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Integration Between Geodesic Active Contour Model and Artificial Neural Network for Classifying Deforestation Area

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Abstract Deforestation is an important factor in global change and this topic has received considerable attention recently. Hence, in this paper, the mathematical model PDE of Geodesic Active Contour (GAC) used to govern the segmentation image of the deforestation area. The GAC model visualizes the contour of the deforestation area from the satellite images. GAC model then integrated with the Artificial Neural Network (ANN) to train the dataset. Performance evaluation of GAC-ANN in terms of accuracy, specificity and sensitivity is compared with the ANN method used without segmentation of GAC model. Thus, from this paper, it is shown that the GAC model enhances an impact on providing better accuracy to detect and classify the deforestation area.

Keywords Artificial Neural Network (ANN); Gray level Co-Occurrence Matrix (GLCM); Geodesic Active Contour (GAC)

1 Introduction

Malaysia is one of the environmentally rich and abundant in natural resource and high biodiversity countries in the world. However, the main environmental problem is deforestation resulted in a negative impact on the loss of biodiversity and global climate change. In Malaysia from 2001 to 2019, 94% of the tree cover loss occurred in areas where the dominant drivers of loss resulted in deforestation [10]. Thus, the probability of deforestation detection is vital as it can become a very important mechanism to avoid deforestation in the future. Accurate zonation of deforestation in advance can help the planners to check it while continuous research should continue to avoid this issue and manage the forest resources [10].

Recently, machine learning methods have drawn notable attention from the research society on environmental modeling, since their methods are helpful in explaining efficiently. The purpose of this paper is to be able to detect the land changes of the deforestation area in Malaysia using ANN based on satellite images presented by the mathematical modeling for GAC Model of PDE and classify using ANN. Besides, to show how effective the GAC Model on ANN can identify the deforestation area by applying process data acquisition, image pre-processing, image segmentation and image classification.

This study will focus on the Nusajaya area which also is called Iskandar Puteri, the city in Johor, Malaysia. Iskandar Malaysia is known as an economic development region located in Johor. Iskandar Malaysia is the most competitive and dynamic economy in terms of economic performance in Malaysia due to its geographical proximity to Singapore. [3]. High-resolution satellite images which can be used to identify features of interest, such as agricultural land, forests, urban areas, roads and water enormous amounts of important and useful data. Meanwhile, the naked human eye is not sufficiently sensitive to detect every small change in satellite images.

Therefore, manual inspection is unsuitable to explore the hidden treasures of information in satellite images. In response to this problem, the GAC model is governed to transform satellite images into the grid besides enhance the edge indicator depending on the image gradient to show the contour toward the boundaries of particular objects. Then, the problem statement addresses in this proposal are how do integrated PDE of GAC model is governed with ANN by using 70% training, 15% testing and 15% validation of the dataset from the images, so that the accuracy of the classification deforestation area of satellite images can be optimized.

The purpose of this study is to detect the deforestation areas. To transmit the signal data of satellite images into a digital data characterization and geospatial data using MATLAB Software. Then, to grow the GAC scheme of nonlinear PDE integrated with ANN method by integrating the sign pressure forces function and some statistical parameters and to analyze the equation by using the numerical method in terms of accuracy, specificity and sensitivity.

2 Literature Review

2.1 Geodesic Active Contour (GAC) Model

Segmentation of an image is a significant task in the analysis of an image, the aim is to separate the entire domain of the image into some distinct regions based on region consistency. But, the complex background, the appearance of noise, and low-intensity contrast with weak edges make the segmentation difficult. Hence, the best-known edge-based model which also well known as the non-linear PDE-based tool for the segmentation image which is the geometric active contour (GAC) model, employs the edge indicator based on the image gradient in order to create forces to direct the outline or contour toward the boundaries and edges of the particular objects. This method is especially efficient in images segmenting with sharp gradients [12]. Some researchers have been proposed this model which is essential to extract local information from inhomogeneity images. Thus, the proposed model is known as an active contour model depending on local image fitting [9].

Other than that, from previous researchers, regarding study SAR river image segmentation by an active contour model which is a well-known global model of the geodesic active contour (GAC) model. Greatly, utilizes the global gradient information of the image to drive the curve evolution instead of the global intensity information. The GAC model can obtain the good segmentation results of the images with strong boundaries [5]. Detecting agricultural land borders from high-resolution imagery. The Region based Chan-Vese active contour and edge based Geodesic Active Contour models (Multiphase Active Contour model). The resulting values for the evaluation criteria were 90.3 for the overall accuracy [4].

2.2 Artificial Neural Network (ANN)

An artificial neural network (ANN) is a computational mechanism capable to represent, acquire and compute a mapping from one multivariate space of information to another given a set of data describing that mapping. There are many kinds of ANN models and perhaps the most popular and widely used ANN architecture is multi-layer perceptron. The neural network which consists of an input layer, hidden layers and output layer is a feed-forward neural network trained by the backpropagation algorithm [11].

Over the last two decades, ANN as a machine learning algorithm has become very famous due to the appearance of powerful computers. ANN enables parallel computation, can be implemented in analog, simulate convoluted decision boundaries, makes no assumption on input pattern classes, input data, units can be sparse, can automatically integrate the relationship between the dependent and independent variables and has the robustness to multicollinearity. These advantages prove that ANN is a very powerful image classification mechanism that works with satisfying efficient computational [6]. Below is the summary listed for literature review by using ANN.

The lack of technical infrastructure is a common challenge in developing countries such that neither the population nor the government authorities are adequately aware of deforestation. Thus, Artificial Neural Networks (ANN) approach is a strong alternative for their accuracy, agility and effectiveness among the existing quantitative methodologies. In addition, the problem of a number of features is well-suited for ANN, for example, the complex nonlinear relationships between variables, the feasibility of using data at different scales and units of measure, the independence of statistical distributions of data, as well as qualitative variables. From this view, ANN is described to be a powerful methodology, given the availability of databases to be used for the learning process [2].

3 Methodology

3.1 Data acquisition

High-resolution satellite images of Nusajaya, Johor, Malaysia will be used as the image data. The data collected from Google Earth satellite images will transmit from signal data into digital data by using MATLAB software. The images then will be used for this research purposed method.

3.2 Image pre-processing by Median Filter

This pre-processing process involves changing the true image color into a grayscale image and remove the noise using a median filter. The median filter is also a sliding window spatial filter, but it replaces the center value in the window with the median of all the pixel values in the window [7].

$$C_{new}(y,x) = med\ \{C_{old}(dy,dx)\} \tag{3.1}$$

where $(dy,dx) \in K_{xy}$, C_{new}, C_{old} are the new and old values of the image pixels spectrum, respectively; Kxy is the kernel window.

3.3 Geodesic Active Contour (GAC Model)

GAC model regarded as a standard active contour method, uses image gradient information from the boundary of the object. Let $I\colon \Omega \subset R^2$ is an image domain, $I\colon \Omega \rightarrow R$ is an input image and $C(q)$ is a closed curve. They proposed the following energy functional:[8]

$$E_{GAC}\big(C(q)\big) = \int_0^1 g\big(\big|\nabla I\big(C(q)\big)\big|\big)C'(q)dq \tag{3.2}$$

where g is the edge stopping function defined as equation (3.3) below:

$$g(\nabla I) = \frac{1}{1 + |\nabla G_\sigma * I|}$$

where $\nabla G_\sigma * I$ is the convolution of an image I with a Gaussian kernel, whose standard deviation is σ. By minimizing the above energy functional the following Euler–Lagrange equation is obtained:

$$\frac{\partial C}{\partial t} = \ C_t = g(|\nabla I|)(k + \alpha)\vec{N} - (\nabla g.\vec{N})\vec{N} \tag{3.4}$$

where k denotes the curvature of the contour and is inward normal of the curve, α is the balloon force, which controls the contour shrinking or expanding. ∇ is the gradient operator and $\nabla\emptyset$ is to controls the interior and exterior of contour. The final level set equation is defined as follows:

$$\frac{\partial\emptyset}{\partial t} = g\left(div\left(\frac{\nabla\emptyset}{|\nabla\emptyset|}\right) + \alpha\right)|\nabla\emptyset| + \nabla g.\nabla\emptyset \tag{3.5}$$

This technique depends on edge-based contour development that can only capture the objects with edges determined by their gradient. If α value is large, the curve cannot be controlled while if α is small then curve cannot evolve efficiently and results in poor segmentation. If region to be segmented has clearly defined boundary, then moderate value of α gives better segmentation

3.4 Feature extraction by Gray-Level Co-Occurrence Matrix (GLCM)

Feature extraction which efficiently represents a region of an image as a compact feature vector or the process in which certain features of interest within an image are detected and represented for further processing. Below shows the formulation used for GLCM [1].

Table 3.1 Formula features of GLCM

No	GLCM Features	Formula	No	GLCM Features	Formula
1	Contrast	$\sum_{i,j=0}^{N-1} P_{i,j}(i-j)^2$	5	Energy	$\sum_{i,j=1}^{N} P_{i.j}^2$
2	Homogeneity	$\sum_{i,j=1}^{N} \frac{P_{i,j}}{1+(i-j)^2}$	6	Maximum Probability	$maxP_{i,j}$,
3	Mean	$\mu_i = \sum_{i,j=1}^{N} i(P_{i,j})$ $\mu_j = \sum_{i,j=1}^{N} j(P_{i,j})$ $\mu = \frac{\mu_i+\mu_j}{2}$	7	Variance	$\sigma_i^2 = \sum_{i,j=1}^{N}(P_{i,j})(i-\mu_i)^2$, $\sigma_j^2 = \sum_{i,j=1}^{N}(P_{i,j})(i-\mu_j)^2$ $\sigma = \frac{\sigma_i^2+\sigma_j^2}{2}$
4	Entropy	$\sum_{i,j=1}^{N} P_{i,j}.(-ln\ P_{i,j})$	8	Correlation	$\sum_{i,j=1}^{N} P_{i,j}\left[\frac{(i-\mu_i)(i-\mu_j)}{\sqrt{(\sigma_i^2)(\sigma_j^2)}}\right]$

where i = reference pixel, j = neighbour pixel, $P_{i,j}$= co-occurrence matrix, μ = intensity of all pixels that contributed to this feature.

3.5 Feature Reduction using Principal Component Analysis (PCA)

A statistical approach which is known as Principal Component Analysis (PCA) is to reduce the data dimensionality. It assumed that large variation of data is important. It attempts to find a unit vector of the first principal component that minimize the average squared distance from the points to the line. Other components are lines perpendicular to this line.

Data that consists of a certain number of variables undergo an orthogonal transformation that projects them into lower-dimensional space, in which the group of linearly independent variables are called principal components under the PCA scheme. Principal components usually retain most of the variability of the data.

Operating with a huge number of features is computationally costly and ordinarily, the data has a small essential dimension. To decrease the data dimension, PCA is applied which assure that no information missed and analyses if the data has a high standard deviation. Hence, PCA supports in confronting the dimensionality curse and the dimensionality is reduced to select only the best few features that adequately describe the data variation. The method for PCA is as follows:

1. Centre the data by subtracting the data from mean vector. The empirical mean is calculated along each feature and this mean used to calculate the deviations from the mean,
$$\mu_i = \frac{1}{n}\sum_{j=1}^{n} x_j$$
2. Next, these deviations used to calculate the p x p covariance matrix, C of the centered data. where $\boldsymbol{Xc}$. denotes the centralized data matrix, while T denotes transpose of matrix $\boldsymbol{Xc}$.
$$\sum = \frac{1}{n-1} X_c X_c^T$$
3. Next, the eigenvectors, v and eigenvalues, λ of the covariance matrix is calculated. $\boldsymbol{\Sigma v}=\lambda \boldsymbol{v}$. where v is the eigenvectors, while λ is the eigenvalues of covariance matrix
4. The matrix column sort in decreasing order of eigenvalues and the cumulative energy content for each eigenvector is computed.
5. Project the data into new reduced dimension by using formula: $Z = Xc^T v$
6. Retain the rows of Z^T as input of classifier

3.6 Artificial Neural Network (ANN)

Training of ANN model described as below:

1) Determine the architecture of ANN model. Initialize the number of hidden layers and number of nodes at each layer, learning rate, α, maximum number of iterations, and error tolerance, ε.
2) Divide the dataset with 70% training, 15% testing and 15% of validation
3) Initialize random number in the interval $[-1,1]$ for weights in every interconnected node randomly.
4) Perform forward propagation which in each neuron, the weighted sum can be defined as net function using formula (3.6) and obtain the output for each output nodes.
$$net_j = \sum_i^m W_{j,i}\, I_i + b_j \tag{3.6}$$
where i is the index of nodes of previous layer, j is the index of nodes of subsequent layer, $W_{j,i}$ is the weight of connection of each input of the neuron, Ii is input to the neuron, bj is the bias term.
Then, the transfer function (hyperbolic tangent) and the slope function calculated as equation (3.7) and equation (3.8):
$$z_j = f(net_j) = \frac{e^{netj} - e^{-netj}}{e^{netj} + e^{-netj}} = \tanh(net_j) \tag{3.7}$$
$$s_j = \frac{\partial zj}{\partial netj} = \frac{\partial f(netj)}{\partial netj} = 1 - tanh^2(net_j) \tag{3.8}$$

Next, the value is entered into the activation function. Thus, the activation function that will be used here is the sigmoid function

$$. o_k = f(net_k) = \frac{1}{1+e^{-net_k}} \tag{3.9}$$

5) Perform backpropagation using traincsg (scaled conjugate gradient) and update the weight of each connection, both output layer and hidden layer
6) After obtaining the value for the output layer, the value of error from the output layer is calculated. This value of error will then become a parameter to change the value of weight. Thus, the error function used is mean square error (MSE) measured according to the following equation.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(Y_i - \hat{Y}_i\right)^2 \tag{3.10}$$

4 Results and Discussion

4.1 Image pre-processing

The pre-processing of images phase is the prime and essential process in any segmentation methods to avoid noise present and enhance the quality of satellite images to achieve good accuracy. This stage includes read images, resize of the images and convert the color of images into grayscale color images. The satellite images were obtained from Google Earth Software. Figures below show the before and after pre-processing images.

Figure 4.1 Original satellite image

Figure 4.2 Pre-processing image

4.2 Image Segmentation GAC Model

The second stage includes the segmentation images pre-processing. By using the segmentation process, an accurate position of the deforestation area found. In this thesis, Geodesic Active Contours (GAC) Model will be applied for the segmentation.

This proposed model was applied to the data acquisition from a high-resolution satellite image of Nusajaya adapted from Google Earth. The intensities range of the image is represented from 0 to 255, while the size in pixels with (length $\times$width) of the image is 200×200. The experiments generated by using Matlab software. In the proposed model, the following parameters are used: $\tau = 5, \Delta x = \Delta y = 1, v = -3, \sigma = 0.5\ and\ m = 200 \times 200$. Figure below show the preprocessing image and the segmented image of deforestation area in Nusajaya.

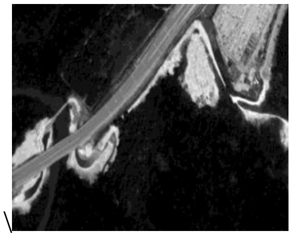

Figure 4.3 preprocessing image

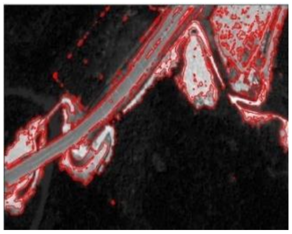

Figure 4.4 segmentation image

4.3 Feature Extraction and Selection

Feature extraction by GLCM efficiently represents a region of an image as a compact feature vector or the process in which certain features of interest within an image are detected and represented for further processing. Table below shows few sample data out of 160 collected satellite images.

Table 4.1 Features of GLCM

Features	Image 1	Image 2	Image 3	Image 4	Image 5
Contrast	0.59873	0.73142	0.49809	0.51556	0.56841
Homogeneity	0.84484	0.80707	0.85553	0.8525	0.81246
Correlation	0.94376	0.91711	0.94048	0.94363	0.94172
Energy	0.27635	0.12227	0.28845	0.29012	0.13257
Entropy	3.44882	3.79089	3.40331	3.41355	3.70843
Mean	72.3311	90.5625	64.7337	67.92596	91.26636
Variance	5587.5	4581.77	4383.83	4787.646	4867.725
Maximum Probability	0.00616	0.00312	0.00741	0.00715	0.00243

Although the features are important to achieve high accuracy but a large number of features will also increase complexity problem and computation time. The reduced set contains the same information as is contained by the original set. This paper chose principal component analysis (PCA) for feature reduction and selection purpose.

Thus, the top eigenvectors containing most of the variations of original data are selected. This data is further used for training the neural network for classifying satellite images into categories such as deforestation and non-deforestation. The number of selected features shows that the suggested algorithm is able to greatly reduce the dimensionality of original data samples and hold only the most useful and valuable features data.

4.4 Classification using ANN

Experiments carried out on the MATLAB R2018a operating on Windows 10 of 64-bit. The experimental dataset consisting of 160 data by four features. For ANN training, the dataset was divided according to 70% for the training dataset, 15% datasets for testing and 15% datasets for validation. During the training and testing phase for integrated of GAC model with ANN, the principal components containing the input feature and the corresponding output classification algorithm for two classes is used. After the mean square error reaches a minimum value, the training stopped.

Total of one hundred and sixty datasets given as inputs to the network for classification. Then ANN classifies the given datasets into deforestation and non-deforestation. Some important metrics like test accuracy can be obtained from an evaluation using test samples. In this study, the number of input neurons set to four features, the number of hidden neurons to 15 and the output neuron to two. The number of hidden neurons is determined using the trial-and-error method ranging between 5 and 50 until a minimum training error percentage obtained. In this paper, 4-

(15)-2 of the ANN layer is used with the Scaled-Conjugate method (MATLAB trainiscg) training result. Finally, the samples are validated to determine the classification accuracy.

Table 4.2 Classification of deforestation area using GAC-ANN

<table>
<tr><th colspan="4">Classification</th><th>Accuracy</th><th>Misclassification</th></tr>
<tr><td colspan="2" rowspan="2">No of samples = 160</td><td colspan="2">Predicted</td><td rowspan="4">93.1%</td><td rowspan="4">6.9%</td></tr>
<tr><td>Deforestation area</td><td>others</td></tr>
<tr><td rowspan="2">True classes</td><td>Deforestation area (97)</td><td>TP=89</td><td>FN=8</td></tr>
<tr><td>Others (63)</td><td>FP=3</td><td>TN=60</td></tr>
</table>

Confusion matrices formed to evaluate the classification results. The first column in Table 4.*2* shows confusion matrices from binary classifiers for images from images for deforestation classes and other (non-deforestation) classes showing the correct and incorrect prediction for every class. TP, FN, FP and TN denote True Positive, False Negative, False Positive and True Negative respectively. The second and third columns in Table 4.2 represent the accuracy and misclassification rates.

The first confusion matrix for classification tables shows that deforestation is one class and others represent non-deforestation classes. The total samples use for this classification system is 160. Generally, from Table 4.6 as overall classification that out of 97 instances of deforestation class, 89 have been classifying correctly while 8 have not been classifying as deforestation. Then for others classes, out of 63 samples, 60 correctly classified as others class while 3 classified as deforestation area. So, the overall accuracy is 93.1% with 6.7% misclassified for the two classes. The Neural Network Toolbox in MATLAB used for the experiments.

4.5 Comparison performance evaluation of classification using ANN

The performance analysis of integrated GAC Model with ANN is compared with the performance of ANN without GAC model using the confusion matrix show at table 4.3 which is the specificity, sensitivity, precision and overall accuracy computed for the images. The same sample images of gray scale color as input features from PCA are used on ANN without segmentation of GAC. The result also is provided by confusion matrices of ANN. Thus, based on the table it shown that integrated GAC-ANN method has higher overall accuracy compare to ANN method without GAC model.

Table 4.3 Comparing between GAC-ANN and ANN derived from confusion matrix showing the excellent of GAC model for better accuracy

Performance Evaluation	GAC- ANN (%)	ANN (%)	Difference (%)
Specificity	93.85	77.27	16.58
Precision	95.65	76.19	19.46
True Skill Statistic	60.15	58.24	1.91
Cohen Kappa Statistic	85.85	65.17	20.68
IoU Score	88.89	69.57	19.32
Sensitivity	66.30	80.95	14.65
Overall Accuracy	93.13	82.50	10.63

4.6 Discussion

As a result, the behavioural performance examined through data analysis of the satellite images using 70 % training, 15% testing and 15% validation dataset for the classification system. The complexity of the ANN model depends on the number of layers and the number of nodes used in the network. In this research of GAC-ANN, the used of a hidden layer of 15 and train the network to classify the deforestation area and non-deforestation area. Then it is compared to ANN without GAC model to evaluate the performance which one of these methods have better accuracy.

In this study, the hypothesis is successful to show that the integrated GAC-ANN model much better than ANN model. From the result, it shows that the GAC-ANN method has better overall accuracy with 93.1% compared to the ANN with 82.5% which improve up to 10.63%. In terms of specificity, the GAC-ANN model success to improve by 16.58% as GAC-ANN model provides better performance with 93.85% while ANN with 77.25%. Then, by comparing precision the result of 95.65% performance is obtained by GAC-ANN while 76.19% by ANN. However, in terms of sensitivity GAC-ANN give 66.30% while ANN gives 80.95% with difference of 14.65%. In addition, based on the IoU score, GAC-ANN model still gives better result with 88.95% while ANN with 69.57%, this gives a big difference with 19.32% for GAC-ANN better than ANN. Hence, it shows that integrated GAC-ANN model overall performance is much better than ANN. This proves that the GAC model enhances the performances in terms of accuracy, specificity, precision, Cohen Kappa statistic, true skills statistic and IoU score for classifying deforestation area.

5 Conclusion and Recommendations

5.1 Research Outcomes

This project demonstrates an enhanced performance in classifying deforestation from the satellite image. The images are pre-processing first to remove noise and unwanted material using a median filter. Then, the satellite images segmented using Geodesic Active Contour from the PDE method to get the contour, edge and boundaries of the deforestation area of satellite images in Nusajaya. The next step would be feature extraction using the GLCM technique and feature selection using Principal Component Analysis. Then the parameter would be the input for classification. The ANN considered an efficient classifier for pattern recognition is employed to predict the classification for the images. The highly correlated texture parameters constructed by GLCM such as energy, contrast, entropy and homogeneity determined from the GLCM. Thus, the features selected by using PCA and only appropriate features would be as input for training using ANN.

Thus, the GAC model integrated with ANN achieved an overall accuracy of 93.1% classification for deforestation area. Other than that, the performance evaluation of GAC-ANN compared with ANN without GAC model. It is shown that the classification of ANN without GAC is lower than ANN which is 82.5%. Therefore, the ANN trained illustrated excellent performance due to the best segmentation image of the GAC Model before extracted features using the GLCM and PCA method image for better classification. It can be concluded that integrated of GAC Model with ANN provide better accuracy in the classification deforestation area compared to ANN only.

5.2 Future Works

For future research, since this study shows that ANN involves a dataset of training and testing with complex convergence, I suggest they can go with high component computing which is big data computing for their research study.

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