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Gender Classification Using Viola Jones, Orthogonal Difference Local Binary Pattern and Principal Component Analysis

Tio Dharmawan , Muhammad Amirul Mukminin , Muhamad Arief Hidayat
Universitas Jember, Jember, Indonesia

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ABSTRACT

Facial recognition is currently a widely discussed topic, particularly in the context of gender classification. Facial recognition by computers is more complex and time-consuming compared to humans. There is ongoing research on facial feature extraction for gender classification. Geometry and texture features are effective for gender classification. **This study aimed** to combine these two features to improve the accuracy of gender classification. **This research used the** Viola-Jones and Orthogonal Difference Local Binary Pattern (OD-LBP) methods for feature extraction. The Viola-Jones algorithm faces issues in facial detection, leading to outliers in geometry features. At the same time, OD-LBP is a new descriptor capable of addressing pose, lighting, and expression variations. Therefore, this research attempts to utilize OD-LBP for gender classification. The dataset used was FERET, which contained various lighting variations, making OD-LBP suitable for addressing this challenge. Random Forest and Backpropagation were employed for classification. **This research demonstrates** that combining these two features is effective for gender classification using Backpropagation, achieving an accuracy of 93%. This confirms the superiority of the proposed method over single-feature extraction methods.

Corresponding Author:

Muhammad Amirul Mukminin, +62895 2395 9623,
Information Systems at Faculty of Computer Science,
Universitas Jember, Jember, Indonesia,
Email: 202410101118@mail.unej.ac.id.

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1. INTRODUCTION

The human face plays a crucial role in individual identification and stores a significant amount of information, including features such as facial shape, skin color, and other attributes like beard, mustache, hair, and eyebrows [1–3]. Gender recognition through facial images is relevant in various machine-learning applications, such as human recognition, biometric verification, and smart human-computer interfaces [4, 5]. Gender recognition through faces several challenges, including the complexity of facial conditions such as variations in image positioning, lighting conditions, and diverse facial expressions [6]. Compression or data extraction steps are required before gender classification processes [7]. Gender classification poses a challenging topic due to variations in facial visual features, expressions, postures, and age factors [8, 9]. One commonly used feature extraction method is Local Binary Pattern (LBP), an effective texture descriptor widely applied in various applications. LBP has properties that favor its usage in interest region description, such as tolerance against illumination change and computational simplicity [10]. As a variation of LBP, research by [11] employed CoLBP, a texture feature extraction method, or a combination of histogram values from LBP images in eight compass directions. The study conducted by [11] aimed to combine texture and geometry features. Geometry features were obtained from calculations using Viola-Jones. The combination of texture and geometry features is a novel approach to gender classification to improve the performance of these two features. The results will also determine whether this combination causes conflicts or not. The classification methods used were Backpropagation and Random Forest. In this study, the highest values were obtained from the combination of texture and geometry features with an accuracy of 87% and an f1-score of 88% using the backpropagation classification method.

Another LBP variation used in the study by [12] the evolution from Local Binary Pattern (LBP) to Orthogonal Difference Local Binary Pattern (OD-LBP) introduces a more robust and effective method for extracting texture features from facial images, thus improving the performance of gender classification tasks based on facial images. OD-LBP is a new LBP variation for face analysis. OD-LBP calculates the gray scale difference at each orthogonal position within a 3×3 pixel window. The resulting binary patterns are combined into a feature vector, and PCA is used for dimensionality reduction as it transforms the original features into a new set of uncorrelated variables (principal components) that retain most of the variance in the data, thus simplifying the complexity of the dataset while retaining its important information. In addition, PCA was used to reduce the number of feature vectors generated by using components 15, 18, 28, 29, and 42. Classification was performed using the Support Vector Machine (SVM) algorithm. The datasets used are ORL, GT, JAFFE, MIT-CLBC, and YALE. The accuracy results of this study are ORL 98.21%, GT 90.22%, JAFFE 97.14%, MIT-CLBC 93.4%, and YALE 76.66%. The use of the Viola-Jones algorithm for geometric feature extraction, as mentioned in the study conducted by [11], aids in detecting key facial areas such as eyes, nose, and mouth while also analyzing any detection failures in these areas. Another study by [13] also utilizes Viola Jones to identify crucial facial components like eyes, nose, and mouth to extract geometric features from facial images. This research combines the extracted geometric features with pre-processed voice features, employing the Adaboost algorithm for gender classification, resulting in satisfactory performance outcomes.

The significant difference between the current and previous research lies in the feature extraction and classification approach. Previous research, as referenced by [11], used the Viola-Jones algorithm to extract geometric features from facial images and used CoLBP to extract texture features. However, this research introduces a new approach, replacing the texture feature extraction using the OD-LBP method with the Viola-Jones method for geometric feature extraction. By performing this innovative combination, **this research aims to improve** the accuracy of gender classification. **There is a gap** that has not been resolved by previous research; namely, the accuracy produced by combining Viola Jones and CoLBP is still not high enough, so this research is made to produce better performance compared to previous research. The selected classification methods are Random Forest and Backpropagation. Random Forest has been proven effective in the study [14] for building gender classification models using features from CoLBP, with satisfactory results in CoLBP histogram testing. **The difference between this research and previous research** is the methodology for texture feature extraction used in this research using OD-LBP. Meanwhile, the Backpropagation method is also employed in the study [11] to construct gender classification models, achieving the highest accuracy compared to Random Forests models. The difference between this research and previous research is that the classification method used in this research uses Random Forest and Backpropagation, and this research also tests whether backpropagation can get higher accuracy than random Forest. This research aims to apply two feature extraction methods that have performed well in previous gender classification cases; the author hopes to enhance the gender classification performance of the proposed method.

2. RESEARCH METHOD

This research falls into the category of quantitative research, aiming to identify the optimal feature extraction method for classifying human gender in facial images. Various combinations were tested to achieve optimal results, and performance was measured using accuracy and f1-score metrics after classification using the Backpropagation and Random Forest methods. The research flow of this research can be seen in Figure 1.

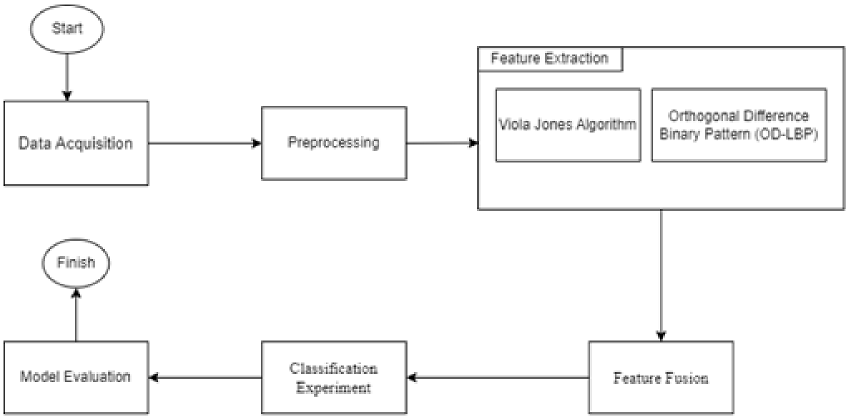

Figure 1. Research Flow

2.1. Data Acquisition

The research data utilizes the Facial Recognition Technology (FERET) dataset from The National Institute of Standards and Technology (NIST), which contains images of human faces, as shown in Figure 2. The data consists of grayscale face images with 384 × 256 pixels dimensions. The randomly selected images are of front-facing faces with neutral expressions without considering age factors.

Figure 2. Colorferet Dataset

2.2. Preprocessing

Cropping is the process of trimming images within specific areas [15]. The Colorferet dataset contains images with backgrounds, while this study requires only the facial area for feature extraction. It needs to be removed to ensure that irrelevant information outside the face does not interfere during modeling. Therefore, facial area cropping is performed using Haar Cascade detection. Image normalization is the process of modifying the pixel intensity values within an image [11]. The normalization results are relevant in this study as the Colorferet dataset exhibits variations in brightness levels across images, which could pose issues in detection using Viola-Jones. Face detection and recognition performance tend to suffer in low-light conditions [14]. This normalization process can also enhance image brightness, preventing images from being overly dark.

2.3. Feature Extraction

In this stage, feature extraction is performed from facial images to obtain crucial information for the modeling phase. This study employs the OD-LBP and Viola Jones methods for feature extraction. The following are the steps of feature extraction to be carried out: Feature Extraction using Viola Jones Algorithm, Despite the continuous development in object detection, particularly in face detection, the VJ method by Paul Viola and Michael Jones 2001 remains a reliable competitor to deep learning-based approaches [16]. Feature extraction using Viola Jones aims to capture the geometry features of the face. These geometric features are obtained by calculating distances on each detected facial feature using the Viola-Jones Algorithm. The geometric features include the distances from the eyes, nose, and mouth on the human face [13, 17]. The distance calculation for each facial feature is done using the Euclidean distance method. Euclidean distance is measured with 9 distances, as shown in Table 1.Feature Extraction using OD-LBP, The OD-LBP method is utilized for facial image feature extraction at this stage. The process begins by dividing the image into 3×3 pixel windows, then split into two orthogonal groups. By calculating the grayscale level differences between the central pixel and its nearest neighbors in orthogonal positions within the pixel window, three grayscale level differences are obtained. The threshold value is computed by dividing the sum of these three grayscale level differences by their variance. The result is a concatenated 1×24 vector from two 1×12 vectors of each orthogonal group. This vector is further divided into three binary patterns, and calculations are performed on each binary pattern, resulting in three OD-LBP transformation images. These images are partitioned into 3×3 sub-regions to extract histograms, and the results are combined into the final histogram of OD-LBP. Subsequently, classification is conducted using Random Forest and Backpropagation. A demonstration of the OD-LBP process can be seen in Figure 3.

Table 1. Geometric features of the face [13]

No	Feature	Description
1	EE	Euclidean distance between the two eyes.
2	LEFC	Distance from the left eye to the center of the face.
3	REFC	Distance from the right eye to the center of the face.
4	LENC	Distance from the left eye to the center of the nose.
5	RENC	Distance from the right eye to the center of the nose.
6	LEMC	Distance from the left eye to the center of the mouth.
7	REMC	Distance from the right eye to the center of the mouth.
8	NCMC	Distance from the center of the nose to the center of the mouth.
9	FCNC	Distance between the centers of the two nostrils.

2.4. Feature Fusion

The features extracted using the OD-LBP and Viola Jones methods are combined in this stage. The facial geometry features are obtained from the Viola-Jones algorithm, generating 9 feature values for each image. Meanwhile, the feature extraction results using OD-LBP consist of a histogram with 6,912 features.

2.5. Modeling

In this research, the algorithms used are random forest and backpropagation. Random Forest (RF) is an ensemble classification model consisting of many decision trees, where each tree is trained independently and sequentially using bootstrapped samples from the training dataset [18]. As a popular method in ensemble-based classification and decision tree clustering, Random Forest is known for its good performance, relatively low error, ability to handle large amounts of data, and effectiveness in estimating missing data [19].Backpropagation is one part of the Neural Network. Backpropagation is a supervised learning method in the sense that it has a target to look for. The backpropagation model has the advantage of accuracy compared to the initial single-layer perceptron method.

2.6. Gender Classification Experiment

In this research, 26 experiments are planned. Each feature extraction method (OD-LBP and Viola Jones) will be tested separately, followed by their combination. Subsequently, classification will be performed using Backpropagation and Random Forest algorithms, with feature dimension reduction using the PCA method with components 15, 18, 28, 29, and 42, as per the approach taken by [12]. Model evaluation will employ K-fold cross-validation, Accuracy, and F1-Score obtained from each experiment. The data will be split into training and testing data using the K-Fold Cross Validation scenario with 10 iterations. This obtains the average classification performance trained and tested on all data variations. Thus, each accuracy and F1-score obtained represents the average result of these values in each cross-validation experiment.

3. RESULT AND ANALYSIS

The data analyzed in this study comes from the Facial Recognition Technology (FERET) dataset The National Institute of Standards and Technology (NIST) provided. To obtain this dataset, the researcher submitted a download request via the official email address of the Colorferet dataset manager, colorferet@nist.gov. Initially, the dataset consisted of 1,012 facial images, with

605 images of male individuals and 407 images of female individuals, as shown in the gender data count comparison. This number represents the original amount of data before cropping with the haar cascade method and other image manipulations. This amount of data may fluctuate because some processes using haar cascade do not always detect the entire object perfectly.

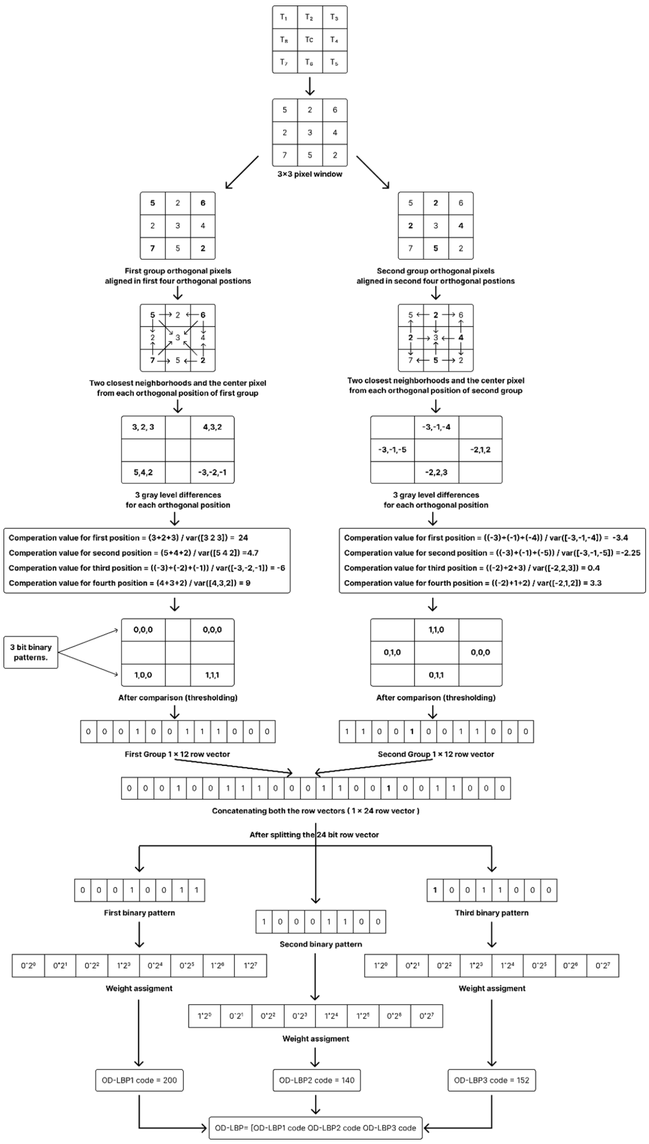

Figure 3. Demonstration OD-LBP process

3.1. Preprocessing

a. Cropping

This study uses 1,012 images for gender classification, applying automated cropping with Haar Cascade to detect facial areas. Despite occasional challenges in accurately detecting faces, resulting in some images being excluded, the dataset is reduced to 967 successfully cropped images for further analysisan example of face cropping results in Figure 4.

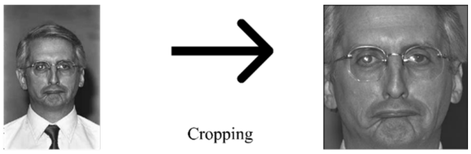

Figure 4. Image Cropping

b. Normalization
Normalization adjusts the pixel range in images using the Min-Max Normalization through the OpenCV Python Library. This type of normalization modifies the pixel range to span between 0 and 1 based on the maximum and minimum pixel values. Beyond regulating the pixel range, normalization enhances image brightness compared to the original state, improving detection quality with the Haar Cascadenormalization result, as shown in Figure 5.

Figure 5. Image Normalization

3.2. Viola Jones Feature Extraction

In this stage, feature extraction is performed on facial images using Viola Jones to obtain geometric features. Detecting Facial Components This stage discusses the extraction of geometric features using the Viola-Jones algorithm, which utilizes Haar Cascade to detect the eyes, nose, and mouth in the face and measure the distances between them. However, it is important to note that Haar Cascade has its weaknesses, including the possibility of errors or even detection failures, which can be influenced by various factors, such as the setting of the "min neighbor" parameter that determines the number of neighbors around the object to be detected and affects the accuracy of Haar Cascade in object detection. The result of haar Cascade Detection is shown in Figure 6.

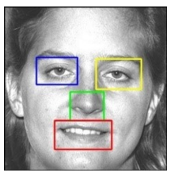

Figure 6. The Results of Haar Cascade Detection

Figure 7 displays successfully detected facial areas with varying min neighbor values. The study emphasizes the importance of optimally adjusting the min neighbor value for each image due to diverse conditions. The research aims to find the optimal min neighbor value to detect the left eye, right eye, nose, and mouth, considered optimal when only one part of the object is detected. Despite being time-consuming, the detection results with optimal min neighbor values enhance quality compared to those without optimal settings. However, some images experience detection failures in certain facial components, such as the mouth remaining undetected despite successful detection of the eyes and nose. Out of the 967 processed images, 173 did not achieve perfect detection for all facial components, leaving 794 successfully detected images. Analysis of Undetected Image In this stage, an analysis is conducted to understand the causes of failure in detecting facial areas by identifying similar patterns among images that fail to detect each facial area. Failed Detecting Eyes in Images Figure 7 illustrates images that failed to detect eye areas, particularly in images of individuals wearing glasses. The presence of glasses negatively impacts the detection accuracy because they are considered an unnatural accessory on the face, causing variations in pixel intensity that do not align with what the Haar Cascade recognizes. Additionally, some images depict eyes that are closed or nearly covered by hair.

Figure 7. Image Failed Detect Eyes

Failed Detecting Mouth in Images Figure 8 illustrates the failure to detect the mouth area in some images. Weaknesses mainly occur in facial images with non-aligned face positions and in images of men with mustaches, causing the mouth area to become blurry and covered. Additionally, images with low brightness levels can also make the mouth area appear darker, complicating the detection process.Failed Detecting Nose in Images Detection of the nose area using Haar Cascade demonstrates high success, with only 4 images from the entire dataset experiencing failure, as shown in Figure 9. Invisible nostrils and the presence of black-framed glasses around the nose area in some images primarily cause this failure. Count Geometry Feature In this stage, successfully identified the facial regions in a total of 794 images, which will be utilized in the subsequent steps. The initial step of geometric feature extraction involves calculating the center of each facial area using the Haar Cascade method, resulting in a rectangular shape, as depicted in Figure 10.

Figure 8. Image Failed Detect Mouth

Figure 9. Image Failed to Detect Nose

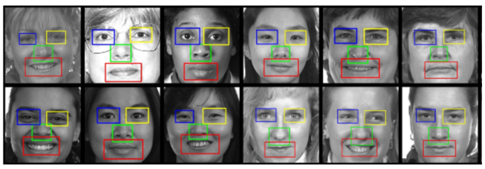

Figure 10. Images with Successfully Detected Facial Regions

In this study, the calculation of distances between the center points of facial regions is conducted after successfully detecting all facial areas. The results of the geometric feature calculations for each image will be presented in a Dataframe format, as shown in Table 2. various distance metrics obtained from each image, providing a comprehensive picture of the geometric variations between images. Thus, researchers can conduct statistical or comparative analysis to identify patterns or significant differences between the various groups of data studied.

Table 2. Geomtery Feature Data

No	EE	LEFC	REFC	LENC	RENC	LEMC	REMC	NCMC	FCNC
1	109.45775	65.75903	62.403926	73.493197	77.493548	134.14358	133.44849	70.215739	19.235384
2	143.55574	79.605276	82.802476	98.328531	107.12726	173.74766	173.46181	84.977938	35.672118
3	67.59068	37.576588	38.762095	46.674404	50.931326	82.068569	82.172076	39.815198	17.564168
4	2.5	73.44726	71.121375	91.934759	90.156808	143.81325	142.76204	66.153231	37.583241
5	84.005952	47.289005	51.04165	63.513778	71.449283	103.17219	106.66068	43.525854	27.372431
...	...	...	...	...	...	...	...	...	...
789	144.04253	83.186537	81.377208	98.290386	105.01071	150.15409	149.37537	59.91035	32.388269
790	149.96666	87.225283	76.58492	104.6518	117.9237	174.79417	174.24408	76.400262	51.480579
791	135.59222	80.131143	78.90659	100.3307	107.05606	162.81585	165.51208	71.142463	37.272644
792	135.59222	80.131143	78.90659	100.3307	107.05606	162.81585	165.51208	71.142463	37.272644
793	107.83552	59.960404	62.699681	78.409183	92.252371	123.87998	129.66592	49.155366	37.566608

3.3. OD-LBP Feature Extraction

At this stage, we will discuss the second method of facial feature extraction, which involves using OD-LBP to describe facial image texture. OD-LBP Process At this stage, the image to be texture-extracted is one image divided into three sub-regional images as depicted in Figure 11. In this study, the OD-LBP process is conducted with a 3×3-pixel image broken down into 2 orthogonal pixels, which will be calculated according to the steps shown in Figure 11.

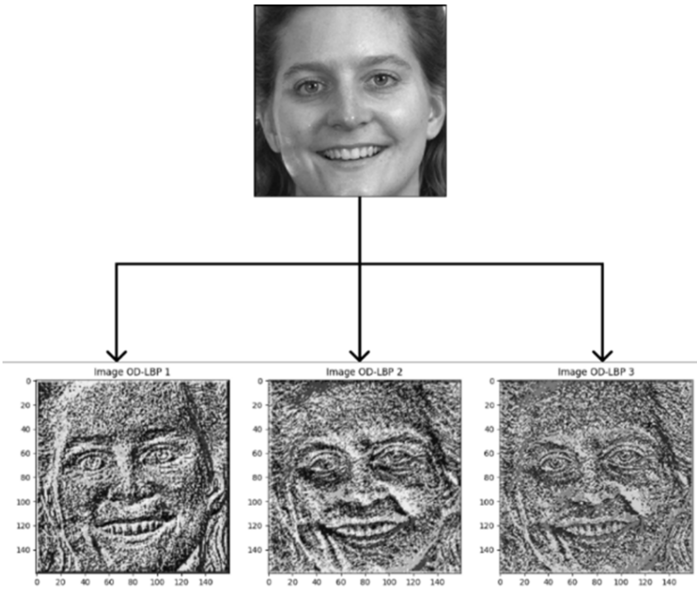

Figure 11. Division of OD-LBP into 3 Sub-Regional Images

Changing Image to Histogram In this stage, the image will transform into a histogram, where the histogram length for each image is 9×256. The conversion process from the image to the histogram is carried out using the Numpy Library, utilizing the histogram function with 256 bins. The steps of transformation from the image to the histogram are illustrated in Figure 12.

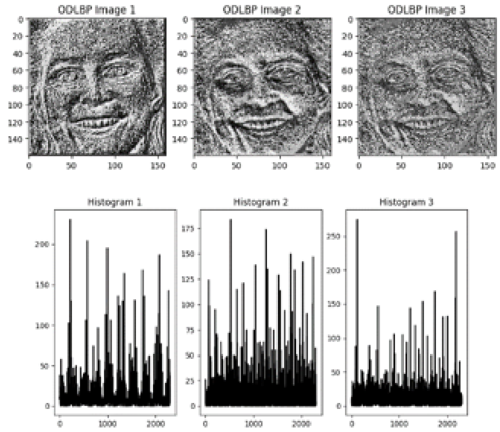

Figure 12. Changing Image to Histogram

Concatenate Histogram, The OD-LBP feature extraction involves the creation of three histograms. Subsequently, these three histograms are combined into a single histogram using the concatenate technique, as depicted in Figure 13. After the histogram merging, each image produces 6,912 bins. This bin count represents the feature extraction result from OD-LBP, which will be used as features in the gender classification modeling process.

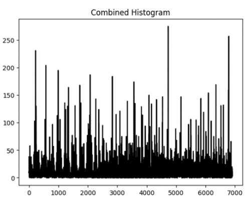

Figure 13. Concatenate Histogram

3.4. Feature Fusion

The main objective of this study is to evaluate the performance of the combined feature extraction methods of Viola-Jones and OD-LBP. After both feature extraction stages are completed, the feature results from each method are combined into one dataset. Data processing is performed using Python's Pandas library. The features have been previously transformed into Pandas DataFrames, and the merging is done by combining two DataFrames. The DataFrames of geometric and texture features have been extracted based on the same image order, ensuring both features have the same number of rows. DataFrames is merged with the 'concat' function using the 'axis=1' parameter for horizontal merging or adding columns. After the horizontal merging, the number of columns increases to 6923 columns. The column structure consists of 1 column for the image name, 9 columns for geometric features, 6912 columns for texture features, and 1 column for gender, indicating the class of each data.

3.5. Model Evaluation

In this stage, 26 gender classification experiments were conducted using Random Forest and Backpropagation as depicted in Table 3. Random Forest was configured with fixed parameters 'n_estimators=105' and 'random_state=42', while Backpropagation involved a simple artificial neural network with dense layers having units of 256, 128, 64, and 1 (output). Training was performed for 100 epochs with a batch size of 8. Dimensionality reduction of features was also carried out using PCA with n_components = 15, 18, 28, 29, and 42. The evaluation results, including accuracy and f1-score, represent the averages from cross-validation experiments. Preprocessing steps included Feature Scaling using a Min-Max Scaler, and data splitting was performed using K-fold cross-validation for 10 iterations.

Table 3. Gender Classification Experiment

No	Experiment		Accuracy	F1 - Score
	Feature Extraction	Algoritma Machine Learning		
1	Viola-Jones	Random Forest	69%	75%
2	Viola-Jones	Backpropagation	73%	78%
3	ODLBP	Random Forest	87%	89%
4	ODLBP	Backpropagation	93%	94%
5	ODLBP+PCA = 29	Random Forest	87%	89%
6	ODLBP+PCA = 29	Backpropagation	92%	93%
7	ODLBP+PCA = 42	Random Forest	86%	89%
8	ODLBP+PCA = 42	Backpropagation	92%	93%
9	ODLBP+PCA = 15	Random Forest	87%	90%
10	ODLBP+PCA = 15	Backpropagation	90%	92%
11	ODLBP+PCA = 28	Random Forest	87%	88%
12	ODLBP+PCA = 28	Backpropagation	91%	93%
13	ODLBP+PCA = 18	Random Forest	87%	90%
14	ODLBP+PCA = 18	Backpropagation	91%	92%
15	ODLBP+PCA = 29 + Viola Jones	Random Forest	88%	90%
16	ODLBP+PCA = 29 + Viola Jones	Backpropagation	90%	92%
17	ODLBP+PCA = 42 + Viola Jones	Random Forest	86%	89%
18	ODLBP+PCA = 42 + Viola Jones	Backpropagation	92%	93%
19	ODLBP+PCA = 15 + Viola Jones	Random Forest	88%	90%
20	ODLBP+PCA = 15 + Viola Jones	Backpropagation	90%	92%
21	ODLBP+PCA = 28 + Viola Jones	Random Forest	88%	90%
22	ODLBP+PCA = 28 + Viola Jones	Backpropagation	91%	92%
23	ODLBP+PCA = 18 + Viola Jones	Random Forest	88%	90%
24	ODLBP+PCA = 18 + Viola Jones	Backpropagation	90%	91%
25	ODLBP+Viola Jones	Random Forest	86%	89%
26	**ODLBP+Viola Jones**	**Backpropagation**	**93%**	**94.2%**

The findings of this study were to produce the highest accuracy of 93% and the highest f1-score of 94.2%. Both metrics were achieved by combining geometry and texture features. Analyzing the results from Table 3, it is clear that combining the Viola Jones and OD-LBP feature extraction methods results in higher accuracy and f1-score compared to using each method separately. In addition, when comparing machine learning models, the Backpropagation Algorithm is superior to the Random Forest Algorithm. Therefore, the most effective combination from this research involves the Viola-Jones and OD-LBP feature extraction methods combined with the Backpropagation algorithm.

The results of this study are in line with or supported by research [6], where the backpropagation algorithm for gender classification shows good and stable performance during the process compared to the random forest algorithm. Although both studies used Viola Jones for geometric features, the combination of OD-LBP for texture feature extraction and backpropagation implementation resulted in significant improvement, achieving 93% accuracy compared to 87% in [6], which also used the Feret dataset and backpropagation classification. A comparison of the results of combining the features of this research with previous research can be seen in Table 4 and Table 5. This study also successfully enhances accuracy compared to the previous research conducted by [11] which utilized Viola Jones and CoLBP for a combination of geometric and texture features, yielding an accuracy of 87% and an f1-score of 88%.

Table 4. Fusion Feature Gender Experiment

No	Experiment		Accuracy	F1 - Score
	Feature Extraction	Algoritma Machine Learning		
1	OD-LBP + Viola Jones	Random Forest	86%	89%
2	OD-LBP + Viola Jones	Backpropagation	93%	94.2%

Table 5. Gender Experiment Comparison [11]

No	Experiment		Accuracy	F1 - Score
	Feature Extraction	Algoritma Machine Learning		
1	Viola Jones & COLBP	Random Forest	83%	83%
2	Viola Jones & COLBP	Backpropagation	87%	88%

4. CONCLUSION

This study integrates facial texture and geometric features using OD-LBP and the Viola-Jones Algorithm for human gender classification utilizing the Color Feret dataset. The research results demonstrate a significant improvement in accuracy and f1-score when both types of features are employed together. The use of combined features achieves an accuracy of 93% and an f1-score of 94.2%, surpassing the performance of using individual features. This study also successfully enhances accuracy compared to the previous research that utilized Viola Jones and CoLBP to combine geometric and texture features. Some suggestions for further development and improvement of this research include exploring different preprocessing stages, utilizing alternative classification methods, experimenting with alternative methods for geometry feature extraction due to potential inaccuracies in the Haar Cascade algorithm, and conducting additional research to optimize the application of PCA for enhanced accuracy.

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The Acknowledgments section is optional. Research sources can be included in this section.

6. DECLARATIONS

AUTHOR CONTIBUTION

Muhammad Amirul Mukminin conducted the research and wrote and revised the manuscript, while Tio Dharmawan provided ideas and reviewed the research. Muhammad Arief Hidayat conducted a review related to manuscript writing.

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COMPETING INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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