Identification of Facial Wrinkles using Gabor Filters and the Naïve Bayes Algorithm

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Abstrak

Facial Wrinkles are one of the key indicators in identifying signs of aging on the skin. Detecting facial wrinkles poses a challenge in image processing due to their complex, coarse texture, which is often difficult for computers to recognize, especially under varying lighting conditions, camera angles, and facial expressions. This study focuses on the application of features using Gabor Filters for the texture feature extraction, with the final results determined by the Naïve Bayes classification algoritm. In this study, 200 facial images were used, divided into two clases, with 100 images per class serving as training data. For the test data, 100 facial images were used, consisting of 50 wrinkled facial images and 50 non-wrinkled facial images. Based on the test result using the Confusion Matrix, the accuracy was 74%, precision 80%, recall 64% and F1-Score 71%. These results indicate that the combination of Gabor filters and Naïve Bayes is quite effective in recognizing wrinkle patterns on the face based on extracted texture feature, and can serve as a faoundation for developing more accurate facial wrinkle detection systems in the future.

Keyword*: Facial wrinkles, Gabor Filter, Naïve Bayes Algorithm, Texture Feature Extraction*

INTRODUCTION

The skin is the outermost and largest organ of the human body and is one of the body's most important assets. Skin aging is a natural process involving structural and functional changes in the skin as a person ages. One of the most visible signs of this process is the appearance of wrinkles on the face. Identifying facial wrinkles is not only important from an aesthetic perspective but also has significant implications for media research and the beauty industry (Wahyuningtyas *et al.*, 2015).

The appearance of wrinkles on the face is one of the most visible signs of aging. This is often a concern for many people, especially women, as it can affect their appearance and lower their self-confidence, and may also lead to psychological effects such as stress, anxiety, and depression. Given the importance of detecting facial wrinkles as an indicator of aging, the need for an accurate automated system is the reason why this research is important. Therefore, to address the impact of this wrinkle problem, this study designs a system capable of identifying the presence or absence of wrinkles on the face.

This study proposes the implementation of feature extraction using Gabor filters and classification using the Naïve Bayes algorithm. Gabor Filters extract complex texture features from facial images, while the Naïve Bayes algorithm provides a simple yet effective probabilistic classification approach.

The primary objective of this study is to develop a facial wrinkle identification system and apply Gabor Filters as a texture feature extraction technique to capture wrinkle patterns in greater detail and with higher accuracy, thereby generating Gabor features such as Mean, Standard Deviation, Energy, and Entropy from the convolution of the facial image with the Gabor filter as determining features in the subsequent process, namely applying the Naïve Bayes algorithm as a classification method to distinguish wrinkled and non-wrinkled facial areas efficiently and automatically.

Numerous studies on wrinkle detection have been conducted in the past using various methods and subjects. A study conducted by Syukri Gazali Suatkab and Alphin Stephanus (Suatkab and Stevie, 2021), titled "An Application for Extracting Human Facial Wrinkle Features Using a Statistical Entropy Randomness Approach," the author developed a MATLAB GUI-based application that extracts wrinkle features from five facial areas using the entropy method as a measure of texture randomness. The process consists of the stages of cropping, conversion to grayscale images, histogram equalization, and feature extraction; this study successfully extracted features from

12 images of male faces within a specific age range.

The study by Batool and Chellappa (Batool and Chellappa, 2015) titled "Fast Detection of Facial Wrinkles Based on Gabor Features Using Image Morphology and Geometric Constraints," aims to develop a fast and accurate facial wrinkle detection system. The researchers used Gabor filters to highlight wrinkle texture patterns and applied image morphology and geometric constraints to remove noise and clarify the shape of the wrinkles. The results were quite good in visually detecting wrinkle locations, particularly for horizontal and diagonal wrinkle patterns.

The Research by Fadhillah Abriyani (Muhimmah dkk., 2018) entitled "Wrinkle Detection in Facial Images Using Image Processing Techniques." This study aims to help users identify the location of facial wrinkles so they can focus their skincare efforts on the areas most affected by aging. The methods used include color segmentation using the HSV model and K-Means clustering, as well as edge detection using the Canny algorithm on five main facial regions. In testing, the system was applied to 39 facial images and was able to detect the presence of wrinkles with an accuracy rate of 89.74%. This indicates that the system is sufficiently effective for clearly visible wrinkles.

Based on the three previous studies mentioned above, it can be concluded that although efforts have been made to detect wrinkles, the approaches remain limited. Some rely solely on visualization, single features, or do not utilize classification. Therefore, this study aims to improve upon previous approaches by applying Gabor filters to capture the directional texture patterns of wrinkles more specifically, calculating features such as mean, standard deviation, energy, and entropy to enhance texture representation, and using the Naïve Bayes algorithm to automatically classify facial areas into wrinkled and non-wrinkled categories.

By integrating these methods, the system is expected to provide more accurate, consistent, and sensitive detection results for wrinkles, which have been difficult for computers to recognize using previous approaches.

LITERATURE RIVIEW

2.1 Image Processing

Image processing is a process that takes an image as input and produces an image as output according to specific requirements. In general, the stages of digital image processing include image acquisition, image enhancement, image segmentation, representation and analysis, recognition, and interpretation. (Sulistiyanti dkk., 2016).

2.2 Feature Extraction

A Gabor filter is a sinusoidal function modulated by a Gaussian function. A sinusoidal wave is a wave that rises and falls in a regular pattern, like ocean waves. Sinusoidal waves are used to detect repeating patterns or textures, such as fine lines, edges, or wrinkles. A sinusoidal wave also has a frequency (how closely spaced the waves are) and an orientation (the direction of the waves), so it can be used to detect patterns in specific directions and at specific scales. Meanwhile, a Gaussian function is a bell-shaped curve that is highest in the middle and tapers off toward the sides. The Gaussian function is used to limit the filter's active area, ensuring it focuses only on the central region and does not spread across the entire image, thereby improving pattern detection accuracy. This method is often used as an edge or line detector. The following equation is used to generate the Gabor kernel: (Nasional *et al.*, 2024).

$$G(x,y) = exp\left(-\frac{x'^2 + \gamma^2 y'^2}{2\sigma^2}\right) . \cos\left(2\pi \frac{x'}{\lambda}\right) \quad (1)$$

Explanation:
G (x,y) = final value of the gabor kernel at point x,y
σ =standard deviations Gaussian envelope
x', y' = rotated coordinates
γ = Aspect ratio
λ = wavelength, which determines the distance between wave crests (frequency).

Since this *filter* can rotate, then $x'$and y' are the result of rotating the coordinates:

$$x' = x \cos\theta + y \sin\theta$$
$$y' = x \sin\theta + y \cos\theta \quad (2)$$

Note:
θ = Gabor filter orientation angle (arah detection direction, e.g., vertical/horizontal).

A feature is a numerical representation of an object's characteristics in an image. Features are used to help systems recognize, compare, or classify objects based on patterns, shapes, or textures. After an image is processed using a Gabor filter, the resulting convolution pixel values can be used to calculate various features that represent the image's conditions. Some features used in this study to detect texture are: Mean, which is the average pixel intensity; Standard Deviation, which measures the spread of pixel values; Entropy, which measures the level of randomness or texture complexity; and Energy, which sums the squares of the pixel values, representing the strength of the texture pattern.

a. Mean

According to the study titled "*Gabor Contrast Patterns: A Novel Framework Extract Features From Texture Images*" by (Muzaffar *et al.*, 2023). In the context of Gabor feature extraction, the mean is defined as the average energy (absolute magnitude) of all Gabor filter responses at each pixel, across all orientations and scales. This average value is used as a threshold to normalize or distinguish pixel responses relative to the overall average of the filter. This implies that the mean serves as a key parameter for constructing a probabilistic model of the texture resulting from Gabor filtering.

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i \qquad (3)$$

Note:
μ = *mean* value
x_i = pixel intensity value resulting from the convolution
N = number of pixels (typically the patch area of the result of a Gabor filter at a single orientation)

b. Standard Deviation

In the study titled "*Texture Feature Extraction from free-Viewing Scan Paths Using Gabor Filters with Down sampling*" by (Griffith, 2020), the study defines standard deviation as a measure of the variation or dispersion of the intensity values of the Gabor filter convolution results for each combination of scale and orientation.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^2} \qquad (4)$$

Note:
N = number of pixels
x_i = value of the I pixel
μ = mean symbol
$(x_i - \mu)^2$ = square of the difference for each value
$\frac{1}{N}\sum_{i=1}^{N} (x_i - \mu)^2$ = mean square

c. Energy

Based on the research (Sheikh, 2022) titled "*Extraction of Man-Made Object from Remote Sensing Images Using Gabor Energy Features and Neural Networks*", The study concludes that Gabor energy is obtained by combining Gabor filters at each orientation. The energy value is calculated as the square root of the sum of the squares of the two responses, which reflects the local intensity or magnitude at a point in the image for a specific frequency and orientation.

$$E = \sum_{i=1}^{N} x_i^2 \qquad (5)$$

Note:
N = number of pixels in the area
x_i = the convolution result of the Gabor kernel at the i pixel

d. Entropy

Based on the study titled "*Entropy of Gabor filtering for Image Quality Assessment*" by (Vazquez-Fernandez *et al.*, 2010), Entropy is used to measure the amount of visual information or the degree of randomness in an image after it has been filtered using a Gabor filter.

$$Entropy = -\sum_{i=1}^{k} p_i \log_2(p_i) \qquad (6)$$

Note:
p_i = probability (likelihood of occurrence) of the I pixel value
K = number of unique values (different pixel intensities)

2.3 *Naïve Bayes* Algorithm

The Naïve Bayes algorithm is a classification method based on probability and statistics, proposed by the English scientist Thomas Bayes. This algorithm predicts future probabilities based on past experience and is known as Bayes' Theorem. A key characteristic of the Naïve Bayes Classifier (NBC) is its strong or "naïve" assumption of independence among individual conditions or events. The advantage of using this method is that it requires only a small amount of training data to determine the parameter estimates needed in the classification process; since the variables are assumed to be independent, only the variance of a variable within a class is needed to determine the classification, not the entire covariance matrix (Putra dkk., 2018). The Naïve Bayes calculation is defined by the equation:

$$P(C|X) = \frac{P(X|C)P(C)}{P(X)} \quad (7)$$

Note:
X = data with unknown class
C = hypothesis that the data has a known
P(C|X) = posterior probability
P(C) = prior probability
P(X) = probability of C
P(X|C) = probability based on the hypothesis

2.4 Confusion Matrix

A confusion matrix is an evaluation method used in the performance analysis of classification models. There are four terms that represent the results of a two-class classification process, where one class is considered positive and the other is considered negative in the confusion matrix: True Positive (TP) indicates correctly predicted positive data, and True Negative (TN) indicates correctly predicted negative data. False Positive (FP), a Type I error, refers to negative data incorrectly predicted as positive; conversely, False Negative (FN), a Type II error, refers to positive data incorrectly predicted as negative. Predicted values are the output of the program, which can be positive or negative, while actual values are the true values, which are True or False. Additionally, these values can be calculated using Accuracy, Precision, Recall, and F1-Score (Indransyah *et al.*, 2022).

METHOD

3.1 Research Stages

This research consists of the stages shown in figure 1.

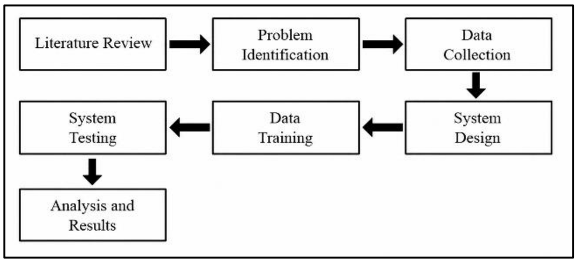


Figure 1. Research stages

3.2 System Design

3.2.1 Context Diagram

A context diagram is used to illustrate how a system interacts with users in general. In this system, user input is required in the form of photo files containing faces in images facing straight ahead. These photo files are then processed using image processing methods such as cropping, resizing, gray scaling, and Gabor filter texture feature extraction, and subsequently classified using Naïve Bayes. The result will indicate whether wrinkles are detected in the facial image; if so, the image will be labeled as having wrinkles.

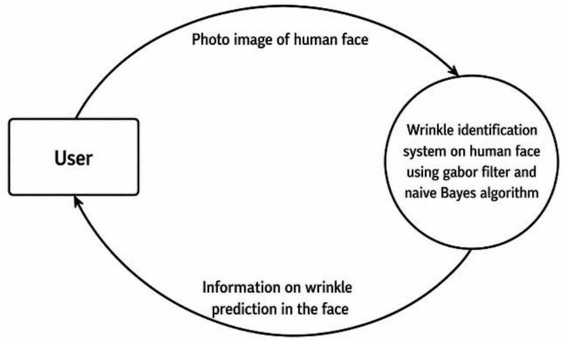


Figure 2. Context Diagram

3.2.2 System Overview

The general overview of this system is illustrated as shown in Figure 3.

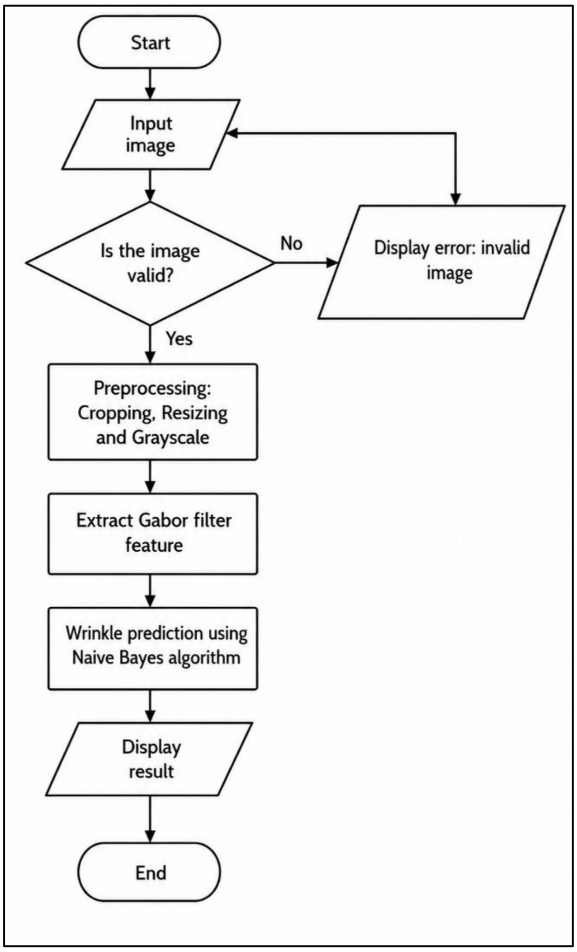


Figure 3. System design flowchart

A facial wrinkle identification system designed to accept facial images as input, followed by a decision-making process based on whether the image is detected or not. If not detected, the user can re-input another image; if detected, the system proceeds to the next stage through pre-processing steps, including cropping to the facial area only, resizing to 128x128 pixels, and conversion to grayscale. The facial image is then processed using Gabor filters and features such as mean, standard deviation, energy, and entropy. The extracted values are subsequently used for classification via the Naïve Bayes algorithm, and the system provides a prediction of the identification result, which is then displayed.

3.2.3 Gabor Filter Extraction Flowchart

In the Gabor filter extraction stage, the process begins with the input of an image of a face, whether wrinkled or not. The system then performs face detection using a Haar Cascade Classifier, which identifies facial areas based on grayscale patterns. If a face is not detected, the user will receive a warning, or the process will restart with the image re-inputted. However, if a face is detected, the system proceeds to the next step: cropping, to focus on the facial area to be analyzed. Next, the image is converted to grayscale and resized to 128x128 pixels to ensure uniform dimensions. The image is then filtered using 24 Gabor kernels with varying sizes (Ksize), orientations (Theta), and phases (Psi), producing 24 convolution results that represent different texture patterns. Each convolution result is then normalized using Min-Max Normalization, and the mean, standard deviation, energy, and entropy values are calculated to describe the texture characteristics of the wrinkles. All these feature values are saved in Excel and used in the subsequent classification stage using the Naïve Bayes method.

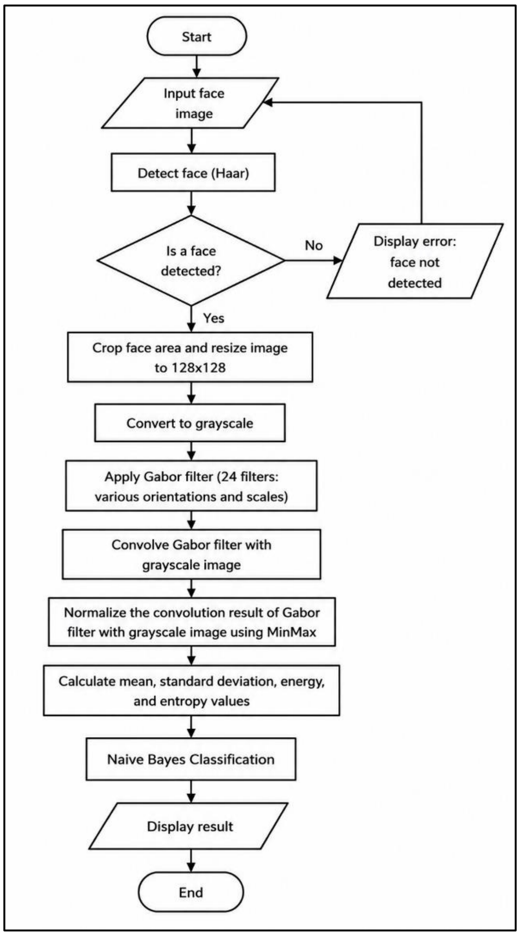


Figure 4. Gabor filter extraction flowchart

3.2.4 Naïve Bayes Algorithm Flowchart

The steps of the classification process using the Naïve Bayes algorithm to identify wrinkles on the face. The process begins by retrieving the feature values from the extraction, followed by calculating the prior probabilities for the two classes: C1 (wrinkled face) and C2 (unwrinkled face). After that, the system calculates the probability $P(X_i \mid C_k)$ for each image feature based on its class. Then, all these feature probabilities are summed and multiplied to obtain the total probability for each class. Next, the system compares the probabilities between the two classes to determine whether the probability of C1 is greater than that of C2. If the probability of C1 is greater, the image is classified as a wrinkled face (C1). Conversely, if the probability of C2 is greater, the classification result is a non-wrinkled face (C2). The results can be displayed, saved, or used for evaluation.

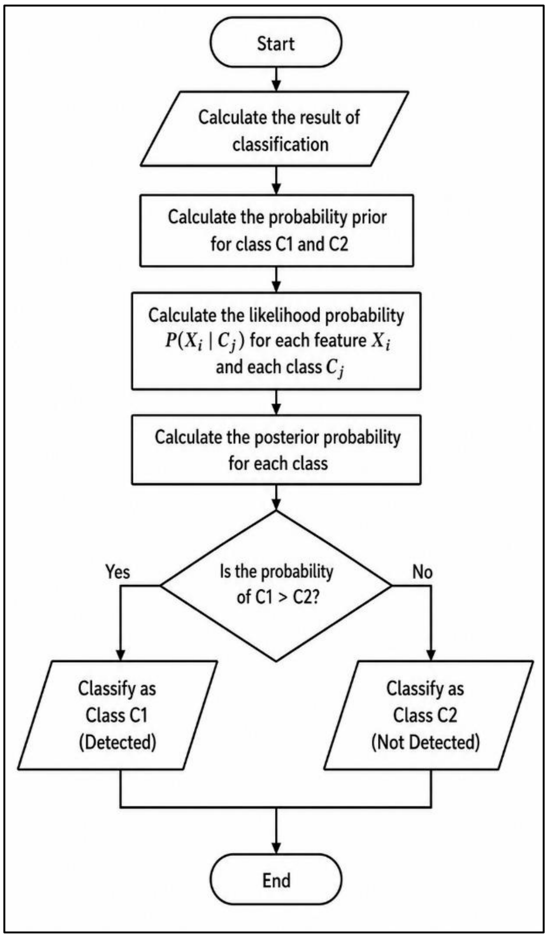


Figure 5. Naïve Bayes algorithm flowchart

RESULTS AND DISCUSSION

4.1 Research Data

The data collection in this study aims to identify facial wrinkles based on facial images. The data used consists of 200 facial images, which will be used as training data and divided into two groups: wrinkled and non-wrinkled. The 100 test data points are divided into two groups, so that each group contains 50 test data points. The data labeling process was carried out by naming each image to make it easy to identify. Each subfolder was named according to its group, namely wrinkled and non-wrinkled.

4.2 Preprocessing

4.2.1 Cropping

Cropping in image preprocessing is a technique for cutting out specific parts of an image to remove unnecessary areas, leaving only the face.

Figure 6. Cropping process

4.2.2 Resize

Resizing is a preprocessing step that serves as a key stage in the transformation of digital data, particularly image data, with the aim of changing the spatial dimensions (resolution) of an image to the desired dimensions. In this study, all images were resized to 128x128 pixels.

4.2.3 Image Conversion to Grayscale

In digital image processing, converting an image to grayscale is an important first step before performing feature extraction. To make image processing simpler and more efficient, color images are typically converted to grayscale images, in which each pixel has a single intensity value ranging from 0 to 255.

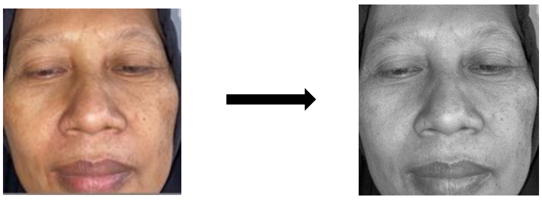


Figure 7. Grayscale process

4.3 Feature Extraction

4.3.1 Gabor Filter

In this study, the author used the Gabor filter method to extract texture from facial images. Gabor filters are used to capture facial texture features such as wrinkles and patterns on the skin's surface. The steps involved in feature extraction using Gabor filters are as follows:

1. Converting the facial image into grayscale format. Then, the image is processed using Gabor filter parameters, including: kernel size [5,9,13], Gaussian scale [2.0], orientation $[0, \pi/4\ (45°), \pi/2\ (90°), 3\pi/4\ (135°)]$, *lambda* $[\pi/20]$, *gamma* [0.05], phase $[0, \pi/2]$.
2. Normalization of Gabor filter convolution results
3. Summing the convolution values with the mean, std, energy, and entropy features.

4.4 Naïve Bayes Algorithm

At this stage, classification is performed using the Naïve Bayes algorithm, a probability based approach that applies Bayes' theorem and assumes that each feature is conditionally independent of the target class. The steps in the classification process using the Naïve Bayes algorithm are as follows:

1. Retrieve feature values from the test data.
2. Calculate the prior probability
3. *Like hood* using a Gaussian distribution
4. Calculate the posterior probability
5. Classification prediction decision

4.5 Results

4.5.1 System Interface Display

The system interface was designed using Tkinter, a built-in Python library used to create GUIs (Graphical User Interfaces).

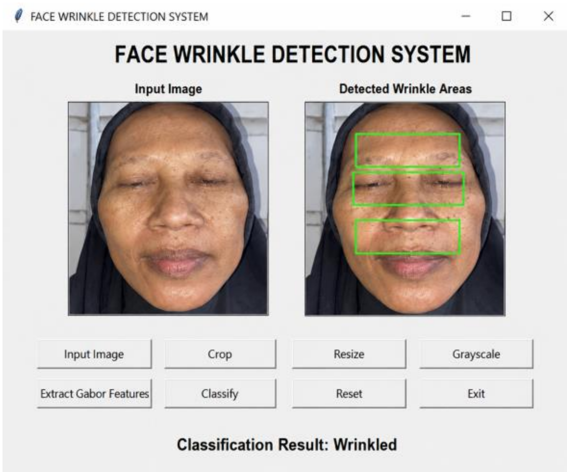


Figure 8. System interface display

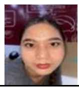
Figure 8 shows the interface of the facial wrinkle detection system. It consists of two image panels: the first displays the original face image uploaded by the user, and the second displays the processed image when the buttons for cropping, resizing, gray scaling, Gabor feature extraction, and classification are clicked. There is also a reset button to restart the entire process from the image input stage.

4.5.2 Test Results

Based on the results of testing a human facial wrinkle identification system using Gabor filtering and the Naïve Bayes algorithm, with an input of 200 facial images divided into two classes wrinkled and non-wrinkled with each class containing 100 facial images. From each class, 100 facial images were used as test data, so each class had 50 test data points. The results of the test data can be seen in Table 1.

Table 1 shows several examples of test results displaying the posterior probabilities from the classification process using the Naïve Bayes method. Some test data have a higher probability for C1 than for C2 (C1 > C2), where C1 represents the wrinkled class and C2 represents the non-wrinkled class. This indicates that the system can predict that the test image belongs to the wrinkled category. Conversely, if the probability value for C1 is smaller than that for C2 (C1 < C2), the test image is predicted to fall into the non-wrinkled category.

Table 1. Example of Test Results

No	Test data	Probability C1	Probability C2	Test results	key
1		0.99	0.09	Wrinkles	TP
2		0.02	0.97	No wrinkles	FN
3		0.99	0.07	Wrinkles	TP
4		0.03	0.99	No wrinkles	FN
5		0.99	0.02	Wrinkles	TP
6		0.13	0.86	No wrinkles	TN
7		0.93	0.06	Wrinkles	FP
8		0.99	0.02	Wrinkles	TN
9		0.93	0.06	Wrinkles	FP
10		0.45	0.54	No wrinkles	TN

To assess the model's performance in recognizing facial wrinkle patterns, a testing process was conducted on the test data. The test results are visualized in the form of accuracy and loss curves against the number of epochs. The test results graph shows that the loss value (red line) decreases as the number of epochs increases, indicating a reduction in the model's prediction error rate for the test data. Meanwhile, the accuracy value (blue line) shows an increase, reaching approximately 74%, meaning the model is capable of recognizing wrinkle patterns on faces quite well. Overall, the downward trend in loss and the upward trend in accuracy indicate that the model has learned effectively and possesses sufficient generalization ability regarding the test data.

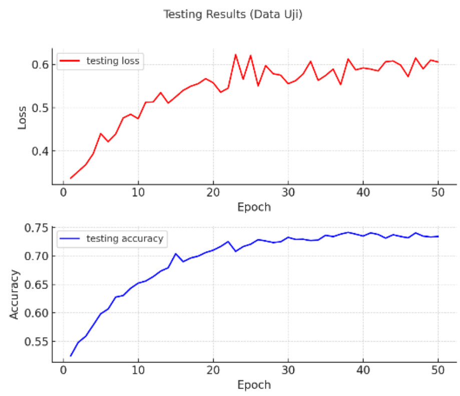


Figure 9. Accuracy and loss graph

4.7 Confussion Matrix

The following table shows the system's prediction accuracy, as illustrated by the confusion matrix in Table 2.

Table 2. *Confussion Matrix* from testing results

Class	TP	FP	TN	FN
Wrinkled	32	0	0	18
Not Wrinkled	0	8	42	0

1. Calculating precision

$$precision = \frac{TP}{TP\ +\ FP}\ = \frac{32}{32\ + 8} = \frac{32}{40}$$
$$= 0.8 \approx 80\%$$

2. Calculating recall

$$Recall = \frac{TP}{TP\ +\ FN}\ = \frac{32}{32\ + 18} = \frac{32}{50}$$
$$= 0.64\ \approx 64\%$$

3. Calculating *F-1 Score*

$$F1\,Score\ =\ 2 \times \frac{Precission\ \times\ Recall}{Precission\ +\ Recall}$$
$$=\ 2 \times \frac{0.8\ \times 0.64}{0.8\ +\ 0.64}$$

$$F1\,Score\ =\ 2 \times \frac{0.512}{1.44} = 2 \times 0.355$$
$$=\ 0.71 \approx 71\%$$

4. Calculating accuracy

$$Accuracy = \frac{TP\ +\ TN}{Total} \times\ 100$$
$$= \frac{32\ +\ 42}{100}$$
$$= \frac{74}{100}\ \times\ 100 =\ 74\%$$

Based on the test results, the overall accuracy was 74% out of 100 test data points.

CONCLUSION

Based on the results of research conducted on the identification of facial wrinkles using Gabor filters and the Naïve Bayes algorithm, it can be concluded that this system successfully detects facial wrinkles by utilizing feature extraction and Gabor filters, as well as classification using the Naïve Bayes algorithm. Testing conducted using 200 facial images as training data and 100 facial images as test data yielded an accuracy of 74%. These results indicate that the applied method is quite effective in recognizing wrinkle patterns. For future research, it is recommended to increase the number and variety of datasets and optimize Gabor filter parameters so that the system can achieve more accurate results and higher accuracy.

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