Brain Tumour Image Classification Using Learning Vector Quantization Based Zoning Method

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Brain Tumour Image Classification Using Learning Vector Quantization Based Zoning Method

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Abstract. Brain tumour identification has been increasingly important area, mainly by using CT scan. Neural network and artificial intelligence methods dominate the processing algorithms; however, new methods are expected to emerge. This paper discusses brain tumour image classification by zoning combination using learning vector quantization (LVQ). The matrix results of the zoning are used as the LVQ inputs. As results from the assessment of the twenty normal and abnormal brain images, identification has been successfully carried out by 80% and 90% subsequently for abnormal and normal brain.

1. Introduction
Image classification is increasingly important in medical field to diagnose recorded images. The artificial intelligence techniques such as neural networks dominate the algorithms used in classifying images. The artificial intelligent technique using wavelet dominant grey level has been used in [3] where the 98% of normal and abnormal brain were accurately identified [3]. Support vector machine (SVM) based on statistic feature set has also been used in [4].

This paper focuses on the use learning vector quantization (LVQ) as the processing algorithm to classifying CT scan images of brain tumour. LVQ has been familiar for classification [5]. The zoning feature extraction is a simple and low complexity method which is fast enough to process and extract a character and position of the studied tumour. The classification is a process in determining classes of the identified object [1]. LVQ is a classification method that is able to train the supervised layers. LVQ is a learning algorithm with single input and output [2].

2. Material and method
The computed tomography (CT) scan is a device that is used to identify inner tissue so that inner problem within human body is not necessary under surgery solution. This device employs x-ray transmitter and uses computer to convert the tomography to axial images as shown in Figure 1.
2.1 Zoning
Initially, zoning as outline in [6] is performed to obtain feature values. Afterward, classification is performed. The Equation 1 is used to determine the feature values with $1 \leq n \leq 512$:

\[ Z_n = \frac{z_n}{Z_{\text{Max}}} \]  

(1)

The brain tumour images are sliced into several zones including zone Z1 to Z512. The process starts by calculating white pixels in each zone of Z1 to Z512. Afterwards, the zone with the highest number of white pixel is determined. Each zone feature value is then quantified.

2.2 The LVQ
LVQ is a classification method that is able to classify on supervised competing layers. LVQ is automatically classifying the input vectors. Some input vectors may have close related feature values which connecting input layer and competing layers. This layer exerts a class which connects output by using activation function. The LVQ architecture with some input and output layers is shown in Figure 2.
The $W_1$ to $W_n$ are the initiation data values and $||X-W_1||$, $||X-W_2||$ are the vector values, while N is the input data. The input values $X_1$ to $X_n$ enter the value quantification determination that is connected to output layers to obtain the output $D_1$ and $D_2$.

Before starting the classification process, LVQ does training to ease the class searching so that input pattern is obtained based on the output values. The LVQ can recognize pattern only if the values close to the neighbouring vectors. The LVQ conducts training and testing.

2.3 Training Process

The training stages are initiated by defining initial values for input $X_1$ to $X_n$, leading to output layers by representing all classes with maximum epoch (MaxEpoch), learning rate parameter ($\alpha$), learning rate decrement (Dec$\alpha$) and minimum error (Eps).

The next step is entering the input data $x(m,n)$ and target data $T(1,n)$. Followed by determining an initial epoch of zero and Err to one. The classification is performed if epoch $<$ MaxEpoch and $\alpha >$ Eps. The epoch is then increase by one. This is repeated from $i = 1$ to n. The value $j$ is determined so that $||X-W_j||$ is minimum. The $W_j$ is then corrected by using Equation 2 and 3.

\[
W_j = W_j + \alpha [X - W_j] \text{ if } T = C_j 
\]

\[
W_j = W_j - \alpha [X - W_j] \text{ if } T \neq C
\]

With $T$ is learning target for the smallest $C_j$ value [7]. $X_1, X_2, X_3, \ldots X_n$ are input, $C_j$ is the $j^{th}$ output and $||X - W_j||$ is the vector values between input and output.

2.4 Testing process

The assessment or the testing process is to identify non training data. Both processes are similar. The test is to show how the performance of LVQ in memorizing cases that are learned at the training process.

3. Results and discussions

Figure 3 shows the graphical interface of the image assessment. By using 20 brain images with 50% for both normal and abnormal conditions, the classification results are shown in Table 1.

![Figure 3. Graphical interface](image-url)
The accuracy of the LVQ is 90% for the normal brain but slightly lower for abnormal brain about 80%. By using contingency table in Table 2, the recalculated accuracy is 85%, precision is 80% and the specificity is 90%.

| Type     | Accuracy |
|----------|----------|
| Normal   | 90 %     |
| Abnormal | 80 %     |

| P       | N       |
|---------|---------|
| Y       | TP = 8  |
| N       | FN = 2  |
| Total   | P       |
|         | N       |

4. Conclusion
To conclude, the zoning method by using the LVQ to classify brain tumour has been reviewed in this paper. As limited data available, by using 20 images of normal and the abnormal brain, it is found that the method successfully detects tumour by 80% precision, 85% accuracy and 90% specificity. In detail, normal brain is 90% accuracy, but abnormal brain is 10% lower.

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