



Recognition of Angry and Happy Facial Expressions with Local Binary Pattern and Support Vector Machine

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Abstract: Looks are a huge sort of nonverbal correspondence for getting a handle on a singular's opinions and sentiments. Look affirmation has various potential applications, including security, tutoring, and prosperity systems. The justification for this assessment is for a look affirmation system using area twofold model and sponsorship vector machine techniques. It is typical that this structure can perceive two kinds of sentiments, to be explicit angry and delighted to get the right assumption. First accumulate fundamental data and assistant data from Kaggle and phone cameras, second preprocessing data with grayscale and resizing, third surface features using Area equal model extraction, fourth assist vector with machining about look request used, finally structure evaluation considering precision, exactness, survey, and F-1 worth. The results show that the look affirmation system works honorably on area matched model and sponsorship vector machine. On this investigation dataset, support vector machine gathering on direct part has favored execution over winding reason ability segment. The most significant precision was achieved with the straight part at 86.25%. This study assumes that the look affirmation structure can work outstandingly with neighborhood matched model and sponsorship vector machine. The straight part shows better execution on this investigation dataset. This assessment can be also advanced by adding more looks, incorporate extraction methods, and plan.

Keywords: Facial Expression, Local Binary Pattern, Support Vector Machine, Angry, Happy.

1. INTRODUCTION

With today's advancements, an increasing number of tasks are being completed online or through electronic devices. Examples include the E- Tilang systems vehicle recognition cameras, the electronic on- board unit system that uses a cellphone to process payments at the toll gate, and an on- board unit system that attaches to the car to accept payment tools. It is



necessary to identify or recognize emotions in the business or educational sectors in order to understand how a person or student feels. A face expression or emotion is called emotion, and emotion is a feeling or response directed at someone. A person can communicate nonverbally by expressing their emotions, sentiments, and attitudes through their facial expressions. Another way to communicate is through facial expressions.

Several previous studies have implemented facial expression recognition systems with various variations and modifications. research conducted by Rizki rafiif amaanullah. et al [1]. The research explains that human emotional conditions can be easily guessed by a person's emotions through the expressions shown, so it is proven that the implementation of the convolutional neural network can detect human emotions or not. Emotion categories that become more specific case studies are angry, happy, afraid, disgusted, surprised, neutral and sad. The results were obtained in the calculation of 40 epochs with an accuracy of 81.92% on training data and an accuracy of 81.69% on test data. The next research is research conducted by dwiki darmawan and handoko supeno [2]. The classification model used in this research is convolutional neural network in the case study of facial images on emotions for education. This education is to determine the level of enthusiasm for online learning, a medium is needed to recognize the enthusiasm of online lectures by looking at real-time webcams. The results obtained were 64% to detect facial expressions on video frames.

Further exploration connected with this examination is research led by Nadya khalisah Zuhail. et al [3]. The model utilized k-implies bunching with a contextual investigation of looks in 3 types of feeling comprising of outrage, loathing and pity. Acquired on karolinska coordinated close to home countenances upwards of 4,900 pictures. the outcomes on karolinska coordinated profound countenances information got an exactness of 38.89%. The following examination is research led by rizqy joventus gunaman. et al [4]. Planning a look acknowledgment framework utilizing the convolutional brain network calculation, the model utilized is the visual math bunch 16 engineering. The dataset on the look acknowledgment framework 35,887 pictures got in look acknowledgment in 2013 comprises of 7 classes of feelings including blissful, astonished, miserable, furious, sickened, and apprehensive. The best consequences of the changed visual calculation bunch 16 model at age 100 with a learning pace of 0.001 accomplished an exactness of 70.63%.

The following research was conducted by Irfan Maliki and Reza Pizki Reynaldo[5]. Facial expression recognition can be made more accurate by using artificial neural networks and the viola jones approach. A collection of 2205 photos with 42 respondents who have normal, fearful, surprised, angry, disgusted, sad, and happy facial emotions were segmented using the viola jones technique. The result obtained is 96.14% at an epoch setting of 10 and a learning rate of 0.001.

2. RELATED WORK

In recent years, facial expression identification has become an interesting research subject. Addressing this problem has been done in various ways, each with a different degree of success.



Convolutional Neural Network has been proven effective for facial expression recognition. For example, research by Rizki Rafiif Amaanullah et al[1]. showed that convolutional neural network can achieve 81.92% accuracy on training data and 81.69% on test data for the classification of seven emotion categories (angry, happy, scared, disgusted, shocked, neutral, and sad).

K-implies Bunching has also been used for facial expression recognition. Research by Nadya Khalisah Zuhail et al[3]. used this method for the classification of three types of feelings (anger, hatred, and pity) with an accuracy of 38.89%.

Visual Geometry Group 16 is a convolutional neural network model that has been used for face recognition. Research by Rizqy Joventus Gunaman et al[4]. used visual geometry group 16 for the classification of seven feeling classes (happy, amazed, sad, angry, disgusted, and worried) with an accuracy of 70.63%.

Viola-Jones is a popular method for face detection. Research by Irfan Maliki and Reza Pizki Reynaldo used a combination of Viola-Jones and convolutional neural network to recognize seven facial expressions (normal, fear, surprise, anger, disgust, sadness, and joy) with 96.14% accuracy[5].

This research uses Local Binary Pattern and Support Vector Machine methods to recognize angry and happy facial expressions. Local binary pattern is a texture operator that generates a local binary pattern from each pixel in the image. Support vector machine is a popular classification algorithm for categorization. This research uses local binary pattern and support vector machine approaches to detect and classify angry and happy facial expressions. The methods used are local binary pattern to extract texture features from facial images and support vector machine to classify the features into angry and happy categories. Local binary pattern has advantages in terms of robustness to intensity changes and lighting variations, making it suitable for facial expression recognition.

After extraction of local binary patterns from facial images, a classification method is required to distinguish different facial expressions. Support vector machine is a popular classification method often used for categorization. Support vector machine generates a classification model based on the concept of maximum margin by utilizing machine learning techniques. This algorithm is able to find the optimal hyperplane that separates the data with the best distance. Support vector machine is also capable of handling non-linear data with the help of kernel techniques.

This research aims to develop an efficient and accurate facial feature recognition system using a combination of support vector machine and local binary patterns. This system is expected to monitor and analyse primary and secondary data, such as the Facial Expression dataset obtained from Kaggle. This dataset contains 168 photos of facial features that show happy and angry expressions. In addition, another dataset consisting of 180 photos of facial expressions was also used in this study. This dataset was collected using a digital camera phone by six students at Yogyakarta University of Technology.

3. RESEARCH METHODOLOGY

A. Research Stages

Research process of applying classification models to recognize facial expressions. s structures the phases of the representation or explanation of the process being performed.

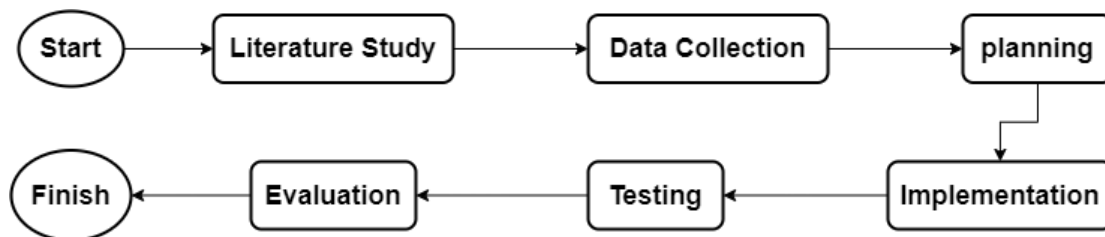


Figure 1. The Flow of Research Stages

This stage is carried out to study theories and related research related to the classification of facial expression recognition using local binary patterns and support vector machines. Literature studies are carried out by looking for reference sources from journals, books and articles.

- 1) Facial expressions are a type of nonverbal communication that can convey a person's emotional state to the viewer [6]. Facial expression recognition identifies a person's emotions based on changes in facial features such as eyes, eyebrows, mouth, and forehead. Facial expression recognition can be used for a variety of purposes, including nonverbal communication, behavioral analysis, and measuring consumer satisfaction.
- 2) Local binary pattern is a grayscale invariant method, or unaffected by uneven lighting in the image, because the local binary pattern operator describes the texture locally [7].

The steps in implementing the method as local binary pattern feature extraction are as follows:

- Converting the image into a grayscale image.
- Selecting the size of the local binary pattern operator, e.g. 3 x 3, and determining the number of neighboring pixels, e.g. 8.
- Calculating the center value of each pixel in the image by summing the gray value of the pixel and its neighboring pixels, then dividing by the number of pixels.
- Comparing the gray value of each neighboring pixel with its center value. If the neighboring value is greater than or equal to the center value, it is assigned a binary value of 1. If the neighboring value is smaller than the center value, it is assigned a binary value of 0.
- Compares the gray value of each neighboring pixel with its center value. If the neighbor value is greater than or equal to the center value, it is assigned a binary value of 1. If the neighbor value is smaller than the center value, it is assigned a binary value of 0.

$$\sum_{i=0}^{n-1} 2^i s_i$$

Where,

n is the number of neighboring pixels

s_i is the i - th binary value

- Replaces the gray value of each pixel with the decimal value obtained from the previous step.
 - Calculates a histogram of all the decimal values in the image and uses the histogram as the texture descriptor.
- 3) In supervised learning, support vector machines are typically employed for regression and classification tasks [8]. The way a support vector machine operates is by identifying a hyperplane with the largest margin that can divide data into two classes. The distance between each class's closest data point and the hyperplane is known as the margin [9]. Using support vector machine classification, one may identify the type of face expression by using the retrieved characteristics. Support vector machines can be used as classifiers by using linear or nonlinear kernels depending on the characteristics of the data [10].

B. Data Collection

During the data collection phase, support vector machine classification models are used on data sets obtained from secondary and primary data. Secondary data is taken from the Kaggle site, which is taken from several images of facial expressions, while primary data comes from smartphone cameras on Yogyakarta University of Technology students. In Figure 2 has two types of facial expressions between happy and angry and the total dataset for each class is 90 images of angry facial expressions, 90 images of happy facial expressions. Then the dataset is divided for train data, and test data with a ratio of 7.5: 2.5.



Figure 2. Example of Facial Expression Image

C. Planning

This step involves implementing or developing a robust research system using support vector machine classification to compare or distinguish between happiness and anger expressions on faces. The design sequence depicted in Figure 3 allows for the implementation of pre-processing, feature extraction, and subsequent classification. Pre-processing first cleans or verifies the data to be used in the next stage. Secondly, the texture is described locally by feature extraction using the Local Binary Pattern technique. Finally, the classification finds the hyperplane that divides the dataset into two groups with maximum margin using the support vector machine technique.

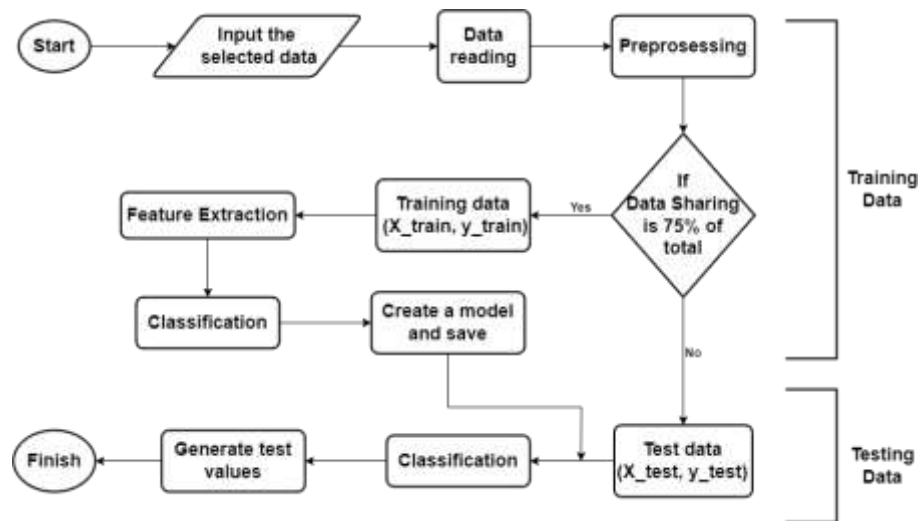


Figure 3. Flow of System Planning

D. Implementation

The system design is realized by using the data contained in the system to classify the differences in the form of angry and happy facial expressions. At this stage the system displays the results of the interface in the Local binary pattern algorithm and support vector machine.

E. Testing

In this phase, take a look at information is tested to check the created device and the accuracy, precision, recall, and F1 rating are determined. Accuracy is a particular degree of the way frequently a version produces accurate predictions. Precision is the exact positive prediction, recall is the degree of positive prediction compared to positive reality, and f1 score is a measure of the balance between precision and recall. The model is then saved in pickle format for system validation on test data. This test aims to ensure the accuracy of the data in the form of a confusion matrix. Confusion is a desk that indicates the overall performance of a version evaluating anticipated and real values. The confusion matrix includes 4 elements: true positive (TP), true negative (TN), false positive (FP), and false negative (FN). True positives (TP) are information in which the end result is in reality high-quality, and the version effectively identifies it as high-quality. True negative (TN) are information in which the end result is in reality poor and the version effectively identifies it as poor. False positive (FP) is information that the version incorrectly identifies as high-quality while the end result is in reality poor. False negative (FN) is information that the version incorrectly identifies as poor while the end result is in reality high-quality. The confusion matrix uses test data of his 80 images classified into two classes: angry and happy. The search computes a confusion matrix and calculates the true positive, true negative, false positive, and false negative in each class.

F. Evaluation

The test results that have been obtained will be calculated to determine whether the system's ability to classify differences in the form of angry and happy facial expressions through Confusion matrix to calculate the accuracy, precision, recall and f1-score values.

4. RESULTS AND DISCUSSION

A. Data Collection

One important aspect of this research is the data used as analysis and testing material. The data used in this research is image data or pictures of human faces which have two types of expressions, namely angry and happy. This facial image data is in .jpg format, which is a format commonly used to store digital images. In Figure 4, facial image data comes from two different sources, namely primary data and secondary data. Primary data is facial image data collected by yourself using a smartphone. Taking pictures of the faces of 6 respondents who are students at Yogyakarta University of Technology. Ask each respondent to show angry and happy expressions alternately, so that 12 facial images are obtained for each respondent, or a total of 72 facial images for primary data. Secondary data is facial image data taken from online sources, namely facial expression recognition in 2013 which has been modified by Rauf Momin on Kaggle. This dataset is called the facial expression dataset, which contains images of faces with various expressions, such as angry and happy. only select facial images that have angry and happy expressions from this dataset, thus getting 180 facial images for secondary data. Thus, the total facial image data used in this research is 180 facial images consisting of 90 facial images with angry expressions and 90 facial images with happy expressions for each data source. After the facial photo data is collected, the dataset is divided into several parts, namely training data and testing data. Training notes are notes that are used to teach the version of the category that was created, while testing notes are notes that are used to check the overall performance of the category version that has been trained. Use a ratio of 7.5:2.5 to divide the dataset, meaning 75% of the data is used as training data and 25% is used as test data. randomly split the data set, to get balanced and diverse training records and view records.



Figure 4 Example of Primary and Secondary Data

B. Planning

Facial expression detection includes 3 stages, namely pre-processing, feature extraction and classification. In Figure 5 and Figure 6, the pre-processing method is proven in various ways, especially gray scale and resizing. Grayscale is a way that converts an RGB (red, green, blue) color photo into a gray depth photo. This method aims to reduce the complexity of the photo

and improve the comparison between pixels. Resizing is a process that adjusts the size of image pixels to fit a specified size. This process aims to make different images have the same dimensions and facilitate feature calculation. Using a size of 100 x 100 pixels for all images used in this study.



Figure 5 Preprocessing Result on Happy Facial Expression Image



Figure 6 Preprocessing Result on Angry Facial Expression Image

After preprocessing, labeling is carried out to determine the class of each facial image, namely 0 for angry facial expressions and 1 for happy facial expressions. Then, convert the class into a numeric value that can be processed by the system. So, this research uses 75% training data and 25% data for test data, with random data selection.

After that, proceed with the feature extraction and classification stages. Local binary pattern for function extraction this approach can simplify the feel and label picture pixels through floating the acquaintances of every pixel and thinking about the end result as a binary number. Local binary pattern can generate histogram patterns that represent image characteristics. Experimented by doubling the value of numpoint, which is the number of neighboring pixels that are threshold. In Figure 7, it can be seen that the best numpoint value is 8, producing the clearest and different histogram patterns for each facial expression class.

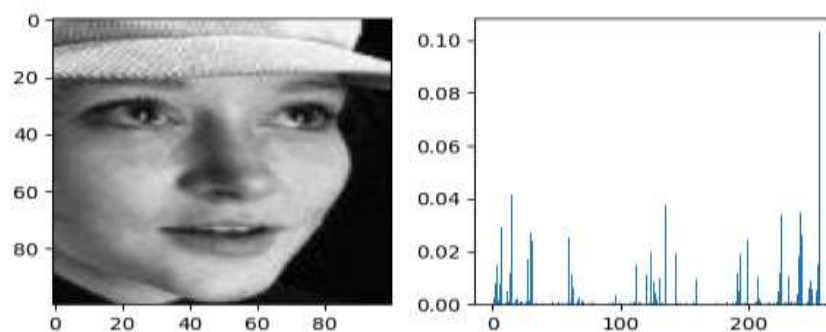


Figure 7 Feature Extraction Local binary pattern and Histogram.

After extracting features with local binary patterns, proceed with classification using a support vector machine. Support vector machines have more mature and clear mathematical concepts compared to other classification techniques. Comparing the two types of kernels used by support vector machines, namely linear kernels and radial basis function kernels. These two kernels were chosen because the results obtained are not too different from other kernels but have their own advantages.

C. Implementation

We are developing an expression recognition system that classifies human facial images into two categories: "angry" and "happy." It consists of three main phases: preprocessing, feature extraction, and classification. Pre-processing is a stage that aims to improve the quality of facial images by performing operations such as conversion to grayscale and face detection. Feature extraction is a stage that aims to retrieve important information from facial images by using methods such as local binary pattern. Classification is a stage in the process of using machine learning techniques, such as support vector machines, to predict facial emotions from facial photographs.

The integrated facial expression recognition system is tested on a set of image data which can be done directly. Built in-house graphical user interface using Python programming language and libraries like OpenCV and scikit-learn. This graphical user interface is shown in Figure 8. It has two main functions: image capture and image storage. Image capture is a feature that allows you to capture facial images in real time from a camera connected to your computer. Once a facial image is captured, the system immediately performs preprocessing, feature extraction, classification, and displays the facial expression prediction results on the screen. Image save is a feature that allows users to save captured facial images to a predefined folder. These stored facial images can be used for further evaluation and analysis. These stored facial images are also accompanied by predictive text containing information about the process and results of this study, including: B. Extracted feature values, probability values generated by the classification model, and predicted facial expression labels. This graphical user interface allows you to easily and quickly test the built-in facial expression recognition system and see the results directly and clearly.



Figure 8 Realtime Face GUI Interface and Image Input



D. Evaluation

In this research, a facial expression recognition system is developed that can classify human facial images into two classes, namely happy and angry. This system uses the support vector machine method with a linear kernel as the classification algorithm. Linear kernels are one of the simplest and easiest to implement kernel types that can generate linear decision functions. Choosing a linear kernel because it assumes that the facial image data used has linear characteristics, which can be separated by a straight line.

This evaluation shows the performance of the facial expression recognition system based on the test data performed. In Table 1, the system uses a linear kernel to predict happy and angry facial expressions on 80 facial images. Of the 80 images, 41 images have true happy facial expressions, and 39 images have true angry facial expressions. The system can correctly predict 33 images that have happy facial expressions, and 36 images that have angry facial expressions. However, the system also incorrectly predicted 3 images with angry facial expressions as happy, and 8 images with happy facial expressions as angry. This shows that the system has a high accuracy rate in recognizing happy and angry facial expressions with the linear kernel.

Table 1 Confusion Matrix on Linear Kernel

N = 80	Actual: Happy	Actual: Angry
Prediction: Happy	TP: 33	FP: 3
Prediction: Angry	FN: 8	TN: 36
	41	39

From the results of the experiments that have been carried out, we can present Table 1, which contains several performance evaluation measures of the classification model used. Table 1 may be utilized to do a mathematical computation of the accuracy, precision, recall, and f-1 score values for every class of labels. Recall shows how much positive data the model detects, accuracy shows how frequently the model predicts the proper label, precision shows how many positive predictions are truly positive, and the f-1 score shows the harmonic mean of precision and recall.

- Accuracy = $\frac{TP+TN}{TP+FP+FN+TN} = \frac{33+36}{33+3+8+36} = \frac{69}{80} = 0,8625 \times 100\% = 86,25\%$
- Precision = $\frac{TP}{TP+FP} = \frac{33}{33+3} = \frac{33}{36} = 0,9167 \times 100\% = 91,67\%$
- Recall = $\frac{TP}{TP+FN} = \frac{33}{33+8} = \frac{33}{69} = 0,4783 \times 100\% = 47,83\%$
- F-1 score = $\frac{2 \times Recall \times Presisi}{Recall + Presisi} = \frac{2 \times 0,4783 \times 0,9167}{0,4783 + 0,9167} = \frac{0,8769}{1,395} = 0,6286 \times 100\% = 62,86\%$

Table 2 shows the prediction results of happy and angry facial expressions based on radial basis function kernels on 80 facial images. Of the 80 images, 41 images have true happy facial expressions, and 39 images have true angry facial expressions. The system can correctly predict 28 images that have happy facial expressions, and 30 images that have angry facial expressions. However, the results of all processes: incorrectly predicted 9 images with angry facial expressions as happy images, and 13 images with happy facial expressions as angry images.



This shows that the system still has a high error rate in recognizing happy and angry facial expressions with the radial basis function kernel.

Table 2 Confusion matrix Kernel on Radial Basis Function

N = 80	Actual: Happy	Actual: Angry
Prediction: Happy	TP: 28	FP: 9
Prediction: Angry	FN: 13	TN: 30
	41	39

From Table 2, we can see that facial expression recognition systems using radial basis function kernels have different precision, precision, recall, and F-1 values for different facial expression classes. The accuracy value is the ratio of the number of correctly predicted images to the total number of images. The accuracy score is a comparison between the number of photos correctly predicted to fall into a particular class and the total number of photos predicted to fall into that class. Recall compares the number of images that actually belong to a class with the number of members of that class that can be predicted accurately. The f-1 score is determined by taking the harmonic mean of the accuracy and recall values. These values can be used to measure overall system performance or per class.

- a) Accuracy = $\frac{TP+TN}{TP+FP+FN+TN} = \frac{28+30}{28+9+13+28} = \frac{58}{78} = 0,7436 \times 100\% = 74,36\%$
- b) Precision = $\frac{TP}{TP+FP} = \frac{28}{28+9} = \frac{28}{37} = 0,7568 \times 100\% = 75,68\%$
- c) Recall = $\frac{TP}{TP+FN} = \frac{28}{28+13} = \frac{28}{41} = 0,6829 \times 100\% = 68,29\%$
- d) F-1 score = $\frac{2 \times Recall \times Presisi}{Recall + Presisi} = \frac{2 \times 0,6829 \times 0,7568}{0,6829 + 0,7568} = \frac{1,0336}{1,4397} = 0,7179 \times 100\% = 71,79\%$

Table 1 and Table 2 show that support vector machines perform best on this research dataset as measured by precision, precision, recall, and F-1 score. Support vector machine uses two types of kernels, namely linear kernels, and radial basis function kernels. The computational results show that the linear kernel is better in accuracy and precision, while the radial basis function kernel is better in recall and f-1 score. The accuracy value of the linear kernel is 86.25%, which is 11.89% higher than the accuracy value of the radial basis function kernel. The accuracy value of the linear kernel is 91.67%, which is 15.99% higher than the accuracy value of the radial basis function kernel. The recall of the radial basis function kernel is 68.29%, which is 20.46% higher than the recall of the linear kernel. The f-1 score value of the radial basis function kernel is 71.79%, which is 8.93% higher than the f-1 score value of the linear kernel.

5. CONCLUSION

One major use of machine learning and image processing is a face expression recognition system. Facial expressions may be employed for a variety of reasons, including human-machine connection, security, health, and entertainment, as they can disclose a person's emotions, intents, and mental state. However, facial expression recognition also faces challenges, such as pose, lighting, occlusion, and individual variations.



We employ support vector machines and local binary patterns in this work to develop a face emotion recognition system. A local binary pattern is a simple but efficient texture descriptor that labels image pixels by shifting each pixel's neighborhood and treating the result as a binary number. Algorithms for supervised machine learning, support vector machines employ kernel functions to carry out linear or nonlinear classification. Compare support vector machine performance using linear and radial basis function kernels

A dataset consisting of 180 facial images with two different expressions: happy and angry. The images are divided into 75% for training data and 25% for test data. Use a local binary pattern for feature extraction and a support vector machine for classification. According to the findings, the system attains an accuracy value of 74.36% for the radial basis function kernel and 86.25% for the linear kernel. On this dataset, the linear kernel performs better than the radial basis function kernel. Because it is clear that the linear kernel performs better in this study in terms of precision, recall, and F-1 score.

Therefore, the conclusion is that facial expression recognition systems work well with local binary patterns and support vector machines, while linear kernels are more effective on the dataset used in this study. This work can be further developed by adding more facial expressions and testing other feature extraction and classification methods, such as: B. Directional gradients, convolutional neural networks, and k-nearest neighbor histograms. The author can also carry out further analysis of factors that influence system accuracy, such as image size, number of neighboring pixels, and support vector machine parameters. Thus, this research can contribute to the development of more accurate and reliable facial expression recognition systems.

6. REFERENCES

1. R. R. Amaanullah, G. R. Pasfica, S. A. Nugraha, M. R. Zein, and F. D. Adhinata, "Implementasi Convolutional Neural Network Untuk Deteksi Emosi Melalui Wajah," *JTIM: Jurnal Teknologi Informasi Dan Multimedia*, vol. 3, no. 4, pp. 236–244, 2022.
2. D. Darmawan and H. Supeno, "Klasifikasi Ekspresi Wajah Menggunakan Metode Convolutional Neural Network (Studi Kasus Kuliah Daring)," *JURNAL PASUNDAN INFORMATIKA*, vol. 1, no. 01, p. 8, 2022.
3. N. K. Zuhail, D. P. Pamungkas, and R. Wulaningrum, "Klasifikasi Emosi Pada Wajah Dengan Menggunakan K-MEANS Clustering dan KDE," in *Prosiding SEMNAS INOTEK (Seminar Nasional Inovasi Teknologi)*, 2021, pp. 243–248.
4. R. J. Gunawan, B. Irawan, and C. Setianingsih, "Pengenalan Ekspresi Wajah Berbasis Convolutional Neural Network Dengan Model Arsitektur Vgg16," *eProceedings of Engineering*, vol. 8, no. 5, 2021.
5. R. R. Reynaldo and I. Maliki, "Pengenalan Ekspresi Wajah dengan Metode Viola Jones dan Convolutional Neural Network," *Komputika: Jurnal Sistem Komputer*, vol. 10, no. 1, pp. 1–9, 2021.
6. Y. Pratama, A. Afiyati, E. Yuniar, and A. Hariyana, "KAJIAN KOMUNIKASI NONVERBAL: BERBICARA TANPA KATA DALAM BUKU BEYOND LANGUAGE KARYA DEENA R. LEVINE DAN MARA B. ADELMAN," *Diglosia: Jurnal Pendidikan, Kebahasaan, dan Kesusastraan Indonesia*, vol. 7, no. 2, 2023.



7. N. Kaur and N. Nazir, "A review of local binary pattern based texture feature extraction," in 2021 9th International Conference on Reliability, Infocom Technologies and Optimization (Trends and Future Directions)(ICRITO), IEEE, 2021, pp. 1–4.
8. R. W. Maharsi and S. Hadi, "Pemilihan Metode Terbaik Support Vector Machine (SVM) Dan Regresi Logistik Biner Untuk Klasifikasi Status Kemiskinan Rumah Tangga Di Provinsi Lampung Tahun 2019," Jurnal Siger Matematika, vol. 3, no. 2, pp. 31–44, 2022.
9. B. C. L. Adiatma, E. Utami, and A. D. Hartanto, "PENGENALAN EKSPRESI WAJAH MENGGUNAKAN DEEP CONVOLUTIONAL NEURAL NETWORK," EXPLORE, vol. 11, no. 2, pp. 75–81, 2021.
10. Wirtjes and Jaceline S, "Pengenalan Ekspresi Wajah Menggunakan Convolutional Neural Network (CNN)," Universitas Sumatera Utara, 2019.