PREDICTION OF OSTEOARTHRITIS USING LINEAR VECTOR QUANTIZATION BASED TEXTURE FEATURE

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ABSTRACT

Osteoarthritis estimated as the eighth-leading nonfatal burden of disease in the world is the one important reason why it is investigated. The status of osteoarthritis is important because it is used as a basis for determining treatment for patients. The aim of this research is analyzing the texture feature of Junction Space Area (JSA) and design system based texture feature in order to predict the severity of osteoarthritis in the knee using a linear vector quantization. Textures extracted in this study are first order, second order, and gray level run length matrix. Several stages involved as the research procedures covering image processing, feature extraction, learning process, and testing process. The result of feature extraction obtained several FO, GLCM and GLRLM features for each cluster with overlapping conditions, making it difficult to classify using linear methods, so learning used linear vector quantization (LVQ). Feature extraction was carried out for both training data and testing data. The training process, which was divided into several stages namely first order learning, GLCM learning data, GLRLM learning data, and combined learning data features. learning process for the aforementioned features of combined learning data used learning parameter rate of 0.5 with epoch values of 1000, 5000, 10000, and 15000. The best results obtained when using a system using LVQ based on GLCM features. But the disadvantage of this system is that it cannot recognize grade 2 well where recognizing grade 2.

Keywords: Osteoarthritis, FO, GLCM, GLRLM, LVQ

1. INTRODUCTION

Osteoarthritis (OA) is a disorder characterized by loss of articular cartilage, bone hypertrophy at the margin, subchondral sclerosis and various biochemistry and changes in morphology of synovial membranes and joint capsule [1]. The severity of osteoarthritis is expressed as grade 0 to grade 4, grade 0 is normal and grade 4 is the worst condition [2]-[4]. Some of the reasons why osteoarthritis is important to study are because the number of osteoarthritis patients is high. Osteoarthritis estimated as the eighth-leading nonfatal burden of disease in the world [5]. Another reason is osteoarthritis cannot be cured, what can be done is how to improve the quality of life of patients [6].

Classification of osteoarthritis based on x-ray image has been carried out by several researchers throughout the world, research based on Junction Space Area (JSA) features or texture-based images. Research that used image processing are segmentation of Junction Space Area (JSA) using active shape model [7], gabor filter based morphology [8], and other methods [9-13]. In [8] and [9] based on the Junction Space Area feature, where [8] discussed about Junction Space Area segmentation using morphological processes and [9] detected the severity of osteoarthritis using the fisher score. Classification using Self Organizing Map (SOM) GLCM-based which was previously used by gabor kernel and CLAHE for the preprocessing [10]. In [11] also based on texture feature with different parameters. However, both researchers [10-11] still discuss classification methods in partial texture-based. So it is needed to investigate the osteoarthritis severity prediction based on texture feature and its combination.

The aim of this research is analyzing the texture feature of Junction Space Area and design system based texture feature in order to
predict the severity of osteoarthritis in the knee using a linear vector quantization. Textures extracted in this study are first order, second order, and gray level run length matrix.

2. METHODOLOGY

2.1 Data
This study used x-ray images of knees as the data obtained from Osteoarthritis Initiative (OAI). The method for conducting an x-ray approached to fixed-flexion PA view (see Figure 1). Moreover, Figure 2, which also became one of data that would be processed in this study, portrayed an example of KL-Grade 0 to KL-Grade 4. The data, further, were classified into two categories namely data for learning and testing. The total data for learning category were five for each KL-Grade and 499 data were for testing category.

2.2 Methods
This study used semiautomatic method, in which determining Junction Space Area (JSA) was still conducted by the users manually. The defined JSA was then put into classifications to reveal the level of severity automatically based on the calculated texture information.

There were several stages involved as the research procedures covering image processing, feature extraction, learning process, and testing process. Image processing was conducted to put the images into different clusters. The process included dimensional normalization, grayscale, intensity normalization processes using CLAHE.

Afterwards, the results of CLAHE process were treated in feature extraction process to extract the features of First Order, Gray Level Co-occurrence Matrix (GLCM) or Second Order, and Gray Level Run Length Matrix (GLRLM) textures.

Some calculated features of First Order included entropy, kurtosis, mean, skewness, and variance, in which the each formula can be referred to Formula 1 to 5 below.

a) \textit{Mean} (\(\mu\))
   Shows the size of the dispersion of an image
   \[
   \text{Mean} (\mu) = \frac{1}{N} \sum_{n=0}^{N} f_n \cdot p(f_n)
   \] (1)
   \(f_n\) = gray intensity value
   \(p(f_n)\) = histogram value

b) \textit{Variance} (\(\sigma^2\))
   Shows variations in elements on the histogram of an image
   \[
   \sigma^2 = \sum_{n=0}^{N} (f_n - \mu)^2 p(f_n)
   \] (2)
   \(\mu\) = mean

c) \textit{Skewness} (\(\alpha_3\))
   Skewness (\(\alpha_3\)) shows the degree of inclination of the relative histogram curve of an image
   \[
   \alpha_3 = \frac{1}{\sigma^3} \sum_{n=0}^{N} (f_n - \mu)^3 p(f_n)
   \] (3)
d) **Kurtosis**

Shows the level of the relative curve of the histogram curve of an image

\[
\alpha = \frac{1}{N^2} \sum_{n=0}^{N} (f_n - \mu)^4 \cdot p(f_n) - 3
\]

(4)

e) **Entropy (H)**

It shows the size of form irregularities from an image that has a non-standard pattern.

\[
H = \sum_{i=0}^{N-1} p(f_i) \log p(f_i)
\]

(5)

GLCM is a relationship between pixels and adjacent pixels [15]. Previously it was normalized using the formula:

\[
p(i, j) = \frac{V(i, j)}{\sum_{i, j=0}^{N-1} V(i, j)}
\]

(6)

where i row value and j value from column.

Furthermore, Formula 6 to 11 show GLCM features that would be calculated in this present study including energy, homogeneity, contrast, mean I, mean j, standard deviation, and variance.

**Contrast**

\[
\text{Contrast} = \sum_{i, j=0}^{N-1} (i - j)^2 \cdot p(i, j)
\]

(7)

**Correlation**

\[
\text{Correlation} = \sum_{i, j=0}^{N-1} \frac{(i - \mu_i)(j - \mu_j)}{\sigma_i \sigma_j} \cdot p(i, j)
\]

(8)

\[\mu_i = \sum_{i=0}^{N-1} i \cdot p(i, j)\]

(9)

\[\mu_j = \sum_{j=0}^{N-1} j \cdot p(i, j)\]

\[\sigma_i = \sqrt{\sum_{i=0}^{N-1} p(i, j)(i - \mu_i)^2}\]

\[\sigma_j = \sqrt{\sum_{j=0}^{N-1} p(i, j)(j - \mu_j)^2}\]

\[\text{Energy} = \sum_{i, j=0}^{N-1} p(i, j)^2\]

(10)

**Homogeneity**

\[
\text{Homogeneity} = \sum_{i, j=0}^{N-1} \frac{p(i, j)}{1 + (i - j)^2}
\]

(11)

The GLRLM features covered Gray Level Non-Uniformity (GLN), High Gray Level Run Emphasis (HGRE), Low Gray Level Run Emphasis (LGRE), Long Run Emphasis (LRE), Short Run Emphasis (SRE), Run Percentage (RP), and (GLN), of which those features were calculated using the following formulas (see Formula 13 to 19 respectively).

**Short Run Emphasis (SRE)**

\[
\text{SRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} \frac{p(i, j)}{j^2} = \frac{1}{n_r} \sum_{j=1}^{N} p_r(j) j^2
\]

(12)

**Long Run Emphasis (LRE)**

\[
\text{LRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i, j) j^2 = \frac{1}{n_r} \sum_{i=1}^{N} p_r(i) j^2
\]

(13)

**Gray Level Non-Uniformity (GLN)**

\[
\text{GLN} = \frac{1}{n_r} \sum_{i=1}^{M} \left( \sum_{j=1}^{N} p(i, j) \right)^2 = \frac{1}{n_r} \sum_{i=1}^{N} p_r(i)^2
\]

(14)

**Run Percentage (RP)**

\[
\text{RP} = \frac{n_r}{\sum_{i=1}^{M} \sum_{j=1}^{N} p(i, j)^2}
\]

(15)

**High Gray Level Run Emphasis (HGRE)**

\[
\text{HGRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i, j) \cdot i^2 = \frac{1}{n_r} \sum_{i=1}^{N} p_r(i) \cdot i^2
\]

(16)

**Low Gray Level Run Emphasis (LGRE)**

\[
\text{LGRE} = \frac{1}{n_r} \sum_{i=1}^{M} \sum_{j=1}^{N} p(i, j) \cdot j^2
\]

**Short Run Low Gray Level Emph (SRLGE)**
Feature extraction was carried out for both training data and testing data. The next process was the training process, which was divided into several stages namely first order learning, GLCM learning data, GLRLM learning data, and combined learning data features. The combined learning data comprised:
- First Order and GLCM
- First Order and GLRLM
- GLCM and GLRLM
- First Order, GLCM, and GLRLM

The whole training process was conducted using LVQ in which the research design could be referred to Figure 3. The learning process for the aforementioned features of combined learning data used learning parameter rate of 0.5 with epoch values of 1000, 5000, 10000, and 15000. The results of the learning process, then, would be used in the testing process.

Testing process was aimed to reveal the accuracy of each process. The process covered:
- First Order features
- GLCM features
- GLRLM features
- The combined features of First Order and GLRLM
- The combined features of GLCM and GLRLM
- The combined features of First Order, GLCM, and GLRLM

### 3. RESULTS

Figure 4 mainly showed the results of image processing, which were defined into three different figures that portrayed the results of dimensional normalization using moment method (Figure 4a), grayscale process (Figure 4b), and intensity normalization process using CLAHE (Figure 4c).

Dimensional normalization was performed to anticipate if the resulting image had different dimensions. By using such normalization process, all images that would be processed had standard dimensions. Then, intensity normalization was carried out to standardize all images’ intensity using CLAHE process. At last, the grayscale process was conducted as the features to be extracted were all based on grayscale data.
Figure 4(c) showed the calculated results of First Order features, Gray Level Co-occurrence Matrix (GLCM), and Gray Level Run Length Matrix (GLRLM) textures. Table 1 becomes an example of first order features (entropy, kurtosis, mean, skewness, and variance) that were produced for KL-Grade 0 to KL-Grade 4. Table 2 portrays the GLCM feature values from several images, and Table 3 depicts the values of the GLRLM feature.

**Table 1. First Order Features (Entropy, Kurtosis, Mean, Skewness, And Variance)**

<table>
<thead>
<tr>
<th>No</th>
<th>Entropy</th>
<th>Kurtosis</th>
<th>Mean</th>
<th>Skewness</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8.65×10^6</td>
<td>2.51×10^11</td>
<td>1.82×10^9</td>
<td>-9.40×10^8</td>
<td>1.33×10^11</td>
</tr>
<tr>
<td>2</td>
<td>9.75×10^6</td>
<td>-3.78×10^8</td>
<td>1.51×10^9</td>
<td>-3.78×10^8</td>
<td>1.57×10^11</td>
</tr>
<tr>
<td>3</td>
<td>9.02×10^6</td>
<td>-7.84×10^8</td>
<td>1.74×10^9</td>
<td>-7.84×10^8</td>
<td>1.41×10^11</td>
</tr>
<tr>
<td>4</td>
<td>9.89×10^6</td>
<td>-2.52×10^8</td>
<td>1.43×10^9</td>
<td>-2.52×10^8</td>
<td>1.60×10^11</td>
</tr>
<tr>
<td>5</td>
<td>9.74×10^6</td>
<td>-3.82×10^8</td>
<td>1.51×10^9</td>
<td>-3.82×10^8</td>
<td>1.57×10^11</td>
</tr>
</tbody>
</table>

In accordance with Table 1 to Table 3, Figure 5 shows the relationship between the values of the First Order features. Figure 5 also illustrates if the classification could not be done with ordinary linear equation processes due to overlapping data between clusters. Consequently, LVQ was performed in the learning process.

In Figure 5, the minimum, average, and maximum entropy values of KL-Grade 0 to KL-Grade 4 are depicted. Figure 5 shows that the entropy values for KL-Grade 0 ranged between 8.65×10^6 and 9.87×10^6 with average value of 9.28×10^6. Moreover, the average entropy values for KL-Grade 0 to 4 were 8.23×10^6, 7.75×10^6, 8.54×10^6, and 6.12×10^6.
Figure 6. Minimum, average, and maximum kurtosis values from KL-Grade 0 to KL-Grade 4

Figure 6 shows that the kurtosis values for each cluster ranged from $9.39 \times 10^6$ to $2.51 \times 10^{11}$ (first cluster), $-1.3 \times 10^7$ to $2.93 \times 10^{11}$ (second cluster), $-3.00 \times 10^7$ to $2.59 \times 10^{11}$ (third cluster), $-1.30 \times 10^7$ to $2.62 \times 10^{11}$ (fourth cluster), and $-2.9 \times 10^7$ to $4.9 \times 10^{11}$ (fifth cluster).

Figure 7. Minimum, average, and maximum mean values from KL-Grade 0 to KL-Grade 4

Figure 7 portrays that the average mean values were directly proportional to the grade values. The average mean values for each cluster were $1.64 \times 10^9$, $1.88 \times 10^9$, $1.92 \times 10^9$, $1.82 \times 10^9$, and $2.13 \times 10^9$ respectively. The range of the mean values for each cluster were $1.43 \times 10^9$ to $1.82 \times 10^9$ (first cluster), $1.66 \times 10^9$ to $1.95 \times 10^9$ (second cluster), $1.61 \times 10^9$ to $2.33 \times 10^9$ (third cluster), $1.58 \times 10^9$ to $1.99 \times 10^9$ (fourth cluster), and $1.74 \times 10^9$ to $2.32 \times 10^9$ (last cluster).

Figure 8. Minimum, average, and maximum skewness values from KL-Grade 0 to KL-Grade 4

Skewness values were different from the mean ones, of which these values tent to decrease along with the increase of KL-Grade values. In other words, skewness values were inversely proportional to the grade values. The skewness values for each cluster were $6.13 \times 10^9$, $1.1 \times 10^7$, $1.3 \times 10^7$, $9.70 \times 10^7$, and $-2.00 \times 10^7$ respectively. The range skewness values from the first to the last clusters were $-9.40 \times 10^6$ to $-2.52 \times 10^6$, $-1.30 \times 10^6$ to $-6.27 \times 10^6$, $-3.0 \times 10^7$ to $-5.45 \times 10^6$, $-1.30 \times 10^7$ to $-4.97 \times 10^6$, and $-2.90 \times 10^7$ to $-7.93 \times 10^6$ respectively.

Figure 9. Minimum, average, and maximum variance values from KL-Grade 0 to KL-Grade 4

The variance values for each cluster were $2.25 \times 10^{-9}$, $1.85 \times 10^{-9}$, $1.92 \times 10^{-9}$, $1.82 \times 10^{-9}$, and $2.13 \times 10^{-9}$ respectively. The range of the variance values for each cluster were $1.43 \times 10^{-9}$ to $1.82 \times 10^{-9}$ (first cluster), $1.66 \times 10^{-9}$ to $1.95 \times 10^{-9}$ (second cluster), $1.61 \times 10^{-9}$ to $2.33 \times 10^{-9}$ (third cluster), $1.58 \times 10^{-9}$ to $1.99 \times 10^{-9}$ (fourth cluster), and $1.74 \times 10^{-9}$ to $2.32 \times 10^{-9}$ (last cluster).
Figure 9 exhibits that the ranges of variance values for each KL-Grade were $1.33 \times 10^{11}$ to $1.60 \times 10^{11}$, $1.17 \times 10^{11}$ to $1.48 \times 10^{11}$, $5.11 \times 10^{10}$ to $1.51 \times 10^{11}$, $1.12 \times 10^{11}$ to $1.53 \times 10^{11}$, and $5.33 \times 10^{10}$ to $1.40 \times 10^{11}$ respectively. The average variance values were $1.47 \times 10^{11}$, $1.25 \times 10^{11}$, $1.16 \times 10^{11}$, $1.31 \times 10^{11}$, and $8.49 \times 10^{10}$.

The results of GLCM features from the extraction process were revealed in Figure 10 to 15. The range of energy values for each cluster were $6.26 \times 10^5$ to $1.83 \times 10^6$, $6.26 \times 10^5$ to $1.83 \times 10^6$, $6.26 \times 10^5$ to $1.83 \times 10^6$, and $6.39 \times 10^5$ to $1.75 \times 10^6$. The average energy values from the first to the last cluster were $1.06 \times 10^6$, $1.17 \times 10^6$, $1.21 \times 10^6$, $1.22 \times 10^6$, and $1.48 \times 10^6$ respectively.

Figure 11 shows the homogeneity values for each cluster, which ranged from $6.80 \times 10^6$ to $8.23 \times 10^6$ (first cluster), $6.80 \times 10^6$ to $8.23 \times 10^6$ (second cluster), $6.80 \times 10^6$ to $8.23 \times 10^6$ (third cluster), $6.80 \times 10^6$ to $8.23 \times 10^6$ (fourth cluster), and $6.81 \times 10^6$ to $8.88 \times 10^6$ (last cluster).

Figure 12 conveys that the average contrast values for each cluster were $8.31 \times 10^6$, $8.04 \times 10^6$, $7.95 \times 10^6$, $7.91 \times 10^6$, and $4.05 \times 10^6$ respectively. The range values from the first to the last cluster were $3.95 \times 10^6$ to $1.18 \times 10^7$, $3.95 \times 10^6$ to $1.18 \times 10^7$, $3.95 \times 10^6$ to $1.18 \times 10^7$, $3.95 \times 10^6$ to $1.18 \times 10^7$, and $2.26 \times 10^6$ to $1.11 \times 10^7$ respectively. The contrast values were inversely proportional to the KL-Grade values.
Figure 13 portrays that the average mean $i$ values for each cluster were $4.84 \times 10^7$, $4.89 \times 10^7$, $4.90 \times 10^7$, $4.91 \times 10^7$, and $5.87 \times 10^7$ respectively. The minimum values for each cluster were $4.58 \times 10^7$, $4.58 \times 10^7$, $4.58 \times 10^7$, $4.58 \times 10^7$, and $4.97 \times 10^7$ respectively, whereas, the maximum values were $5.24 \times 10^7$, $5.24 \times 10^7$, $5.24 \times 10^7$, $5.24 \times 10^7$, and $6.64 \times 10^7$ respectively.

Figure 14 shows that the average mean $j$ values for each grade were $4.84 \times 10^7$, $4.89 \times 10^7$, $4.90 \times 10^7$, $4.91 \times 10^7$, and $4.97 \times 10^7$ respectively. The range values for each cluster were from $4.58 \times 10^7$ to $5.24 \times 10^7$ (first cluster), $4.58 \times 10^7$ to $5.24 \times 10^7$ (second cluster), $4.58 \times 10^7$ to $5.24 \times 10^7$ (third cluster), $4.58 \times 10^7$ to $5.24 \times 10^7$ (fourth cluster), and $4.97 \times 10^7$ to $6.64 \times 10^7$ (fifth cluster).

Figure 15 shows that the average variance values from KL-Grade 0 to 4 were $6.48 \times 10^7$, $6.62 \times 10^7$, $6.66 \times 10^7$, $6.68 \times 10^7$, and $8.87 \times 10^7$ respectively. The minimum and maximum variance values for each cluster were $4.94 \times 10^7$ and $8.43 \times 10^7$ (first cluster), $4.94 \times 10^7$ and $8.43 \times 10^7$ (second cluster), $4.94 \times 10^7$ and $8.43 \times 10^7$ (third cluster), $4.94 \times 10^7$ and $8.43 \times 10^7$ (fourth cluster), and $6.49 \times 10^7$ and $1.07 \times 10^8$.

The extraction results of GLRLM features from the first to the last cluster were revealed in Table 4. The features were then processed in learning process using LVQ.

<table>
<thead>
<tr>
<th>KL-Grade 0</th>
<th>KL-Grade 1</th>
</tr>
</thead>
<tbody>
<tr>
<td>min</td>
<td>6.10E+10</td>
</tr>
<tr>
<td>average</td>
<td>7.20E+10</td>
</tr>
<tr>
<td>max</td>
<td>8.10E+10</td>
</tr>
</tbody>
</table>
4. DISCUSSION

The learning process using LVQ was conducted through seven steps of experiment covering:
- Learning features of FO
- Learning features of GLCM
- Learning features of GLRLM
- Combined learning features of FO and GLCM
- Combined learning features of FO and GLRLM
- Combined learning features of GLCM and GLRLM
- Combined learning features of FO, GLCM, and GLRLM

The whole learning process used learning rate value of 0.5 and epoch values of 1000, 5000, 10000, and 15000. Table 6 shows the results of times required in the learning process. Results implied that the more times required in the process, the more increase the epoch values.

Table 6. Times Required In Learning Process Using LVQ

<table>
<thead>
<tr>
<th>Epoch</th>
<th>Time (second)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1000</td>
<td>0.9204</td>
</tr>
<tr>
<td>5000</td>
<td>2.9796</td>
</tr>
<tr>
<td>10000</td>
<td>8.6581</td>
</tr>
<tr>
<td>15000</td>
<td>12.2929</td>
</tr>
<tr>
<td>1000</td>
<td>1.0920</td>
</tr>
<tr>
<td>5000</td>
<td>4.7424</td>
</tr>
<tr>
<td>10000</td>
<td>7.5348</td>
</tr>
<tr>
<td>15000</td>
<td>13.3069</td>
</tr>
<tr>
<td>1000</td>
<td>1.0452</td>
</tr>
<tr>
<td>5000</td>
<td>4.5396</td>
</tr>
<tr>
<td>10000</td>
<td>4.9140</td>
</tr>
<tr>
<td>15000</td>
<td>6.1620</td>
</tr>
<tr>
<td>1000</td>
<td>0.9828</td>
</tr>
<tr>
<td>5000</td>
<td>4.5396</td>
</tr>
<tr>
<td>10000</td>
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<td>12.9793</td>
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<td>1000</td>
<td>1.0296</td>
</tr>
<tr>
<td>5000</td>
<td>4.3836</td>
</tr>
<tr>
<td>10000</td>
<td>8.5177</td>
</tr>
<tr>
<td>15000</td>
<td>6.1932</td>
</tr>
<tr>
<td>1000</td>
<td>1.2168</td>
</tr>
</tbody>
</table>
After learning, we get the weight which is then used when testing. Accuracy obtained from the testing process is as in Table 7.

Table 7. Accuracy for each stage

<table>
<thead>
<tr>
<th>Learning Stage</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning of FO features</td>
<td>24.012</td>
</tr>
<tr>
<td>Learning of GLCM features</td>
<td>52.94</td>
</tr>
<tr>
<td>Learning of GLRLM features</td>
<td>19.98</td>
</tr>
<tr>
<td>Learning of combined features between FO and GLCM</td>
<td>18.862</td>
</tr>
<tr>
<td>Learning of combined features between FO and GLRLM</td>
<td>51.28</td>
</tr>
<tr>
<td>Learning of combined features GLCM and GLRLM</td>
<td>47.28</td>
</tr>
<tr>
<td>Learning of combined features FO, GLCM and GLRLM</td>
<td>43.28</td>
</tr>
</tbody>
</table>

Globally, the best accuracy is determined by using GLCM. But in detail it is illustrated in Table 8.

Testing using FO ability to classify according to the cluster can best determine grade 2. Classification using the GLCM feature can best determine grade 4 which is 73% accuracy. Using RLM the ability to classify is lower by using the GLCM feature. RLM cannot classify grade 0 and grade 2. Applying a better result combination feature to recognize grade 4. All combination features produce 83.4% accuracy. But this combination feature has the disadvantage of being very difficult to classify in clusters 2 and 3.

Table 8. Accuracy For Each Stage

<table>
<thead>
<tr>
<th>Stage</th>
<th>Accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>FO</td>
<td>34.65 23 50.98 9.43 2</td>
</tr>
</tbody>
</table>

5. CONCLUSION

The process of image processing, feature extraction, learning, and testing has been implemented. The best results obtained when using a system using LVQ based on GLCM features. But the disadvantage of this system is that it cannot recognize grade 2 well where recognizing grade 2 only results in an accuracy of only 50%. Based on this research, it is needed further research in order to obtain better accuracy.

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