculated.

Step 3: If the STOP condition i.e. has not reached the desired error or the maximum iteration is met, perform steps 4 to 9.

Step 4: For each data pattern, do steps 5 to 8.

Step 5: Receive input signals from data patterns

Step 6: Calculate the pi-sigma network output with equation (7)

$$h_j = \sum_k w_{kj}x_k + \Theta_j \; and \; y_{PSN} = f\left(\prod_j h_j\right) \quad (7)$$

Step 7: Calculate the pi-sigma network weight delta with the following:

$$\delta_1 = \eta(d - y)y \prod_{z=1}^{j} h_z \; \Delta w_{kl} = \delta_l x_k \; and \; \Delta w_{0l} = \delta_l \quad (8)$$

Step 8: Update the weight and can $\Delta w_{kl}(new) = \Delta w_{kl}(old)$

Step 9: Check STOP conditions for check conditions, the following MSE (Mean Square Error) criteria are used:

$$e^2 = \frac{1}{2*p}\sum_p (d^p - y^p)^2 \quad (9)$$

Step 10: Calculate polynomial ridge network output. Calculate the polynomial ridge network output equation with equation (10)

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$$y_{RPNN} = \sum_{j=1}^{Nj=1} \prod_{i=1}^{j} \left(\sum_{k=1}^{n} w_{ijk} x_k + \theta_{ji} \right) \quad (10)$$

3. RESULTS AND DISCUSSION

This paper focuses on the process of searching for parameter intervals in getting the results of early detection of brain cancer. Where the process and algorithm used is RPNN. The data used in this paper were obtained from the radiology installation at Haji Adam Malik General Hospital Medan, which is owned by Dr Elvita R Daulay, M.Ked(Rad), Sp.Rad(K). Some overall processes for predicting the number of unemployed include input parameter process, a process which enters the initial parameters namely the number of pi-sigma layer (PSN) neurons, the maximum number of iterations, the desired error at the polynomial ridge layer (RPNN), the learning rate before the network is trained. The learning parameters specified are the maximum number of iterations = 5000, the desired error at the RPNN layer = 0.0001, the desired error at the PSN layer = 0.00018. Data standardization process, a process in which all data is normalized to be in the range of values [0, 1]. Initialization process, is the process of initializing weights and biases in neural network training, every time the PSN layer neurons are added. The algorithm used to determine the initial weight and bias values is the chaos optimization algorithm (COA). The parameters specified are the narrowed range $p = 0.4$; first search range [a0, b0] = [-50, 50]; second search range [a1, b1] = [-3, 3]; first maximum iteration = 500; second maximum iteration = 800. The training process, is a process to obtain optimal weight and bias values using the RPNN method. The architecture to be trained uses the number of PSN neurons between 1 and 7. The sub focus in this paper is for perform training to artificial neural network with the algorithm ridge polynomial neural network. Before conducting training, the network determines initial weights and biases with chaotic optimization algorithms. Perform an artificial neural network test with initial weight and from previous training.

3.1. Training artificial neural network

The results of the first experiment are the results of network training using parameters in the ridge polynomial neural network and in chaotic optimization algorithms results from NASA project data. The parameter is a ridge polynomial neural network is the learning rate where when each PSN is added the learning rate decreases with the divisor 1.7, the error in the initial PSN = 0.00007 when each PSN is added decreases with the divisor 10. The parameter in the chaos optimization algorithm is the maximum first search iteration N_1 = 5000, the maximum second search iteration N_2= 10000 and the narrower range p is 0.1. The first search interval = [-50+50] and the second search interval = [-2+2]. For errors in the initial PSN = 0.00007, the results of the training data are different. Training will stop if you get an MSE <RPNN error, where the RPNN error is the desired error target, which is the difference between the target data and the network output. If MSE is not met then training will stop at the maximum entered iteration. Each network architecture has a final weight that will be used for the initial weighting of the testing process. The results of the training are shown in Tables 2.

Table 2. Conclusions of the results of training with training 1 to 7

Trial	Training	Learning rate	Iteration to	MSE
1	1	0.3	393	0.022099
2	2	0.3	451	0.021954
3	3	0.4	519	0.022058
4	4	0.4	1020	0.022045
5	5	0.2	2198	0.022096
6	6	0.1	3155	0.022093
7	7	0.3	4999	0.022119

The training process was conducted with 7 trials, the smallest MSE results obtained in the second experiment, namely: Learning rate = 0.3, training 2, maximum iteration = 451, MSE = 0.0219. To test the effect of chaos optimization algorithm input parameters on the polynomial ridge network, a test is performed by performing variations on the maximum iteration and search interval on the first search and the second search.

3.2. Effect of search interval parameters

The search interval determines the process of finding the optimal solution. If the initial value has been determined on the results of the first calculation, it will never be the same as the initial value on the results of the second calculation which is almost close to the first initial value. In this discussion we will observe the effect of the search interval on the system by expanding or narrowing the search interval. The first experiment is to take a parameter on the polynomial ridge network that is learning rate where when every time PSN is added learning rate decreases with divider 1.7, the error at initial PSN = 0.00007 when every time PSN is added decreases with divider 10. And the parameters in chaos optimization algorithm are maximum first search iteration N_1 = 5000 and maximum second

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search iteration N_2 = 1000. And Learning rate = 0.3, architecture = 6-2-1, maximum iteration = 5000. By adding and subtracting search intervals and still using the same other parameter values. After different experiments, results such as Table 3 were obtained by changing at the first search interval.

Table 3. Effects of search interval parameters on the first search

First Search	Second search	Iteration to	MSE
[-100, 100]	[-2, 2]	445	0.022138
[-90, 90]	[-2, 2]	580	0.022142
[-80, 80]	**[-2, 2]**	**427**	**0.022011**
[-70, 70]	[-2, 2]	452	0.022269
[-60, 60]	[-2, 2]	478	0.022129
[-50, 50]	[-2, 2]	451	0.022037
[-40, 40]	[-2, 2]	408	0.022189
[-30, 30]	[-2, 2]	420	0.022101
[-20, 20]	[-2, 2]	415	0.022029
[-10, 10]	[-2, 2]	383	0.022145

From Table 10, it is known that the smallest MSE value is **0.022011** reached with the number of iterations 427 with the first search interval [-80, 80] and the second search interval [-2, 2].

3.3. Effect of maximum iteration parameters

The number of iterations will determine the process of finding a better solution. The more number of iterations, the search process is more likely to get the desired solution. In this discussion we will observe the effect of the smallest amount of penetration on the MSE value. In this experiment is to take the number of the second iteration = 10,000, the first search interval [-80, 80] and the second search interval [-8, 8] on the chaos optimization algorithm. The next experiment is to increase the number of iterations and still use the same param ether values as in the previous experiment. After a different experiment, the results obtained as in Table 4 by changing the maximum iteration on the first search.

Table 4. Effect Of Maximum Iteration Parameters On The First Search

First Search	Second search	Iteration to	MSE
1000	10.000	428	0.022324
2000	10.000	440	0.022640
3000	10.000	437	0.022104
4000	10.000	423	0.022069
5000	10.000	406	0.022188
6000	10.000	382	0.022650
7000	10.000	435	0.022253
8000	10.000	493	0.022141
9000	10.000	450	0.021943
10.000	**10.000**	**436**	**0.021844**

From Table 11 it is known that the smallest MSE value of 0.021844 was achieved with the number of iterations of 436 with a maximum iteration of the first search of 10,000 and a maximum of iterations on the second search of 10,000. Conclusions from the same value at the maximum iteration on the second search in each experiment obtained a variable MSE value.

4. CONCLUSION

For all summaries, the ridge polynomial neural network has a good ability with the smallest MSE result of 0.021844 in detecting cancer in the first search 10.000 and the second search 10.000 in the 427th iteration. Prediction for detecting brain cancer using the pi-sigma two-neuron network architecture unit. However, the use of the first and second search intervals on the ridge polynomial neural network algorithm does not have a significant effect on the training process.

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