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HANDWRITING PREDICTION WITH LEARNING VECTOR QUANTIZATION METHOD IN MOBILE APPLICATION

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ABSTRACT

Advances in technology are now increasing bringing people towards digital and mobile applications. To determine the owner of a handwriting, one of the manual techniques commonly used by humans that can be facilitated by mobile application technology is handwriting recognition. Learning Vector Quantization is one of the machine learning methods used to perform handwriting recognition and is one of the Artificial Neural Network (ANN) methods. This study aims to build a handwriting recognition system using the Learning Vector Quantization method on a mobile application, with feature extraction as the basic step in interpreting and classifying images. The results obtained from testing the prediction of learning vector quantization from 16 new data with a total of 80 tests. The results showed that 54 data were correct and 26 were incorrect, so the accuracy was 67.5%. Then obtained precision = 75.17%, recall = 67.5%, learning rate = 0.005, alpha value = 0.05 and iteration = 100

Keywords: *Android, Feature Extraction, Handwriting, Learning Vector Quantization, Mobile Application*

1. INTRODUCTION

The term Industry 4.0 refers to the fourth mechanical uprising that is branded by developing patterns in the areas of mechanization, Web of Things (IoT), Big Information, and Cloud Computing innovation. Just like previous adaptations of steam, electricity and computers in the past, the integration of these advances will lead to the transformation of future businesses into smarter ones. Advances in technology are now increasing bringing people towards digital and mobile applications. Therefore, the equipment that used to be in the form of human imagination is now gradually being realized. Examples include modern equipment, especially mobile phones, personal tablet computers, etc., with various other mobile applications available.

To determine the owner of a handwriting, one of the manual techniques commonly used by humans that can be facilitated by mobile application technology is handwriting recognition. The manual technique is done by sequentially comparing the handwritten files that have been saved with the handwritten files that will be recognized. This technique usually uses the human sense of sight and requires a lot of time and effort.

Handwriting recognition can be done using machine learning/data mining, therefore users only need to enter handwritten data as training data and check for new handwriting from the results of the training model that has been created.

One of the machine learning methods that can perform handwriting recognition is vector quantization learning which is also one of the Artificial Neural Network (ANN) methods. The principle of operation is to reduce the neighboring nodes to finally select only one node and then calculate the minimum distance difference. Learning Vector Quantization automatically learns to classify input vectors on the competitive layer and the resulting class based on the distance vector. When there are two vectors that have a fairly close or equal distance, then they are grouped into the same class.

Several previous related studies have been carried out by different researchers. Satia Budhi conducted research on Javanese Handwriting Character Recognition using Several Artificial

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Neural Network Methods. From these results, it is known that the combination of Chi2 and Backpropagation neural network methods performs better than the evolutionary neural network method with 1 or 2 layers for character recognition in Javanese. The recognition accuracy rate reaches 98% for data that has been trained previously and 73% for data that has not been trained before [1].

Jasril conducted research on Learning Vector Quantization 3 (LVQ3) and Spatial Fuzzy C-Means (SFCM) for Beef and Pork Image Classification. The results obtained are the application of Spatial Fuzzy C-Means in image segmentation and several other processes such as object area cropping, Hue Saturation Value (HSV) color feature extraction and texture feature extraction of the Gray Level Co-occurrence Matrix (GLCM) meat . image objects. It was found that the LVQ3 classification was able to recognize the image of beef and pork with the highest percentage accuracy value of 91.67% [2].

Davin conducted research on inner product applications to analyze digital handwriting based on texture features based on web applications. the goal is to build a web application system that can find out the owner of the document through a handwritten form, in this case it is hoped that document forgery can be prevented. The study was conducted on 100 data from 20 correspondents who each provided 5 handwritten data. The results of 40 data, 22 identified data owners are well managed and the percentage of accuracy is 55% [3].

Shamim conducted research on Handwriting Digit Recognition using Machine Learning Algorithms. The results show that in any recognition process, an important problem is to overcome feature extraction and the correct classification approach. The proposed algorithm tries to address both factors and both in terms of accuracy and time complexity. The highest overall accuracy achieved was 90.37% in the recognition process by Multilayer Perceptron, [4]

Haviluddin conducted research on Handwriting Character Recognition with Vector Quantization Techniques. This study explores the stages of the Learning Vector Quantization (LVQ) process to recognize the Makassar Bugis Lontara script and explain its accuracy. The LVQ test results show an accuracy rate of 66.66%. Furthermore, the most optimal network architecture variant in the recognition process is the variation of the learning rate of 0.02, the maximum epoch of 5000 and the hidden layer of 90 neurons, which are the results of the introduction based on 8 features[5].

Rasika R. Janrao conducted a research on Handwriting English Character Recognition using LVQ and k-nearest neighbor (KNN). Handwritten character recognition system using soft computing method is made with two datasets. The first is the database itself, which consists of 26 letters, 10 numbers and 5 special characters written by different individuals, while the second is the CEDAR standard database. The results of the LVQ test showed an accuracy of 77.80% and KNN showed an accuracy of 100%[6].

Syaifudin conducted research on Handwriting Document Security Using Internal Products with the aim of designing a software system that can recognize handwriting using computer technology from the process of digitizing written forms. the results of his research concluded that the deep product method would provide more accurate and clear results. With its weight, the distance becomes larger but if the distance is very low nothing changes. Because if the distance is obtained from a smaller handwriting, the handwriting is more similar[7].

David did research on handwriting recognition. Based on previous research methods, Learning Vector Quantization (LVQ) is able to recognize images with an accuracy rate of 61.07%. In this study, the process of the LVQ method is combined with the characteristics of the Directional Element Feature Extraction Method. The DEF method is used to obtain the characteristics of an image by looking at the difference in contours and without the skeletonization process. so that the result of the latest handwriting recognition accuracy is 73.80% [8].

The visible difference between this study and previous studies is the use of new methods and mobile applications. This study aims to build a handwriting recognition system using the Learning Vector Quantization method on a mobile application.

2. METHODOLOGY

2.1 Learning Vector Quantization

The term Industry 4.0 refers to the fourth industrial revolution marked by growing trends in automation, Internet of Things (IoT), Big Data and Cloud Computing technology. Like previous versions of steam, electric and computer, the integration of these technologies will lead to the transformation of future industries into smarter industries. Advances in technology are now increasingly bringing people towards digital and mobile applications. Therefore, the equipment that used to be in the form of human imagination is now gradually being realized. Examples include modern equipment specifically for mobile phones, personal tablet computers, etc., with various other existing mobile applications. Learning Vector Quantization (LVQ) is a training method for learning at the supervised learning layer with a single layer network architecture. The classes obtained as a result of this competitive layer depend only on the distance between the input vectors. When two input vectors appear equal, the competitive layer places both input vectors into the same class. LVQ is a method of classifying the pattern of each output unit representing a particular category or class (multiple output units must be used for each class). The advantage of the LVQ method is its ability to provide training to the competitive layer in order to automatically classify a given input vector. LVQ is a method of classifying the pattern of each output unit representing a particular category or class (multiple output units must be used for each class). The advantage of the LVQ method is its ability to provide training to the competitive layer in order to automatically classify a given input vector. LVQ is a method of classifying the pattern of each output unit representing a particular category or class (multiple output units must be used for each class). The advantage of the LVQ method is its ability to provide training to the competitive layer in order to automatically classify a given input vector.

The steps in the LVQ training algorithm consist of:

1. Initialization of initial weight (W) and LVQ parameters, namely maxEpoch,α, decα and minα.
2. Enter the input data (X) and target class (T).
3. Set initial condition: epoch = 0
4. Do it if: (epoch <maxEpoch) and (α≥ minα).
   a. epoch = epoch+1.
   b. Determine J such that Xi-Wj‖ is minimal using the Euclidian distance formula calculation. D(j) = (Wij - xi) 2
   c. Justify Wj with the following conditions:
      If T = Cj then
      Wj(t + 1) = wj (t) (t)[x(t) – wj]
      If T Cj then
      Wj(t + 1) = wj(t) + (t)[x(t)– wj(t)]
   d. Subtract the value by:α = Decα
5. Stop the condition test with optimal weight output [9].

2.2 Extraction Feature

Feature Extraction is the process of transforming input data into a feature set to retrieve relevant information from the input data with the aim of taking a minimal representation of the input data [10]. Feature extraction (or sometimes called indexing) is the basic step in interpreting and classifying images. There are many ways to extract features, depending on the data. In image data, features that can be extracted are color, shape, and texture. And in this study, researchers used textures. Texture is an intrinsic character of the image related to the level of roughness, granulation, and regularity of the structural arrangement of pixels. Texture is defined as the spatial distribution of gray levels in a set of neighboring pixels. Extraction of image features based on first-order textures can use statistical methods, namely by looking at the statistics of the grey level distribution on the image histogram. From the histogram values, the feature parameters can be calculated:

2.2.1 Variance (σ2)

Shows the variation of elements in the image histogram. The value of variance is used by researchers to assess the extent to which word variations exist in each handwritten document. The greater the value of variance, the more varied the pattern in the writing. The formula is:

$$\sigma^2 = \sum_n (f_n - \mu)^2 P(f_n)$$

Where is the average pixel value in the image, is the gray intensity value, $(p()$ is the histogram value (probability of intensity in the document image) and is the 2a variance value.

2.2.2 Skewness *(α3)*

Skewness will show the relative historical level of the histogram curve of an image. In this study, the skewness value will be used to assess the slope of the pole stroke direction in each document. If the value is close to 0, the direction of the slope is symmetrical. The formula is:

$$\alpha^3 = \frac{1}{\alpha^3} \sum_n (f_n - \mu)^3 P(f_n)$$

2.2.3 Entropy (H)

Entropy will indicate the degree of irregularity of a pattern, and it will also be used in researching handwritten documents. The higher the entropy

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value, the variation and information contained in the writing pattern, the more irregularities.

$$H = -\sum_{n} p(f_n).Log_2 P(f_n)$$

2.2.4 Relative Smoothness (R)

Relative smoothness is a value that will indicate the relative smoothness of the shape and pattern of an image, and researchers will also use it to determine how smooth or rough the handwriting strokes of each document are. The higher the relative smoothness value, the smoother the stroke pattern and the faster the writing motion.

$$R = 1 - \frac{1}{(1+\sigma^2)}$$

In this study, another feature added is the mean feature, which will show the value of the right feature to represent the entire handwriting pattern representation [11].

3. RESULTS AND DISCUSSION

3.1. Data collection

Data collection in this study was carried out through direct tracing from a number of sources (randomly people close to the researcher) or at a certain time interval. They are recorded in a book on a white background, at intervals of three consecutive days once, and once a week at intervals, and once in a month intervals. This is done to see if there is a change in the form of a person's handwriting in a certain period of time [12]. So the number of documents collected for each resource is two documents. The total data that has been collected is 34 of the 17 authors.

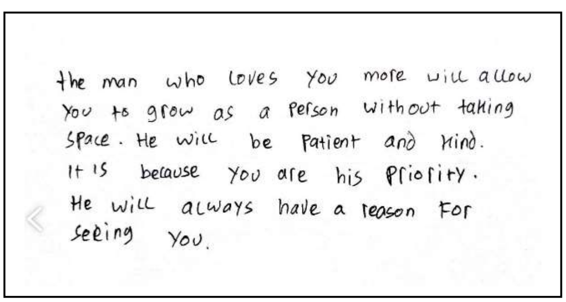

Figure 1: Handwritten Samples.

3.2. Extraction of data set by java on android

This system is built using the android java language using the Android Studio IDE. The data used in this research are handwritten images (500x200 pixels) in greyscale format with jpg type. Data will be taken from several feature values, including Variance, Skewness, Entropy, and Relative Smoothness. The feature values that have been retrieved will be stored in a SQLite database which is used as a reference to determine the owner of the document against the data examiner. The feature interval difference will be automatically converted by the system to a value of 0 to 1. If the feature produces a very small value so that it can produce a NaN value, it will be converted to a value of 0. The study carried out feature extraction from 34 handwritten image data.

Of the seven texture features that have been used to investigate the authenticity of handwriting, the Skewness and relative smoothness features are the most difficult to apply to distinguish document ownership because they have the same value for all tested data. This can happen because a perfectly symmetrical dataset will have a slope of 0, because slope is usually described as a measure of the dataset's symmetry - or lack of symmetry. As for Relative Smoothness, which is related to flexibility or speed, where handwriting is basically made automatically by individual abilities or without fabrication, so that all documents have a maximum relative smoothness value of 1 [11].

3.3. Python LVQ Extraction Processing

After extracting the feature data stored in the mobile application's SQLite database, you can proceed with making predictions using the new handwritten image to be checked. This new data will be carried out a feature extraction process, where the results will be compared with the data already stored in the database to see which data has the closest resemblance to the distance between the smallest feature value and the name of the owner. Images are displayed as predicted results from the classification results.

To calculate the closest distance and the classification of the owner of the image, the calculation of the closest distance in this study uses the Learning Vector Quantization (LVQ) method.

The Learning Vector Quantization classification process is carried out on a python flask, the flask is used as a framework for data processing from feature extraction of mobile applications to python algorithms. Learn Vector Quantization on pumpkins. process data transfer between mobile App and flask using JSON HttpURLConnection in package via ngrok link.

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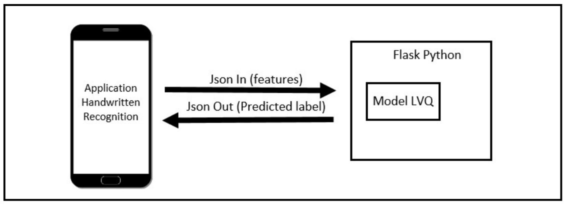

Figure 2: Prediction process schema model.

After obtaining the extraction results from the input data, the extracted values will be entered into a new method, namely array_train and array_target, this process is used when conducting LVQ training and LVQ testing. Several parameters were used: epsilon = 0.05 to help estimate the limit value and the truth of the value. n_classes = 17 to specify the Number of classes in the data set. n_inputs = 35 Number of input units. show_epoch = 1 controls how often the network will display information about training [13].

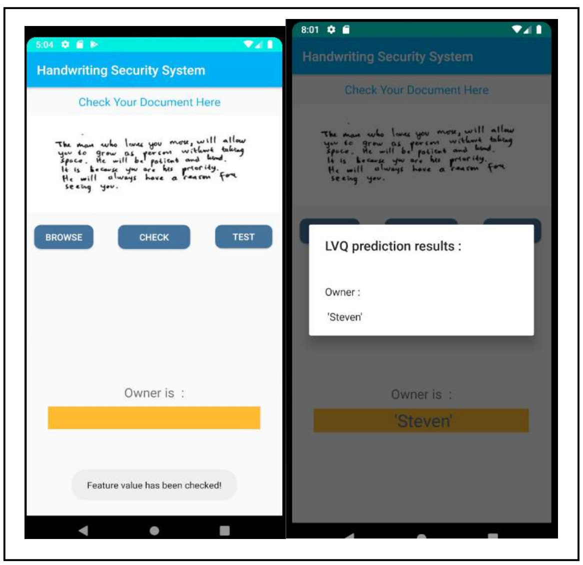

Figure 3: Display of prediction process results.

3.4. Confusion Matrix

Confusion Matrix is a performance measurement for machine learning classification problems where the output can be two or more classes. This is very useful for measuring Recall, Precision, and Accuracy values. In the Confusion Matrix there are the terms True Positive, True Negative, False Positive, and False Positive.

True Positive, if the predicted Positive and true, the true value is Positive. True Negative, if predicted is Negative and true, the true value is Negative. False Positive, if predicted Positive, but true value is Negative (False / Error type 1). False Negative, if it is predicted to be Negative, but the actual value is Positive (False / Type error 2) [14].

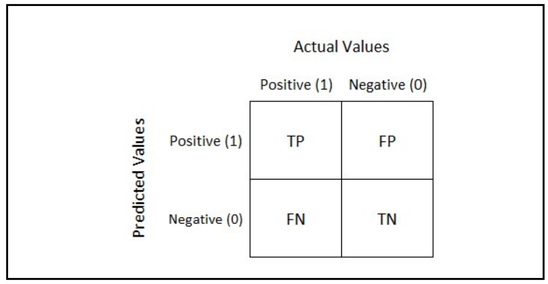

Figure 3: Display of prediction process results.

Accuracy describes how accurately the model can classify correctly. Precision describes the level of accuracy between the requested data and the prediction results provided by the model.

$$\text{Accuracy} = \frac{\sum_{i=1}^{l} \frac{TP_i+TN_i}{TP_i+T\ _i+FP_i+FN_i}}{l}$$

Precision describes the level of accuracy between the requested data and the prediction results provided by the model.

$$\text{Precision} = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l}(FP_i + TP_i)} * 100\%$$

Recall describes the success of the model in recovering information.

$$\text{Recall} = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l}(TP_i+FN_i)} * 100\%$$

3.5. Test Result

Tests were carried out to see the performance of the learning vector quantization method by inputting 16 new image data with 5 tests for each image, so the total test was 80 times. testing was carried out to see the performance of the learning vector quantization method by inputting 16 new image data with 5 tests for each image, so the total test was 80 times. The test results can be seen in table 2 of the learning vector quantization test.

The results obtained from testing the prediction of learning vector quantization from 16 new data with a total of 80 tests. The result is 54 correct data and 26 incorrect data, so the accuracy is 67.5%. This accuracy is obtained because the Learning Vector Quantization model was created using a learning rate = 0.005, alpha value = 0.05, and iteration = 100. From testing 16 new data, precision and recall values were obtained, the results were quite good because everyone had an average precision value. 75.17% and the system has a recall value of 67.5%.

Accuracy can be improved again if more data is used as training data in SQLite database, because the value of the features to be matched will be more varied to allow the details of various post features to be more visible and the system can more easily recognize patterns. So that the system built by the researcher can be used to help handwriting recognition to find out the owner of the handwriting quickly and easily. But this also depends on the data collection/collection technique used. Because the processed handwritten object is very sensitive to changes. So if the test data used has a different method of retrieval/acquisition with the data stored in the database (or reference data), it will be difficult to know the similarities so that it can reduce the accuracy of the system in recognizing the authenticity of the owner's handwriting.

The results of this study are better than previous studies conducted by Haviluddin where his LVQ model has an accuracy rate of 66.66%. An analysis of the recognition of the Bugis Lontara Makassar script has been carried out using the LVQ method. obtained from the 5th simulation of feature 8 with 92 data that can be recognized from a total of 138 input data. While the testing time required is 6 minutes 38 seconds. It can be said that parameters such as the learning rate, the number of neurons in the hidden layer and the maximum number of epochs, greatly affect the results of data recognition and the accuracy of the recognition results. In this study, the best parameter of the BPNN method is the learning rate = 0.02, the number of neurons in the hidden layer = 90, epoch = 5000 which is used to get the best accuracy.

Then when compared with the LVQ research conducted by Jasril, the accuracy rate is below because the research conducted by Jasril has an accuracy rate of 91.67% in classifying images between beef and pork. The data is divided into two parts, 60 images of beef and 60 images of pork. The test is carried out based on a combination of texture and color feature extraction with a comparison of training data and test data of 108 data: 12 data (90%: 10%) using the concept of confusion matrix. The test uses several learning rate (α) parameter values in the training process, namely 0.0001 and the maximum epoch used is 1000 iterations [2].

Then when compared with the LVQ research conducted by Rasika R. Janrao, the accuracy level is below because the research conducted has an accuracy rate of 77.80% in classifying images from the CEDAR standard database dataset with Neural network parameters = 100 and epoch = 200 [9].

The use of lvq will be more suitable when classifying image data because of its high classification accuracy (LVQ research by Jasril and Rasika) while the use of lvq for handwritten data has lower accuracy than image data accuracy (LVQ research by Haviluddin)

4. CONCLUSION

The implementation of texture-based feature extraction with Learning Vector Quantization in developing mobile applications has a fairly good success rate of 67.5% with precision of 75.17% andthe system has a recall value of 67.5%. The LVQ helps handwriting recognition to find out the owner of the handwriting quickly and easily. This evidenced by the results of the learning vector quantization prediction test obtained 16 new data with a total of 80 tests. The result is 54 correct data and 26 incorrect data. Of the seven texture features that have been used to investigate the authenticity of handwriting, the skewness and relative smoothness features are the most difficult to apply to distinguish document ownership because they have almost the same value for all tested data. Thus, the implementation of LVQ can be stated to have a fairly good success in correcting the authenticity of the owner's handwriting.

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