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# Integration of Colbp and Viola Jones Feature Extraction Methods in Gender Classification Based on Facial Image

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ABSTRACT

Nowadays face recognition still being a hot topics to be discussed especially it's utility for gender classification. Gender classification is an easy task for human but it's a challenging task for computers because it doesn't have capability for recognizing human gender without feature extraction. There are still many researches about facial image feature extraction for gender classification. Geometry features and Texture Features are well perform features for gender classification. This paper will presents fusion of those feature in order to find an improvement for gender classifications task. Each features will be extracted using Viola Jones Algorithm and Compass Local Binary Pattern method. Both features will be combined using concatenated method in dataframe format. Viola Jones algorithm has an issues when detecting each facial regions so it causes outliers in each geometry features. The proposed method will be evaluated on color FERET dataset that contains facial images. Classification task will be done using Random Forest and Backpropagation. The result is fusion features present an improvement in gender classification using Backpropagation with 87% accuracy. It prove that proposed method perform better than single feature extraction method.



## 1. INTRODUCTION

The development of current technology allows computers to have human-like intelligence. One is computer now can detect human's gender based on facial images. Nowadays, facial features are used as an aspect of human biometrics besides fingerprints, DNA, voice and retina. Face recognition is still continuously being developed, especially for gender classification task. Gender classification has an important role in many kind of applications such as biometric authentication, intelligent user interfaces, user identification, social interaction, collecting demographic statistics for marketing [1]. Gender classification task has several difficulties mainly due to the complexity of faces such as lighting, image positions, postures and different expressions which have high dimensions so it need to be compressed or any extraction processes before being trained with the classification algorithm [2]. Gender classification is currently still being a interesting topic to discuss due to differences in facial visual points, expression, posture and age [3].

The facial image has clear information on facial features such as eyes, nose and mouth region. These frontal face informations have been used as features in the gender classification process by calculating distance of each detected facial features [4]. This process uses the Viola Jones Algorithm to detect facial features. This algorithm has several advantages such as speed and accuracy relatively high detection, low computational power requirements, ability to use in real-time [5] After all the geometry features are extracted, it used for modeling using the Adaboost Classifier algorithm to test the performance of the geometry features in gender classification cases. Facial geometry feature extraction is also relatively easy to understand because the process is not a black box and this process utilizes information that humans generally understand.

In addition to using geometric features, image texture can also be used as a feature for the gender classification process. A popular algorithm for facial image texture feature extraction is called Local Binary Pattern (LBP). LBP is an image descriptor to extract textures from images [6]. LBP does not require a lot of data or a large computational load, and it can capture texture details well [7][8]. LBP has many variations, as demonstrated in [9] by adding an additional kernel for LBP namely Kirsch Compass Mask to generate eight Edge Responses images where Edge Responses exploit the spatial relationship between neighboring pixels in each edge response image. Spatial relationships between local directional gradients will provide more structural information than Local Directional Pattern (LDiP) and other LBP variants. This study [9] applied the Kirsch Compass Mask function to the Local Binary Pattern for feature extraction compared to 10 other LBP variants and CoLBP obtained 93.92% which is the highest accuracy compared to other LBP variants. The SVM algorithm is used for classification only based on gender classification cases regardless of the feature extraction used. This study shows that CoLBP has good performance compared to other LBP variants when tested using color ferret datasets [9].

The addition of the Kirsch Compass Mask can be done with a low computational load. CoLBP is recommended for high-performance facial gender classification due to the balance between classification performance and computational complexity. This method is called Compass Local Binary Pattern (CoLBP). The CoLBP feature extraction method is combined with the Random Forest algorithm in [10] where this algorithm was tested in several experiments to obtain the optimal histogram length and number of trees parameters for gender classification. There are 3 tests scenario for classification in [10], namely histogram length test, number of trees test and facial image data test with accessories. All tests use CoLBP feature extraction. Tests using facial data without accessories get an 91.8% average of accuracy compared to the average accuracy of image data with accessories which only 85.2%. From the histogram length test, it was found that the histogram length was 256 x 8 to get the best accuracy of 88.6%. This study provides a clear description of the stages of the feature extraction process using CoLBP. From this research the authors were able to determine the optimal histogram length and number of random forest trees to use in modeling [10].

Based on the description above, both feature extraction methods have good performance for gender classification even though both algorithms have different approach. So the authors want to test the combination of the Viola Jones Algorithm and Compass Local Binary Pattern for gender classification cases with the assumption it can improve the classification performance. As was done in [11] which combines the extracted features of the Local Binary Pattern and Local Directional Pattern methods to get an increase in accuracy of up to 99.23% when compared to other LBP variants. in [4] also tested a combination of facial features with speech features to be used in gender classification and facial recognition. Found that the combined features showed a good increase in performance compared to each feature when tested individually.

It's explained on description above that combining to method could trigger the improvement of performances. In this paper, the authors wants to conduct an experiment to combine Texture Feature and Geometry Feature that haven't been combined before in gender classification case in order to get improvement by combination of these features. The result will also prove that this combination causes conflict or not. The classification algorithm that will be used is the Backpropagation and Random Forest algorithms.. Random Forest has been used in [10] to built a gender classification model using features of CoLBP with quite good results on the CoLBP histogram Length test. Backpropagation method used in [12] to built a gender classification model and it obtains the highest accuracy when compared to the SVM and Adaboost models. By using two feature extraction methods that have worked well in gender classification cases, the authors expected an improvement of gender classification performance from the proposed method.

## 2. METHOD

This research is included in the type of quantitative research, with the aim of this research is to find the best feature extraction method for facial images to be used for human gender classification. Several trial combinations are needed to get the best feature extraction method. Performances will be measure using accuracy and f1-score metrics after classification using the Backpropagation and Random Forest methods.

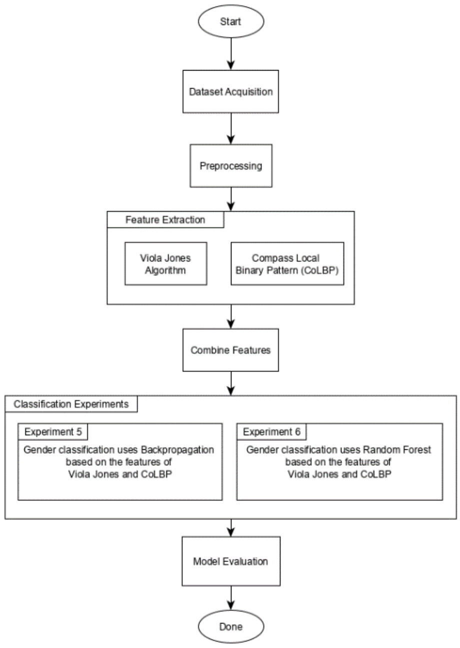


**Figure 1 - Research Methodology**

### 2.1. Data Acquisition

Dataset to be used in this research is the Facial Recognition Technology (FERET) dataset provided by The National Institute of Standards and Technology (NIST) which contains images of human faces. Data are grayscale images in the Colorferet dataset, all images with dimensions of 384×256. The image data to be used is frontal facial image data with a neutral expression that is randomly selected without considering age.

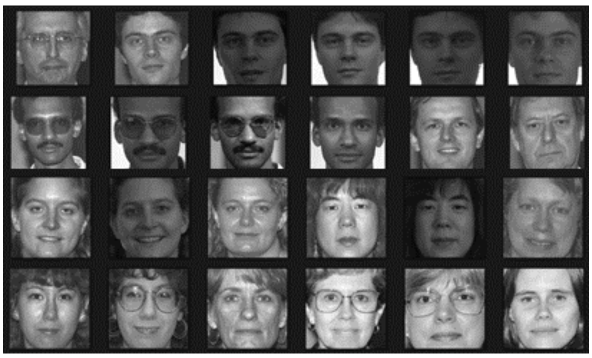

**Figure 2 - Color FERET Dataset**

### 2.2. Preprocessing

#### 2.2.1. Cropping

The Colorferet dataset contains images that still have a background, while this research only requires the face area to be used so other than faces does not become noise when used for modeling. For this reason, cropping of the facial area will be carried out by utilizing the Haar Cascade to detect the facial area before cropping is carried out.

#### 2.2.2. Normalization

Image normalization is process of modifying pixel values in an image. Image normalization process can also increase the brightness of the image. The results of this normalization are also useful in this research because Colorferet dataset does not have the same brightness so that there are images that appear dark. This condition allows for errors when detection is carried out using Viola Jones because the performance of face detection and recognition is not so good when lighting conditions was low [18]. So by applying Normalization the image will be brighter than the initial conditions.

### 2.3. Feature Extraction using *Viola Jones*

The purpose of feature extraction using Viola Jones is to get geometric features from faces. This geometric feature is obtained from calculating the distance of each facial feature detected using the Viola Jones Algorithm. The geometric features to be used are the distance from the human face, namely the eyes, nose and mouth. [4]. Distance of each facial feature will be calculated using Euclidean distance. Features that will be extracted are as shown in **Table *1***.

**Table 1 - Facial Geometry Features** [4]

| No. | Feature | Description |
|---|---|---|
| 1. | EE | Euclidean distance between the eyes |
| 2. | LEFC | Distance between left eye and face center |
| 3. | REFC | Distance between right eye and face center |
| 4. | LENC | Distance between left eye and nose center |
| 5. | RENC | Distance between right eye and nose center |
| 6. | LEMC | Distance between left eye and mouth center |
| 7. | REMC | Distance between right eye and mouth center |
| 8. | NCMC | Distance between nose center and mouth center |
| 9. | FCNC | Distance between face center and nose center |

### 2.4. Feature Ectraction using CoLBP

The first stage is combining the original image with the Kirsch Mask. In Original LBP we will get only one image histogram, but CoLBP method will have eight spatial histograms to be combined. Then each convolutioned image will be applied with LBP process so it will be generated eight histograms. Those histograms will be combined using concatenate. All of CoLBP process are shown in Figure 3. The size of the histogram to be used is 256×8 as in [10] was stated that the histogram length is directly proportional to the accuracy obtained.

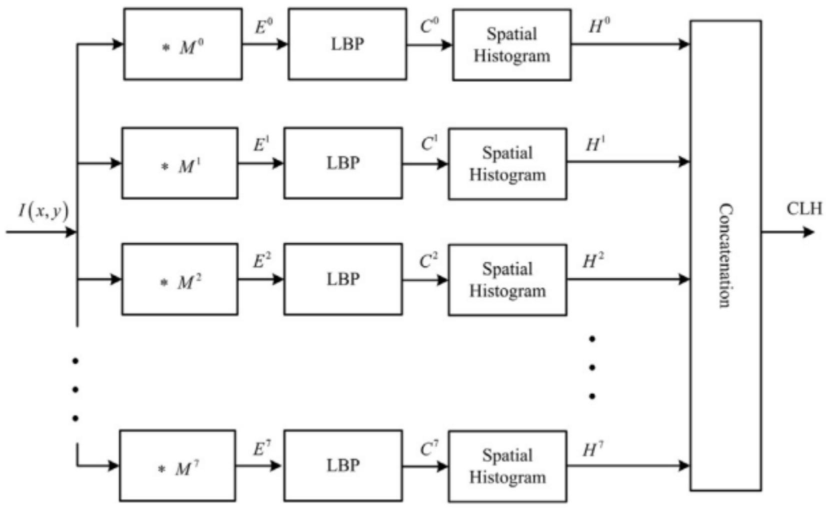


**Figure 3 - CoLBP Method**

### 2.5. Combine Feature

The extracted features using the CoLBP and Viola Jones method will be combined. the results of facial geometry features using the Viola Jones algorithm will be in the form of 9 features for each image. Then the feature extraction results using the Compass Local Binary Pattern is a spatial histogram with a size of 256×8. The two features will be combined to obtain 2.057 features for each im ages.

### 2.6. Gender Classification

In this research 6 experiments will be carried out according to Table 2. Each feature of the CoLBP and Viola Jones feature extraction methods will be trained out once, then a combination of the two feature extractions will be carried out so that 3 feature extractions will be done. Then classification will be conducted using two algorithms, Backpropagation and Random Forest. Each of these algorithms will be applied to each feature extraction experiment to compare the accuracy of each feature extraction method and classification algorithm, so there are total of 6 experiments will be carried out.

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**Table 2 - Classification Experiments**

| No. | Feature Extraction | Classification Algorithm | Description |
|---|---|---|---|
| 1. | Viola Jones | Backpropagation | Gender Classification using Backpropagation Algorithm based on geometric features |
| 2. | Viola Jones | Random Forest | Gender Classification using Random Forest based on geometric features |
| 3. | CoLBP | Backpropagation | Gender Classification using Backpropagation Algorithm based on texture feature (histogram) |
| 4. | CoLBP | Random Forest | Gender Classification using Random Forest based on texture (histogram) |
| 5. | Viola Jones & CoLBP | Backpropagation | Gender Classification using Backpropagation based on a combination of geometric and texture features (histograms) |
| 6. | Viola Jones & CoLBP | Random Forest | Gender Classification using Random Forest based on a combination of geometric and texture features (histograms) |

## 3. RESULT AND DISCUSSION

### 3.1. Dataset

The initial dataset that will be used is 1.012 data with the amount for each gender is 407 female images and 605 male images as compared to the amount of this gender data as shown in Figure 4.

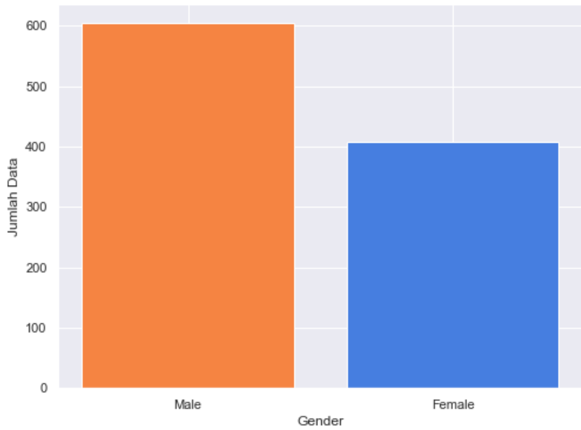


**Figure 4 - Proportion of gender class**

### 3.2. Cropping

Haar Cascade will be used in this cropping process. Cropping image using Haar Cascade is very effective for large amounts of data because cropping process can be done automatically for each image. However, there are several obstacles in the cropping process using the Haar Cascade which lies in the detection process. For some images, Haar Cascade cannot detect facial areas precisely so that there are several images that cannot be cropped. This affects the amount of image data that has been successfully cropped. In this research, the image is classified as a successfully cropped when the image is detected on the face correctly and cropped according to the face area. The amount of data after cropping process was reduced to 978 data.

### 3.3. Image Normalization

The image normalization process is carried out to adjust the range pixels in the image. The type of normalization used in this process is Minmax Normalization, which adjustment of pixel range based on the maximum and minimum values of the pixels so that the pixel range will be between 0 and 1. Normalization process also shows changes images become brighter. from the previous condition. This change can also help in the detection process using Haar Cascade to be better.


**Figure 5 - Image Normalization**

## 3.4. Viola Jones Feature Extraction

### 3.4.1. Facial Area Detection

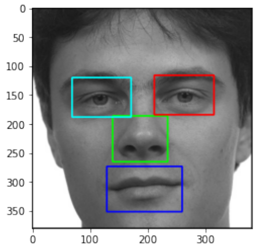

**Figure 6 – Facial Regions Detected**

Viola Jones Algorithm will be applied using Haar Cascade. Haar Cascade will be used to detect each part of the face, such as the eyes, nose and mouth, which will calculate the distance to get geometric features. There are a weaknesses while using the Haar cascade. Sometimes errors occur when detecting it, even cannot detecting at all. This can happen due to several factors, one is the value given in the min neighbor parameter in the Open-cv library. This parameter determines how many neighbors around the object will be detected to determine the accuracy of the Haar Cascade while detecting objects. The higher min neighbor value, the fewer object detection results and the accuracy tends to be more accurate. Otherwise, the smaller min neighbor value is, the more sensitive system will be in detecting faces so that it tends to be even more inaccurate because there are so many detected objects [19].

Figure 6 shows that the image has been successfully detected for all areas of the face correctly, but this is obtained by using different min neighbor values to detect each part of the face. To detect the nose, the value of min neighbor is used 200, the mouth uses a value of 200, the left eye uses a value of 410 and the right eye uses a value of 150. However, each image has different conditions so that each image has a different optimal min neighbor value to be able to detect objects correctly. This condition occurs in almost all images used in this study. This condition is shown in Figure 7 where two images are given the same min neighbor value, but the detection results only work optimally on one of the images.

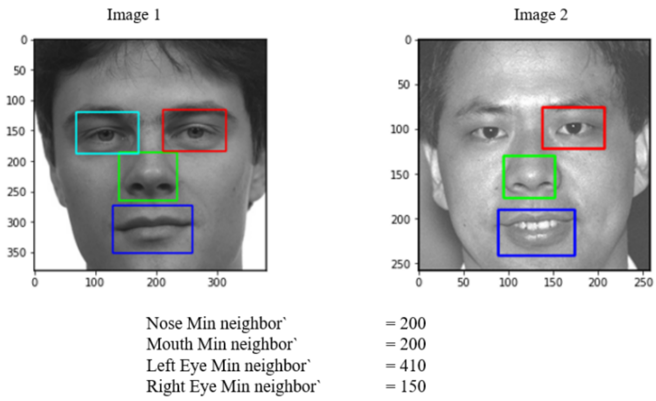


**Figure 7 - The difference results of image detection while given same min neighbors**

Therefore, each image cannot be treated equally in terms of including min neighbor parameters. Each image needs to be given the most optimal parameters according to the conditions of each image. So the most optimal value of the min neighbor parameter will be searched when detecting objects. In this study, the min neighbor value is said to be optimal when it succeeds in detecting only 1 part of the object for the left eye, right eye, nose and mouth.

Even the optimal value of min neighbor have been searched for each images, There are several images that still fail to detect facial objects. The detection failure factor is due to various problems, for example there are images that fail to detect the mouth but succeed in detecting the eyes and nose. The image conditions that failed to detect the faces are failed to detect nose, failed to detect mouth, and failed to detect eyes. It was recorded that 212 of the 978 processed image data failed to detect all parts of the face perfectly. Of all the parts of the face, nose is the part of the face that has the highest detection success rate because there are only a few failures, recorded only 4 images that fail to be detected. Then for the images that have the most detection failures were the eyes with a total of around 116 images that failed to detect the eye.

### 3.4.2. Analysis of each undetected category

a. Failed to detect eyes area

Figure 8 shows an example of an image that failed to be detected in the eyes area. Based on Figure 8 it can be identified that the majority of facial images are use glasses. This affects the accuracy of detection because glasses are an accessory and unnatural part of the face resulting in a change in pixel intensity in the eye area which causes it to not match what is recognized by the Haar Cascade. In addition, in Figure 8 it's shown that the glasses cause light reflection from the front of the face so this will also affect the intensity of the black and white pixels in the eyes area. Besides that, there are also several images whose eyes are closed and several images whose hair almost covers the eye area.

**Figure 8 - Images Failed to be detected the eyes area**

b. Failed to detect mouth area

**Figure 9 - Images Failed to be detected the mouth area**

Figure 9 shows sample of an image which cannot detect mouth area. Male images failed to be detected more frequently with a total of 84 images, while female images only failed to detect as many as 19 images. Based on Figure 9 it can be seen that the majority of images that fail to detect the mouth are images of men who have mustaches so that the mouth area seems to be covered by the mustache and becomes obscure. The presence of a mustache makes the area around the mouth darker. This condition might affect the intensity of the black pixels around the mouth area so that Haar Cascade cannot find the pattern of the mouth area according to the haar like feature. In addition, there are several images that not only have a mustache but also have a beard so that the mouth area becomes more obscure and closed. Other problems may be due to the image having low brightness, the mouth area is darker, and the position of the face in the image is not straight.

c. Failed to detect nose area

Nose is the area of face that has the fewest failures when detected using the Haar Cascade. From out of all the images used, only 4 images failed to detect the nose area according to Figure 10 From the 4 failed images, this is caused by two things, the nostrils are not visible and the presence of black eyeglass frames around the nose area.

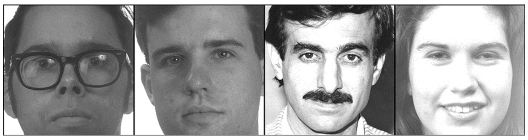

**Figure 10 - Images Failed to be detected the nose area**

### 3.4.3. Calculation of Geometry Features

At this stage, facial area detection has been carried out for all images and a total of 766 images were obtained which were successfully detected for all facial areas so that this data will be used next. Based on research conducted in [4] facial geometric features are the distance between the midpoints of each facial area where the facial area to be used is the midpoint of the face, mouth, nose and both eyes. If a straight line is drawn between two points on the face area, an oblique line will be formed when reflected in Cartesian coordinates as shown in Figure 11.

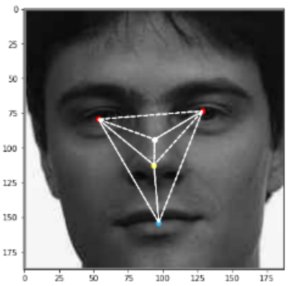


**Figure 11 - The line between the midpoints of each face area**

The distance between the two coordinate points of this face area can be calculated using the Euclidean distance formula. The calculation of the midpoint distance of this face will become a geometric feature according to research in [4] which produces 9 features according to Table 3.

**Table 3 - Extracted Geometry Features**

| No. | EE | LEFC | REFC | LENC | RENC | LEMC | REMC | NCMC | FCNC |
|---|---|---|---|---|---|---|---|---|---|
| 1. | 109,4578 | 65,75903 | 62,40393 | 73,4932 | 77,49355 | 130,5996 | 128,2312 | 65,51717 | 19,23538 |
| 2. | 67,59068 | 37,57659 | 38,76209 | 46,6744 | 50,93133 | 86,78277 | 87,48857 | 45,22444 | 17,56417 |
| 3. | 143,5557 | 79,60528 | 82,80248 | 98,32853 | 107,1273 | 180,3358 | 181,4284 | 92,80356 | 35,67212 |
| 4. | 126,0635 | 72,09022 | 68,47627 | 90,51243 | 91,31539 | 159,4882 | 159,6073 | 81,05554 | 34,53259 |
| 5. | 2,5 | 73,44726 | 71,12138 | 91,93476 | 90,15681 | 154,7361 | 153,6376 | 74,56038 | 37,58324 |
| … | … | … | … | … | … | … | … | … | … |
| 763. | 148,9732 | 86,12781 | 76,32169 | 103,5917 | 117,5383 | 175,9787 | 187,831 | 84,17987 | 51,48058 |
| 764. | 107,8761 | 59,75366 | 62,69968 | 78,01442 | 92,25237 | 135,9678 | 140,1588 | 61,98387 | 37,56661 |
| 765 | 113,2486 | 61,05121 | 67,23095 | 80,80842 | 91,06179 | 138,4215 | 142,0572 | 63,94138 | 34,55792 |
| 766 | 136,6108 | 89,22023 | 65,94126 | 101,4717 | 101,1187 | 171,9564 | 171,0921 | 82,53787 | 40,67247 |

## 3.5. CoLBP Feature Extraction

### 3.5.1. Image Convolution with Kirsch Compass Mask kernel

The first step is to perform image convolution with eight Kirsch Compass Mask kernels. Before further processing, the color of the image needs to be converted to grayscale. Then images will be convoluted using 8 Kirsch Compass Mask kernels so that one image will produce 8 convolution images.

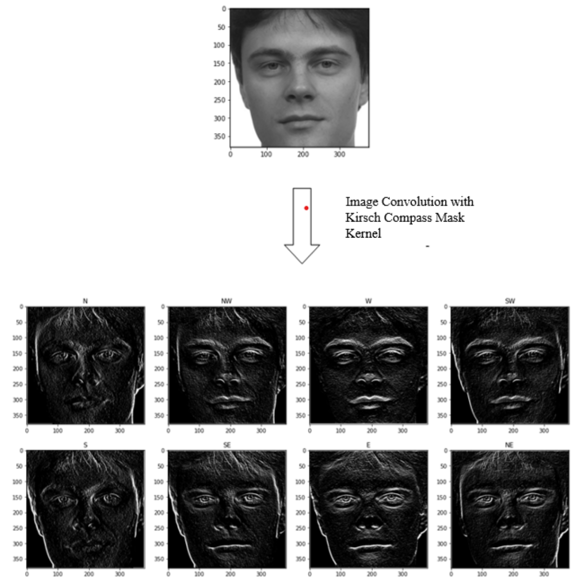


**Figure 12 - Image Convolution with Kirsch Compass Mask**

### 3.5.2. Local Binary Pattern Process

In this LBP process, the images to be extracted are the eight images resulting from the previous convolution. The parameters that must be provided for this LBP process are the radius and number of points (num_points). In this study the arguments radius = 1 and num_points = 8 will be used where these numbers are in accordance with research conducted in [9]. The eight images resulting from the convolution were processed by the LBP so that the changes in the resulting LBP process were as shown in Figure 13 The resulting LBP image will be converted into a histogram in the next step.

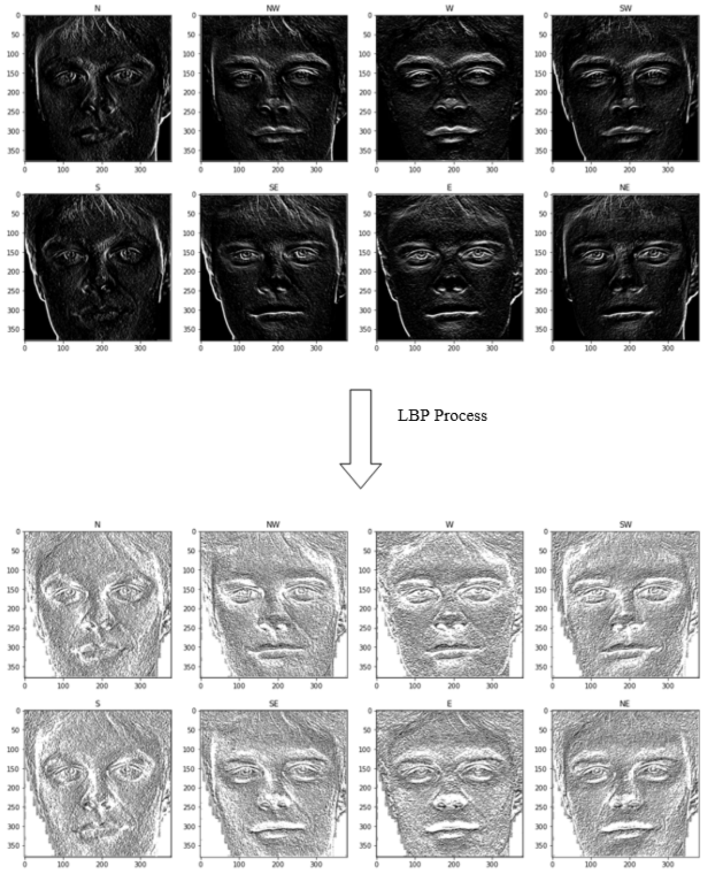


**Figure 13 - LBP Process**

### 3.5.3. Changing image to a histogram

At this stage the image will be converted into a histogram with the length of the histogram for each image being 256×8. This histogram length was chosen because it has been tested in a study conducted in [10] where this histogram length has better performance compared to other histogram lengths. The process of changing from image to histogram is shown in Figure 14.

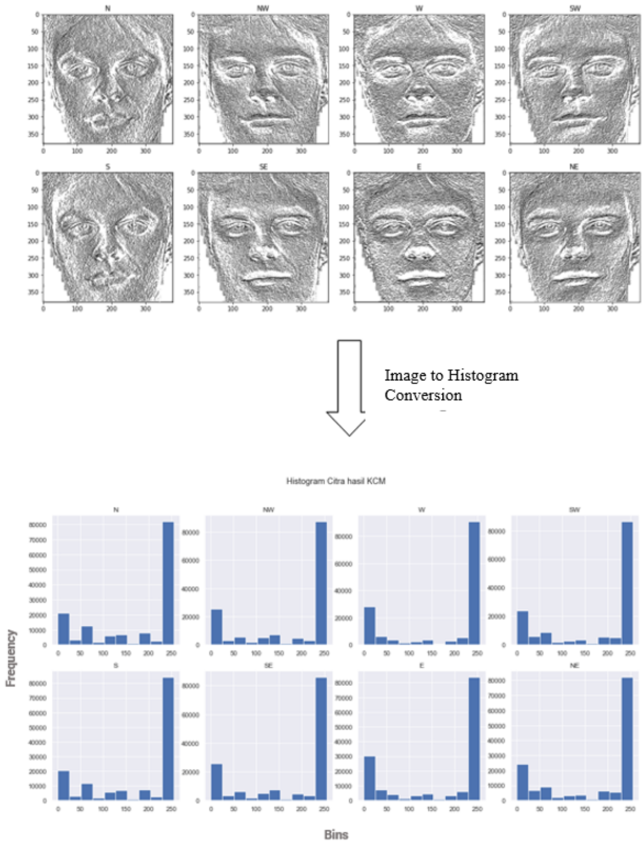


**Figure 14 - Convert Image to Histogram**

### 3.5.4. Concatenate Histogram

The feature extraction process of the Compass Local Binary Pattern produces eight histograms, so these eight histograms will be combined into one histogram using the concatenate method. After the histograms are combined, each image produces as many as 2048 bins. The number of bins will be a feature extracted from CoLBP which will be used for modeling gender classification.

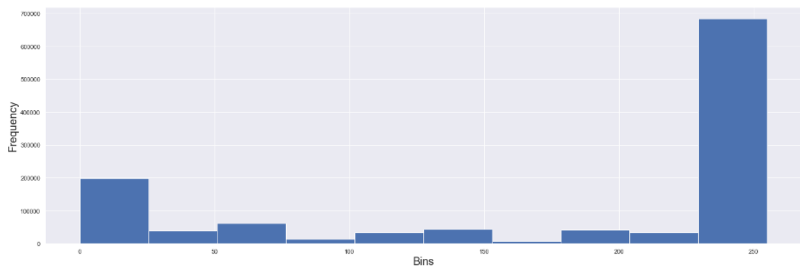


**Figure 15 - Concatenated Histogram**

### 3.6. Combine Features

In the previous stage, each feature has been converted into a Pandas Dataframe, so feature merging will be carried out as if combining two dataframes. Geometry feature dataframes and texture feature dataframes have been extracted based on the same image sequence so that both features have the same number of rows. Then merging dataframes will be done with the concat function with parameter axis is given 1 to combine dataframes horizontally or by adding columns. As the merging that has been done horizontally, the number of columns increases to 2,059 columns consisting of 1 image name column, 9 geometry feature columns, 2048 texture feature columns, and 1 gender column indicating the class of each data. Table 4 shows details of the combined data of geometric features and texture features such as the data type and description of the contents of each data row.

**Table 4 - Combined features detail**

| No. | Column Name | Description | Data type |
|---|---|---|---|
| 1 | pic_name | Image name | String |
| 2 | EE | Euclidean distance between the eyes | Float |
| 3 | LEFC | Distance between left eye and face center | Float |
| 4 | REFC | Distance between right eye and face center | Float |
| 5 | LENC | Distance between left eye and nose center | Float |
| 6 | RENC | Distance between right eye and nose center | Float |
| 7 | LEMC | Distance between left eye and mouth center | Float |
| 8 | REMC | Distance between right eye and mouth center | Float |
| 9 | NCMC | Distance between nose center and mouth center | Float |
| 10 | FCNC | Distance between face center and nose center | Float |
| 11 | 0 | 1$^{st}$ bin | Float |
| 12 | 1 | 2$^{nd}$ bin | Float |
| 13 | 2 | 3$^{rd}$ bin | Float |
| 14 | 3 | 4$^{th}$ bin | Float |
| 15 | 4 | 5$^{th}$ bin | Float |
| … | … | … | … |
| 2057 | 2046 | 2047$^{th}$ bin | Float |
| 2058 | 2047 | 2048$^{th}$ bin | Float |
| 2059 | gender | Gender | Int |

### 3.7. Descriptive Analysis

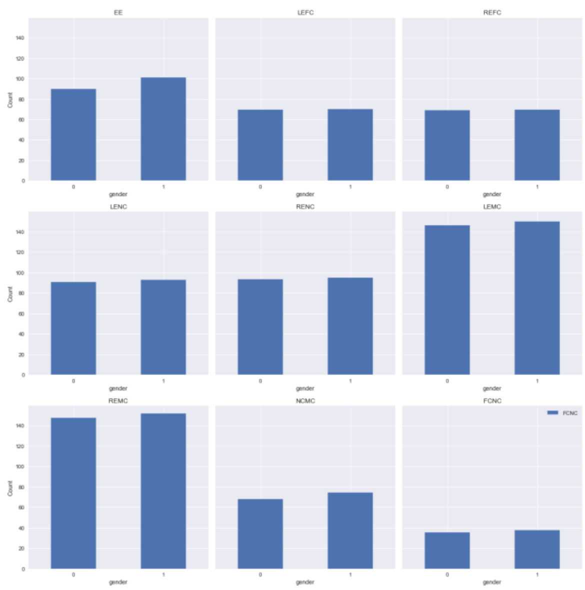


**Figure 16 - Comparison of geometric features mean value by each gender**

**Figure *16*** shows the comparative value of each geometry feature for each gender. Almost all the average geometric features of gender 1 (male) are higher than gender 0 (female). This information can be one of the characteristics that differentiate between male and female gender.

### 3.8. Classification Experiments

The total number of experiments conducted in this study were 6 experiments as shown in Table 2 The Random Forest algorithm requires parameters for training, the parameters used for the Random Forest algorithm are n estimators and random state. N estimators value is given 105 and random state value is 42. These parameters will always be used for every experiment in this research involving Random Forest. Then for Backpropagation it is done by creating a simple neural network architecture, 4 dense layers with each unit layer of 256, 128, 64, 1 (output) which will be trained using 100 epochs and a batch size of 8.

Feature Scaling are also applied for data Before modeling. This stage is carried out because there are differences in data ranges that are very far from geometric features and texture features, so to equalize the range of data a Feature Scaling process is carried out using the Min Max Scaler algorithm where the range of data that previously varied will change to 0 to 1. Splitting data of the train and test data was carried out using K-fold Cross Validation with the number of folds or cross validation being carried out 10 times so that the proportion of train and test data for each cross validation experiment was 90:10.

### 3.9. Model Evaluation

At this stage, the performance results of the classification model that has been carried out for each experimental scenario will be discussed. The accuracy value and f1-score written at this stage are the average values obtained from cross validation experiments.

**Table 5 - Gender Classification Experiments**

| No. | Eksperimen | | Accuracy | F1-Score |
|---|---|---|---|---|
| | Ekstraksi fitur | Algoritma Machine Learning | | |
| 1. | Viola Jones | Random Forest | 65% | 68% |
| 2. | Viola Jones | Backpropagation | 68% | 70% |
| 3. | CoLBP | Random Forest | 84% | 85% |
| 4. | CoLBP | Backpropagation | 86% | 87% |
| 5. | Viola Jones + CoLBP | Random Forest | 83% | 83% |
| **6.** | **Viola Jones + CoLBP** | **Backpropagation** | **87%** | **88%** |

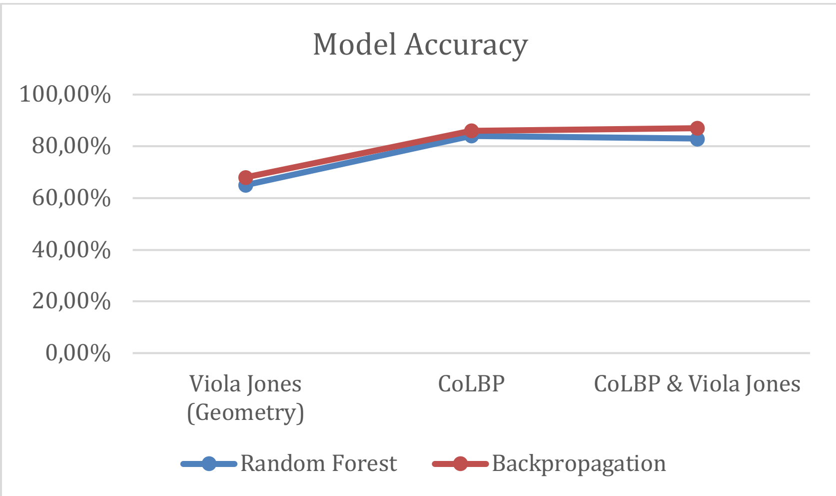


**Figure 17 – Accuracy comparison of gender classification by feature extraction method**

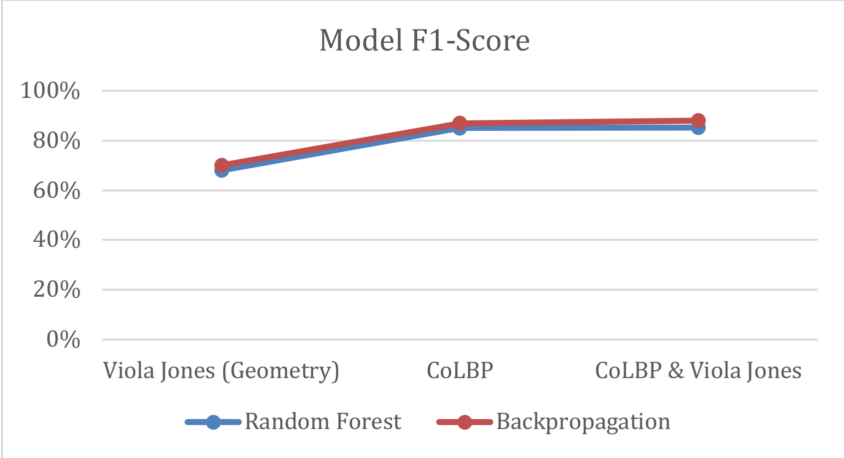


**Figure 18 - F1-Score Comparison of gender classification by feature extraction method**

In this experiment modelling obtained the highest accuracy of 87% and the highest f1-score value of 88%, both of which were obtained from modeling results using a combination of geometric features and texture features. Figure 17 shows the increase in the accuracy of the combination of geometric features and texture features when compared to the accuracy value when using only one of the features. Based on the test results in Table 5 found that the combined feature extraction method of Viola Jones and CoLBP obtained a higher accuracy and f1-score compared to the test results which only used one of the feature extraction methods. Then when compared based on machine learning models the Backpropagation Algorithm shows higher performance compared to the Random Forest algorithm. So that the best combination obtained from this study is a combination of the Viola Jones and CoLBP feature extraction methods using the Backpropagation algorithm. When using only one of the feature extraction methods, the CoLBP feature extraction method has better performance than the Viola Jones method because the comparison of accuracy values is quite far. In this research the test results that have the lowest value are when only using geometric feature data. In all experiments, shown that the f1-score is always above the accuracy value, which means that even though the number of male and female class data is not too balanced, the model can still recognize well for each class and does not tend to be smart in recognizing one class only.

## 4. CONCLUSION

This research combine Compass Local Binary Pattern and Viola Jones Algorithm to extract texture features and facial geometry features for human gender classification. The result of the combined features show improvement based on accuracy and f1-score metrics. The accuracy of gender classification using combined features is 87% and the f1-score is 88%. The accuracy of each geometry features and texture features for gender classification test is 68% and 86%. It means that combined features of geometry and texture features perform better than using only single feature in gender classification. When it was tested by single feature, geometry features perform less than texture features, but it becomes quite better when it was combined with texture features. It means that texture features by CoLBP method could be the method to consider to boost the geometry features by Viola Jones Algorithm and there is no issue to combine these features.

## REFERENCES


[1] F. H. K. Zaman, "Gender classification using custom convolutional neural networks architecture," *International Journal of Electrical and Computer Engineering*, vol. 10, no. 6, pp. 5758–5771, Dec. 2020, doi: 10.11591/ijece.v10i6.pp5758-5771.

[2] U. D. Rosiani, R. A. Asmara, and N. Laeily, "PENERAPAN FACIAL LANDMARK POINT UNTUK KLASIFIKASI JENIS KELAMIN BERDASARKAN CITRA WAJAH," *JIP (Jurnal Informatika Polinema)*, 2019.

[3] A. Venugopal, Y. O. Yadukrishnan, and R. N. Nair, "A SVM based Gender Classification from Children Facial Images using Local Binary and Non-Binary Descriptors," in *Proceedings of the 4th International Conference on Computing Methodologies and Communication, ICCMC 2020*, Institute of Electrical and Electronics Engineers Inc., Mar. 2020, pp. 631–634. doi: 10.1109/ICCMC48092.2020.ICCMC-000117.

[4] K. Prasada Rao, M. V. P. Chandra Sekhara Rao, and N. Hemanth Chowdary, "An integrated approach to emotion recognition and gender classification," *J Vis Commun Image Represent*, vol. 60, pp. 339–345, Apr. 2019, doi: 10.1016/j.jvcir.2019.03.002.

[5] D. M. Abdulhussien and L. J. Saud, "AN EVALUATION STUDY OF FACE DETECTION BY VIOLA-JONES ALGORITHM," *World Economics & Finance Bulletin (WEFB)*, vol. 14, pp. 159–164, 2022, [Online]. Available: https://www.scholarexpress.net

[6] S. Fekri-Ershad, "Gender classification in human face images for smart phone applications based on local texture information and evaluated Kullback-Leibler divergence," *Traitement du Signal*, vol. 36, no. 6, pp. 507–514, 2019, doi: 10.18280/ts.360605.

[7] M. Annalakshmi, S. M. M. Roomi, and A. S. Naveedh, "A hybrid technique for gender classification with SLBP and HOG features," *Cluster Comput*, vol. 22, pp. 11–20, Jan. 2019, doi: 10.1007/s10586-017-1585-x.

[8] C. Zhang, H. Ding, Y. Shang, Z. Shao, and X. Fu, "Gender classification based on multiscale facial fusion feature," *Math Probl Eng*, vol. 2018, 2018, doi: 10.1155/2018/1924151.

[9] B. Patel, R. P. Maheshwari, and B. Raman, “Compass local binary patterns for gender recognition of facial photographs and sketches,” *Neurocomputing*, vol. 218, pp. 203–215, Dec. 2016, doi: 10.1016/j.neucom.2016.08.055.

[10] M. Wahyu, B. Santoso, R. Cahya Wihandika, and M. A. Rahman, “Ekstraksi Ciri untuk Klasifikasi Jenis Kelamin berbasis Citra Wajah menggunakan Metode Compass Local Binary Patterns,” 2019. [Online]. Available: http://j-ptiik.ub.ac.id

[11] K. Chengeta and S. Viriri, *A Survey on Facial Recognition based on Local Directional and Local Binary Patterns*. Information Communications Technology and Society, 2018.

[12] A. Jaswante, A. U. Khan, and B. Gour, “Gender Classification Technique Based on Facial Features using Neural Network,” 2013. [Online]. Available: www.ijcsit.com

[13] A. Geetha, M. Sundaram, and B. Vijayakumari, “Gender classification from face images by mixing the classifier outcome of prime, distinct descriptors,” *Soft comput*, vol. 23, no. 8, pp. 2525–2535, Apr. 2019, doi: 10.1007/s00500-018-03679-5.

[14] M. N. Chaudhari, M. Deshmukh, G. Ramrakhiani, and R. Parvatikar, *Face Detection using Viola Jones Algorithm and Neural Networks*. Fourth International Conference on Computing Communication Control and Automation, 2018.

[15] E. L. Santoso, E. Setyati, and Y. Kristian, “Klasifikasi Citra Daun Memanfaatkan Angular Partition, Edge Detection dan Neural Network,” *Insyst*, vol. 1, no. 1, pp. 27–33, 2019, doi: 10.52985/insyst.v1i1.32.

[16] L. Breiman, “Random Forests,” *Machine learning*, vol. 45, no. 1, pp. 5-32, 2001.

[17] G. A. B. Suryanegara, Adiwijaya, and M. D. Purbolaksono, “Peningkatan Hasil Klasifikasi pada Algoritma Random Forest untuk Deteksi Pasien Penderita Diabetes Menggunakan Metode Normalisasi,” *Jurnal RESTI (Rekayasa Sistem dan Teknologi Informasi)*, vol. 5, no. 1, pp. 114–122, Feb. 2021, doi: 10.29207/resti.v5i1.2880.

[18] H. Tran, C. Dong, M. Naghedolfeizi, and X. Zeng, “Using cross-examples in viola-jones algorithm for thermal face detection,” in *Proceedings of the 2021 ACMSE Conference - ACMSE 2021: The Annual ACM Southeast Conference*, Association for Computing Machinery, Inc, Apr. 2021, pp. 219–223. doi: 10.1145/3409334.3452083.

[19] I. S. Hutomo and H. Wicaksono, “A smart door prototype with a face recognition capability,” *IAES International Journal of Robotics and Automation (IJRA)*, vol. 11, no. 1, p. 1, Mar. 2022, doi: 10.11591/ijra.v11i1.pp1-9.