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Enhancing Facial Recognition Accuracy through Feature Extraction Techniques: A Comparative Study of GLCM and LBP Algorithms in Backpropagation Neural Networks

Abstract: - As technology develops, information security is becoming increasingly important, but it also faces many challenges. Face recognition is one of the technologies that can be used. The facial recognition system has been studied extensively, but its accuracy has not been optimized. Therefore, further research is needed to improve accuracy. The feature extraction process is one that can be used to improve accuracy. This technique seeks to extract important information from an image that can be used as reference to distinguish one image from another. Facial recognition uses a variety of feature extraction techniques, such as Gray Level Co-occurrence Matrix (GLCM) and Local Binary Pattern (LBP). GLCM and LBP algorithms are used to increase the accuracy of face recognition by detecting local texture patterns in the image. Backpropagation is a type of artificial neural network used in this research, because it is relatively light and fast. According to the trials, the accuracy with feature extraction GLCM is 89%, accuracy with LBP is 88%, an increase from testing without feature extraction algorithms which has 73% accuracy, so GLCM is better than LBP in terms of accuracy.

Keywords: Backpropagation; Face recognition; Feature extraction; GLCM; LBP; Texture

1. Introduction

Due to the surge in fraud and the abuse and rigging of many conventional techniques, such as passwords and personal identification numbers[1], enhancing information security or physical property becomes increasingly vital and challenging. Credit card fraud, computer hacks, and security breaches by businesses or governments are all too common. The genuine identity of a person can already be verified by technology today[2]. Face recognition[3] is one such innovation. The scientific discipline of biometrics, which uses physical traits to identify and expose a person's identity, includes a component called facial recognition[4]. According to a poll by Xenophon Strategies, most travelers utilize facial recognition technology to increase safety and shorten wait times. After a 1955 passenger survey, 87 percent of respondents claimed they would favor the employment of facial recognition techniques to identify criminals and terrorists[5].

Feature extraction, a step in the preprocessing procedure, is one for recognizing face image data[6]. The objective of the feature extraction[7] step is to extract critical information from an image that can be used as a benchmark to identify one image from another. Face recognition uses a number of feature extraction techniques, including the Gray Level Co-Occurrence Matrix (GLCM)[8], the Local Binary Pattern[9], the Scale Invariant Feature Transform[10], the Linear Discriminant Analysis[11], and the Local Mapped Patterns-Based[12]. In straightforward situations where textures can be easily discriminated visually[13], GLCM performs better in the context of classification than semi-variograms and Fourier spectrums. Whereas the LBP approach has good discriminative power, is simple to use, and is a relatively quick feature extraction method with a cheap

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computational cost. It has worked well to describe textures[14]. The aim of this study is to compare the accuracy of the GLCM and LBP algorithms for face recognation.

Facial recognition frequently suffers from the requirement for an accurate input pattern to match the recognized pattern[14]. This results in repetitive input because the input is frequently not recognized. The usage of artificial neural networks (ANN)[15] is the quickest way to implement face recognition. The size of an image that has been patterned with later weighting to produce a unique pattern for each image[16] is determined, and this size is used to identify the ANN pattern. Backpropagation, often known as reverse computing, is a technique that can be employed as part of an ANN to assist in the classification of objects. Because of its distinct capacity to reduce errors and accelerate computations, this method is favoured over other neural network approaches[17].

Backpropagation[18] neural networks are feed-forward neural networks with one or more hidden layers that may, to a certain degree of accuracy, approximate any continuous function with just one hidden layer. The problem's input variable is correlated with using the input layer, the non-linear interactions between the variables are captured using the hidden layer, and the predicted values are presented using the output layer[19]. In comparison to other algorithms, backpropagation requires less memory and produces results with tolerable error rates at processing speeds that are reasonable.

2. Materials and Methods

2.1. Face Recognition

Face recognition is a technology that enables users to identify a person's face from a digital image[3]. Typically, face recognition involves the following steps:

1. Acquisition module, which can use data from digital photos and cameras as input for the face recognition process.

2. Pre-processing module, which consists of image adjustment process input like image size normalization, median filtering to remove noise from moving frame or camera, histogram equalization for quick image recognition by fixing image quality without losing key information, high pass filtering to get the edge of an image, background removal to remove portions of the background so that only the face is processed, and grayscaling to turn RGB images into grayscale. Pre-processing is carried out to fix any issues that may come up during the face recognition procedure.

3. Feature extraction module, to obtain the key components as a vector that accurately depicts a face and is distinctive.

4. In module classification, when pattern separation is present, the face's features are compared to those in the database to see if the image of the face can be identified.

5. In the training set, in this training set, this module is employed throughout the identification and recognition phases of the learning process (training), and the more intricately it is used and how frequently it occurs, the better.

2.2. Gray Level Co-occurrence Matrix (GLCM)

In order to extract the texture features from the image, a co-occurrence matrix was first created, and the spatial link between the reference pixels and surrounding pixels was established using the angle and distance d. To create a symmetric matrix, the co-occurrence matrix and the transpose matrix were combined. After that, the symmetric matrix was normalized by figuring out how likely each matrix component was to occur. As illustrated in Figure 2, the last step was to calculate the texture characteristics at a distance of one pixel in each of the four directions (0°, 45°, 90°, and 135°) to look for co-occurrence.

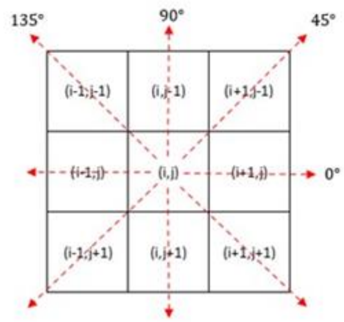

Figure 1. Neighbor relationship between pixels and spatial distance.

The surrounding pixels for the illustration in Figure 2 can be chosen to the east (right). One approach to depict this relationship is in the form of (1,0), which shows the relationship between two horizontally aligned pixels with the values of 1 and 0. The number of pixel groups that satisfy the connection is determined by this composition.

2.3. Local Binary Pattern

Local Binary Pattern is a technique for measuring grayscale texture that has been proven to be reliable and unaffected by changes in lighting. Due to its ability to detect details and tolerance for monotatic grayscale shifts, this approach has been shown to be successful in characterizing textures[9].

LBP, or the application of the LBP approach to the face extraction process, is a very effective method since it is simple to apply, requires little processing power, and has a high level of discriminant accuracy[20]. by applying pixel labels to the thresholding environment for each pixel in the image and treating the resulting binary number as the input.

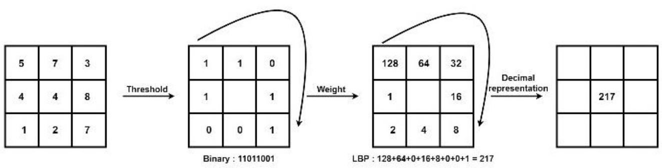

Figure 2. Calculation Using LBP

The center will then be assigned a value of 0. Once the threshold value (threshold) has generated the binary value 11011001, each value is multiplied by two and squared, then added together to produce the new middle pixel value, which now has a value of 217[21]. Only a few nearby pixels are covered by the LBP Operator's straightforward computation processes. The following equation can be used to calculate LBP:

$$LBP_{P,R} = \sum_{P=0}^{P-1} S\left(I_{p,R} - I_c\right)2^{P-1-p} \quad (2.1)$$

$$S(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \quad (2.2)$$

LBP P, R represents the decimal value of the binary value conversion results, Ic signifies the center pixel intensity, IP, R denotes the pixel intensity value adjacent with radius R, and P denotes the number of adjacent points and R the radius between the center point and the neighboring points. Thresholding is a function of S (x). The following image serves as a demonstration of the LBP Pixel computation method.

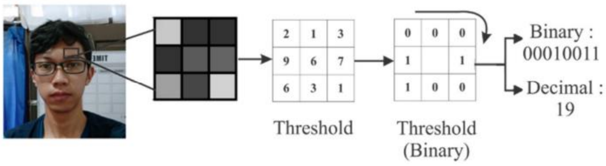

Figure 3. Calculation LBP. Source[22].

2.4. Backpropagation

Using the Pareto principle, the data were split into training data (80%) and test data (20%). An explanation of the Backpropagation flowchart is provided below:

- To provide consistent analysis during the backpropagation training phase, all data must be standardized before being used. The following equation was used to determine Z-score normalization:

$$Z = \frac{x-\mu}{\sigma} \qquad (2.3)$$

Where Z is the Z-score value, x is the value to be normalized, μ is the average of all columns and rows, and σ is the standard deviation

- The input layer procedure made use of an 80x70 one-dimensional picture array. There were 5600 nodes in the picture.
- For an artificial neural network model to be trained to produce a good function, the hidden layer is essential. The Backpropagation neural network just needs one hidden layer[23] to estimate a continuous mapping from input pattern to output pattern with varied degrees of precision. In this investigation, only one hidden layer was utilized. Using hyperparameter tuning, the estimated number of hidden nodes was determined. The bias in each hidden unit is calculated for each weighted input signal (Zj, j = 1, 2.., p) as follows:

$$Z - in_j = V_{0j} + \sum X_i V_{ij} \qquad (2.4)$$

- The establishment of the recognition process leads to the creation of the output layer. In this study, there were 41 output nodes, representing the number of labels from the 41 photos of various persons. The Rectified Linear Unit (Rectified Linear Unit) activation function is used to calculate the output signal from the hidden unit is:

$$Z_j = f\ Z - in_j = f_{max}\ 0, Z - in_j \qquad (2.5)$$

- A linear value thresholding operation is carried out at zero by the ReLU activation function. The ReLU function has the following mathematical form:

$$\sigma\ (x)\ =\ \max(0, x) \qquad (2.6)$$

ReLU is an operation with inputs that has a range of 0-max (x, 0), and it has the characteristic that the gradient line's end must not touch the value 0. accelerating the convergence rate during neural network training. According to Krizhevsky et al., the ReLU function's convergence during the training phase is six times quicker than the tanh function's.

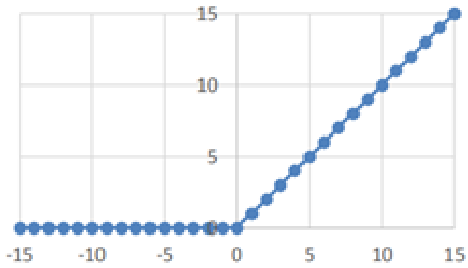

Figure 4. ReLU Function Distribution [24].

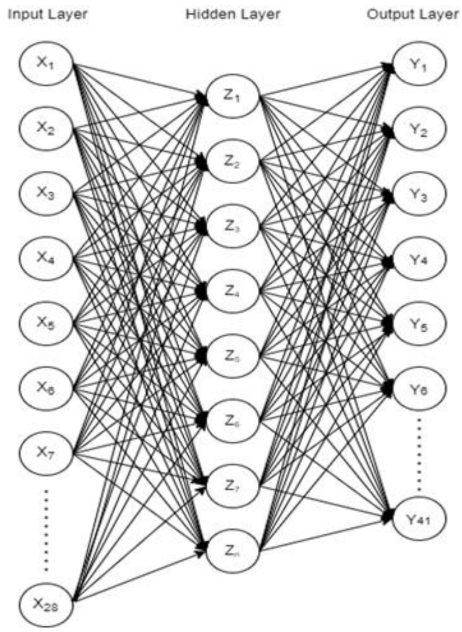

Figure 5. Neural Network Architecture.

2.5 Testing Scenario

2.5.1 Testing Scenario Gray Level Co-occurrence Matrix (GLCM)

1. In the extraction process with GLCM, seven main features (ASM, contrast, correlation, homogeneity, dissimilarity, entropy, and autocorrelation) of GLCM and four angle directions (0◦, 45◦, 90◦, and 135◦) with three neighboring distance trials (1, 2, and 3) were used to extract features from images.
2. The training process used Backpropagation ANN by providing a limitation of the training process iteration and error tolerance, with a maximum epoch of 100000 and an error tolerance of 0.01 [25] [26].
3. The learning rate parameters used were 0.6, 0.8, and 0.9, obtained through hyper-parameter tuning.
4. The hidden layer nodes used in the test were 45, 120, and 370.
5. The ReLU activation function was chosen as it performs a threshold from 0 to infinity, which makes the stochastic gradient descent (SGD) convergence process faster than the sigmoid and tanh activation functions.

2.5.2 Testing Scenarion Local Binary Pattern (LBP)

Test scenarios conducted include:

1. In the extraction of LBP features, 6 features were used consisting of mean, variance, standard deviation, skewness, kurtosis, and entropy.
2. The training process using JST backpropagation is done by giving limits on iteration process training and target error (error tolerance). In research, this is used with an error tolerance of 0.

3. The learning rate parameters used in testing are 0.7, 0.8, and 0.9. Parameters have been tested through hyperparameter tuning. As a result, creating a testing with that value.

4. Size Parameter of hidden layer or hidden layer node used in the test is 55, 100 and 125. Parameters have been tested through hyperparameter tuning, so get testing with that value.

5. The ReLU activation function was chosen as it performs a threshold from 0 to infinity, which makes the stochastic gradient descent (SGD) convergence process faster than the sigmoid and tanh activation functions.

3. Results

3.1. Results Gray Level Co-occurrence Matrix (GLCM)

By combining four different angles and seven different GLCM features, the process of texture extraction with GLCM yields 28 data features. Table 1 displays the outcomes of feature extraction from one-on-three facial photos at a distance.

Table 1. Feature extraction with distance one on three face images.

GLCM angle	Feature	Face Image Label		
		1	2	3
0°	ASM	0,008531772	0,032136336	0,017680585
	Contrast	377,9811594	514,2309783	347,2313406
	Correlation	0,950068037	0,925910347	0,958325376
	Homogeneity	0,226148131	0,296177081	0,261196676
	Dissimilarity	9,422463768	10,12228261	9,97192029
	Entropy	0,514302788	0,468840701	0,547148681
	Autocorrelation	21000,22482	15013,29312	15020,31341
45°	ASM	0,008028347	0,029782706	0,016962212
	Contrast	534,1194276	714,3663548	512,2247294
	Correlation	0,928875588	0,895831908	0,938455294
	Homogeneity	0,206833969	0,251318616	0,222531675
	Dissimilarity	11,56099798	13,63474592	13,31223629
	Entropy	0,536924058	0,504824973	0,571751104
	Autocorrelation	21055,5388	15049,52706	15088,71271
90°	ASM	0,010284818	0,035244368	0,020267291
	Contrast	259,6649186	380,9377939	310,8761302
	Correlation	0,966431303	0,945889028	0,963290487
	Homogeneity	0,273132374	0,293426014	0,264572325
	Dissimilarity	7,53761302	9,555877034	10,03381555
	Entropy	0,497815165	0,475323166	0,552271929
	Autocorrelation	20963,35027	15039,94828	14980,2519
	ASM	0,007888225	0,030293452	0,016778238
	Contrast	536,4999083	613,8567235	494,1348376

	Correlation	0,928558598	0,910488109	0,940623063
135°	Homogeneity	0,191361911	0,253358044	0,222107051
	Dissimilarity	12,39423959	12,91781325	13,41680426
	Entropy	0,547077517	0,504271567	0,571896496
	Autocorrelation	21054,34856	15099,78187	15098,7894

Tests with varied hidden and learning rates result in the same epoch without GLCM. The iteration may be terminated when it reaches a given point because the model enters a divergent situation, which causes the loss value to drift further from the goal error with each iteration (epoch). Additionally, if the learning rate is too high during training, the ReLU function may cause the neurons to become brittle. According to Table 2, this study had the highest accuracy (73% in the concealed node of 120) and learning rate (0.6).

Table 2. Testing without Algorithm

Hidden Node	Learning Rate	Accuracy (%)	Epoch	Training Time (second)
45	0.9	61	111	17.22
	0.8	57	111	18.39
	0.6	66	111	18.23
120	0.9	70	111	31.85
	0.8	59	111	36.96
	0.6	73[1]	111	37.77
370	0.9	65	111	88.48
	0.8	72	111	86.05
	0.6	67	111	89.43

Table 3 shows an increase in accuracy when using GLCM when compared to without algorithm. In the tests with GLCM feature extraction, the highest accuracy reached 89% with 370 hidden nodes and a learning rate of 0.8 at a GLCM neighboring distance of 1 pixel. The number of input nodes during Backpropagation when using GLCM extraction was less than without algorithm, leading to a shortening of the training time. The training time was in the range of 1 to 4 seconds, with the fastest time being 1.16 seconds with a hidden node of 45 and a learning rate of 0.8 at a GLCM neighboring distance of 3 pixels, and the longest time was 4.79 seconds with a hidden layer of 370 and a learning rate of 0.6 at a GLCM neighboring distance of 3 pixels. This study also found that facial recognition accuracy tends to decrease along with increasing the GLCM neighboring distance. Thus, the optimal GLCM neighboring distance to produce the best accuracy is 1 pixel.

Table 3. Testing with GLCM

Distance	Hidden Node	Learning Rate	Accuracy (%)	Epoch	Training Time (second)
1	45	0.9	87	133	1.50
		0.8	87	132	1.43
		0.6	84	131	1.17
	120	0.9	87	128	2.55
		0.8	84	132	2.84
		0.6	82	131	1.91
	370	0.9	85	127	4.50
		0.8	89	138	3.53

		0.6	82	130	3.35
2	45	0.9	84	135	2.35
		0.8	84	135	2.16
		0.6	87	137	2.22
	120	0.9	84	129	1.75
		0.8	80	128	2.32
		0.6	83	131	1.83
	370	0.9	80	128	3.36
		0.8	80	132	3.45
		0.6	80	129	4.76
3	45	0.9	80	136	2.29
		0.8	79	131	1.16
		0.6	78	135	1.25
	120	0.9	87	128	2.71
		0.8	84	127	2.34
		0.6	82	130	1.77
	370	0.9	78	134	4.06
		0.8	85	128	4.01
		0.6	79	131	4.79

[1] max accuracy.

3.2. Results Local Binary Pattern (LBP)

In Table 5, it can be seen that the classification process demonstrates improved accuracy by using features of LBP when compared with the experimental test results accuracy without using LBP. In the tests performed, it can be seen that the method of local binary pattern accuracy is best obtained by using radius = 2, which obtains the highest accuracy of up to 88% with a hidden node 125 and a learning rate of 0.9. The information in Table 2 demonstrates how the radius parameter influences the degree of face recognition accuracy, allowing it to be determined that the parameters are ideal to generate the best accuracy on the parameter with radius 2 (R = 2) as shown in Figure 7.

Table 4. Test Results Of Data Training Scenarios With the LBP Method

Radius	Hidden Node	Learning Rate	Accuracy	Epoch	Training Time
1	55	0,7	73%	180	0.16 s
		0,8	68%	168	0.18 s
		0,9	68%	168	0.16 s
	100	0,7	63%	169	0.18 s
		0,8	63%	174	0.17 s
		0,9	60%	181	0.17 s
	125	0,7	60%	166	0.29 s
		0,8	58%	171	0.22 s
		0,9	55%	169	0.23 s
	55	0,7	80%	176	0.24 s
		0,8	80%	182	0.19 s
		0,9	83%	163	0.16 s

2	100	0,7	80%	181	0.22 s
		0,8	83%	175	0.19 s
		0,9	83%	163	0.15 s
	125	0,7	85%	170	0.24 s
		0,8	83%	166	0.20 s
		0,9	88%	164	0.20 s
3	55	0,7	80%	165	0.23 s
		0,8	80%	162	0.15 s
		0,9	83%	167	0.15 s
	100	0,7	78%	171	0.19 s
		0,8	75%	162	0.19 s
		0,9	78%	161	0.20 s
	125	0,7	80%	168	0.19 s
		0,8	78%	168	0.27 s
		0,9	83%	164	0.21 s
4	55	0,7	78%	167	0.15 s
		0,8	78%	171	0.15 s
		0,9	80%	162	0.16 s
	100	0,7	78%	164	0.18 s
		0,8	78%	163	0.16 s
		0,9	78%	169	0.17 s
	125	0,7	75%	164	0.59 s
		0,8	75%	157	0.20 s
		0,9	75%	158	0.20 s
5	55	0,7	68%	173	0.16 s
		0,8	63%	158	0.14 s
		0,9	65%	162	0.13 s
	100	0,7	70%	153	0.18 s
		0,8	70%	151	0.15 s
		0,9	70%	155	0.17 s
	125	0,7	68%	151	0.18 s
		0,8	70%	154	0.19 s
		0,9	70%	157	0.18 s
	55	0,7	63%	159	0.13 s
		0,8	63%	168	0.15 s
		0,9	65%	161	0.15 s

6	100	0,7	68%	159	0.18 s
		0,8	68%	163	0.16 s
		0,9	68%	154	0.16 s
	125	0,7	63%	160	0.20 s
		0,8	63%	159	0.19 s
		0,9	63%	160	0.18 s
7	55	0,7	60%	160	0.13 s
		0,8	60%	162	0.15 s
		0,9	60%	156	0.13 s
	100	0,7	65%	157	0.15 s
		0,8	68%	170	0.18 s
		0,9	65%	157	0.17 s
	125	0,7	65%	156	0.18 s
		0,8	68%	155	0.18 s
		0,9	68%	151	0.16 s
8	55	0,7	65%	158	0.19 s
		0,8	65%	164	0.16 s
		0,9	65%	160	0.13 s
	100	0,7	68%	169	0.19 s
		0,8	63%	170	0.17 s
		0,9	65%	166	0.17 s
	125	0,7	65%	158	0.19 s
		0,8	63%	164	0.20 s
		0,9	68%	174	0.20 s

The same as testing the GLCM algorithm, the accuracy and speed of training time increases, this proves that feature extraction can be needed in facial recognition.

4. Discussion

According to this study, integrating the seven key GLCM features can boost the accuracy of picture classification by producing detailed texture information that can be utilized to tell one image from another. This is obtained because there are many GLCM neighbors in the1 pixel distance. So it can be concluded that the use of GLCM feature extraction affects the accuracy of face recognition because the combination of 7 main features of GLCM is able to produce specific features, namely texture information of an image in detail, where these texture features can distinguish one image from another so that the resulting accuracy is even increase. A further benefit of GLCM is that it can reduce training time from 17–89 seconds to 1–4 seconds. This is because there are less input nodes in the artificial neural network with GLCM than without, only important features are inputted into the ANN, thus reducing the number of calculations. On the other side, the GLCM neighboring distance negatively impacts accuracy, with a tendency for accuracy in facial recognition to decline as the GLCM neighboring distance rises.

Evaluation of the performance of the best Backpropagation model with hidden node parameters of 370 and a learning rate of 0.8 when the GLCM neighbor distance of 1 pixel is carried out using a confusion matrix [27]., able to produce accuracy values reached 89%, while the recall, precision, and f1-score values were taken from the macro average value with a recall value of 86%, a precision of 85%, and an f1-score of 85%. According to the confusion matrix in Figure 7, it has been determined that the diagonal elements represent the number of accurate classifications for each class on the label. A total of 35 faces were accurately identified when the results were added up. There are 5 incorrectly predicted face images.

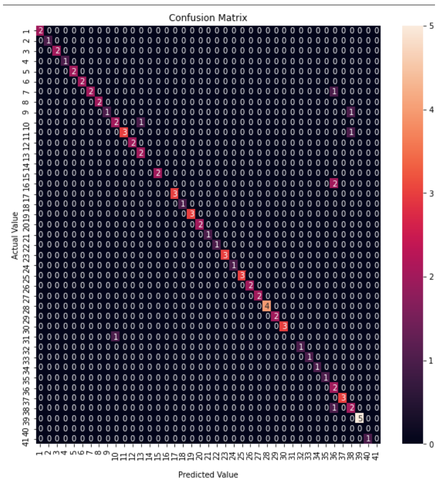

Figure 6. GLCM Confusion Matrix Results

Based on the test results, the use of LBP feature extraction increases the accuracy at radius 2 , due to the combination of 6 features producing more specific features and many pixels into one pixel value. The implementation of LBP feature extraction also shows an increase in data training speed in the range of 0.13 seconds to 0.59 seconds. Evaluation of the performance of the best Backpropagation model on hidden node 125 and a learning rate of 0.9 is able to produce an accuracy value 88%, 92% precision, 88% recall, and 88% f1-score.

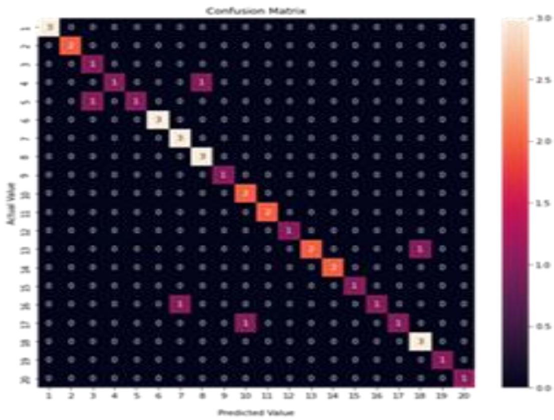

Figure 7. LBP Confusion Matrix Results

Based on the confusion matrix in Figure 8, the diagonal elements show the number of correct identifications for each class on a label of 35 images. While the elements outside the diagonal are identification errors, there are 5 face images that are predicted to be wrong. The same as testing the GLCM algorithm, the accuracy and speed of training time increases, this proves that feature extraction can be needed in facial recognition. In accordance with previous studies on different objects [28].which state that GLCM has a better performance than LBP. However, the value of the increase in accuracy and speed in the results of this study cannot be used as a benchmark, because there are many influencing factors that must be investigated more deeply, for example the selection of the number of nodes, activation functions and others in the ANN.

5. Conclusions

The Gray Level Co-occurrence Matrix and Local Binary Pattern algorithms have succeeded in increasing accuracy and shortening training time for facial recognition systems. Face recognition with GLCM has an accuracy rate of

89% with a training time of 3.53 seconds, while the LBP accuracy is 88%, training time is 0.20 seconds. Increased compared to the accuracy of facial recognition without feature extraction algorithm by 73% with a time of 17.22 seconds. In terms of accuracy, the GLCM algorithm has a better accuracy rate than LBP because the number of features extracted is more so that the details are more specific, but in terms of time it has a longer time because there are more features that must be calculated. Further research can be done to find the best accuracy using algorithm extraction and deep learning features, because this has better performance than ANN.

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Conflicts of Interest: no conflict of interest

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