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VGG-19 and histogram equalization for human face shape classification on mobile platforms

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Abstract

The human face functions as a distinct identity and holds significant importance in several applications, particularly within the fashion industry. Facial features have a substantial impact on haircut, eyewear, makeup, and overall aesthetic. The research challenge pertains to the identification of the most precise and effective approach for facial recognition, taking into account various facial forms. The aim is to ascertain the ideal convolutional neural network (CNN) architecture and picture enhancement strategy that can reliably and consistently recognize facial features. This study aims to evaluate the efficacy of different Convolutional Neural Network (CNN) architectures, including InceptionV3, MobileNetV3, Visual Geometry Group (VGG-19), and a simple CNN, in the domain of facial recognition. Furthermore, the study investigates the effects of histogram equalization on improving image quality. The aim of this study is to determine the most precise approach for facial identification, taking into account the variability in facial morphology. The research results, based on a dataset of 4979 images, demonstrate that using the VGG-19 neural network architecture, along with applying histogram equalisation, achieves a significant accuracy rate of 79.84% in the field of facial recognition. The research's results make important progress in the fields of computer vision and fashion by demonstrating the potential of advanced convolutional neural network (CNN) structures and image enhancement approaches to improve the accuracy of facial recognition systems.

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1. Introduction

The face is a prominent feature of a person and is commonly used for identification or distinguishing one person from another. Human faces come in various shapes such as oval, round, rectangular, heart, and square [1]. The facial proportions play a significant role in shaping the initial perception of a person's attractiveness [2]. This influence extends to elements like hairstyles, eyewear styles, and makeup, all of which are essential in creating an overall appearance. Making mistakes in choosing an inappropriate hairstyle can lower someone's confidence, especially in social interactions with the opposite gender [3][4]. Similarly, selecting eyeglass frames that don't match the facial contours can cause discomfort and potentially affect eye health [5]. Moreover, improper makeup application that doesn't complement the facial shape can alter proportions and emphasize existing flaws [6]. The particular issues with choosing a hairstyle, pair of glasses, and cosmetics highlight how crucial it is to accurately recognise facial shapes in order to provide individualised advice on grooming and beauty procedures.

The shape of a face significantly impacts its overall appearance, creating challenges in self-identification due to factors like facial size, expressions, jawline, and angles. Recognizing one's own face shape accurately can be difficult, highlighting the need for a practical and accessible system for face shape recognition [7]. Based on the mass availabillity [8] and efficiency of mobile devices [9], the aim of this research is to build a face shape recognition system on mobile device. The system will utilize various machine learning techniques and image enhancement method to precisely identify different face shapes, addressing the complexities associated with facial recognition.

There have been a multitude of research conducted that have examined various aspects of facial morphology. An investigation conducted by [10] utilized the K-means clustering algorithm to differentiate the borders between hair and skin on the facial region. The study achieved an accuracy rate of 80% by utilizing a dataset consisting of 10 photographs. A further investigation conducted by [11] employed a dataset consisting of 500 data points and employed several Convolutional Neural Network (CNN) architectures, such InceptionV3, Inception-ResNetV2, Xception, and ResNet50, for the purpose of facial form recognition. The study achieved accuracies ranging from 89% to 92%. Furthermore, the utilization of a hybrid approach involving Support Vector Machines (SVM) and Histogram of Oriented Gradient (HOG) techniques, combined with InceptionV3 for the task of classification, resulted in an accuracy rate of 70.3%. This performance was evaluated based on a dataset consisting of 500 data points [12]. Moreover, the application of You Only Look Once (YOLOV4) method for the purpose of face shape classification, as demonstrated by reference [13], yielded an accuracy rate of 87.45%. This achievement was attained by the utilization of a dataset consisting of 8000 data points sourced from the CelebA dataset. Furthermore, investigations conducted by [14] have demonstrated that including histogram approaches into the preprocessing stage can effectively enhance the performance of machine learning models in the specific context of osteoporosis diagnosis. This study will build upon prior research and specifically find the application of the VGG-19 algorithm to identify human facial shapes on a mobile platform.

This study aims to evaluate the efficacy of different Convolutional Neural Network (CNN) architectures, including InceptionV3, MobileNetV3, Visual Geometry Group (VGG-19), and a simple CNN, in the domain of facial recognition. The research incorporates Histogram Equalization as a preprocessing technique for image analysis to determine the most effective method in this context, the study seeks to understand the performance of different algorithms. Furthermore the project also aims to incorporate the CNN structure that performs the best onto a mobile platform. This research is expected to improve facial recognition systems' precision and efficacy, especially for fashion-related applications. It explores parameters like optimizer and activation function in the CNN architectures. The dataset comprises 4979 images categorized into five distinct classes: oval, heart, round, square, and oblong, sourced from the Kaggle dataset titled "Face Shaped Preprocessed" [11].

2. Research Method

Basically, this research is separated into five basic steps, including data collecting, data processing, system design, testing and evaluation, and system implementation. These details can be found in Figure 1, the Research Flowchart. It starts with identifying everyday life problems, followed by a full literature analysis incorporating the examination of pertinent earlier research. Subsequently, data is gathered and submitted for additional processing. Then, the system is thoroughly set up and subsequently executed. The final stage involves testing and assessing the system, based on parameters such as accuracy, precision, and recall. These measures are rooted in studies made by [15].

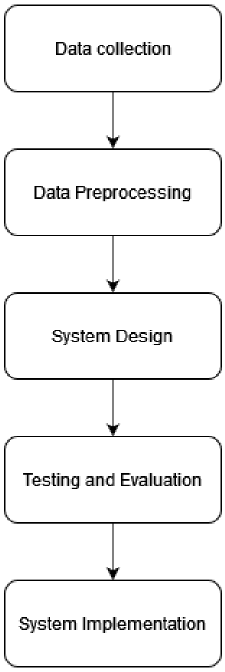

Figure 1. Research Framework

2.1 Data Colleting

In this research, data was collected from a dataset available on kaggle.com, specifically named "Face Shaped Preprocessed" [16]. This dataset comprises photographs of celebrities' faces stored in jpg format, each with dimensions of 250 × 190 pixels. The dataset was divided into 998 images for testing and 3981 images for training purposes. It included a total of 5 distinct classes. Prior to usage, the dataset underwent preprocessing steps, which included face detection and conversion of images to grayscale. Figure 2, Dataset Samples, visually represents the categorization of different facial shapes found within the dataset.

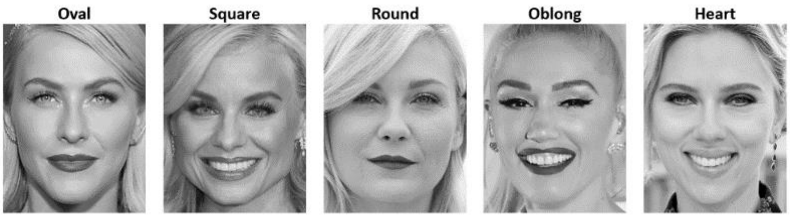

Figure 2. Dataset Sample

2.2 Data Preprocessing

In addition with the previous preprocessing procedures employed on the dataset, a further preprocessing strategy that was implemented involved the utilization of histogram equalization. The procedure of preprocessing is crucial in order to standardize the dataset, hence ensuring consistency for subsequent stages of processing [17]. Histogram equalization is a commonly used method in image processing that aims to improve the distribution of pixel intensity values within an image [18]. The mathematical expression for histogram equalization is presented in equation (1).

$$P(j) = \frac{n_j}{MN}, j = 0,1, \dots, L-1 \quad (1)$$

This equation is utilized to calculate the grayscale level of an image denoted by the letter 'j.' Here, 'n_j' represents the number of pixels with a grayscale value of 'j,' and 'MN' indicates the total number of pixels in the image. Subsequently, histogram equalization ensures that these values uniformly cover the entire dynamic range, as formulated in equation (2).

$$s_k = T(k) = (L-1)\sum_{j=0}^{k} P(j) \tag{2}$$

The function of this equation is to map each pixel value 'k' to 's_k,' where 'L' represents the maximum intensity value within the grayscale level of an image. The outcome of applying histogram equalization can be observed in Figure 3, Result of Histogram Equalization.

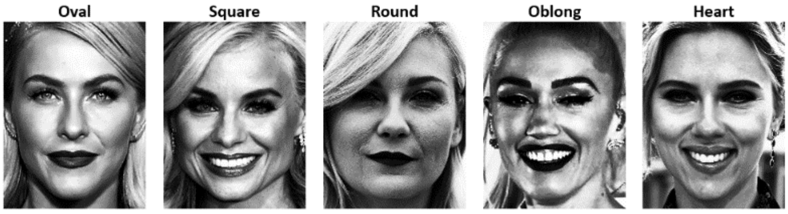

Figure 3. Histogram Equalization Result

2.3 System Design

The Convolutional Neural Network (CNN) is a specialized form of neural network that has been specifically developed to handle input that exhibits grid-like features. Convolution layers, which serve as the fundamental constituents of convolutional neural networks (CNNs), are present within the network architecture. The concept of "convolution" pertains to a mathematical procedure in which the output of one function is subjected to the application of another function [19]. The convolution equation is expressed as follows in equation (3) 's(t)' denotes the outcome of the convolution, 'x(t)' represents the initial input function in the convolution operation, 'w(t)' signifies the second input function, and 'a' is a variable that spans from negative infinity to positive infinity.

$$s(t) = \sum_{a=-\infty}^{\infty} x(a)w(t-a) \tag{3}$$

The growth of CNN design has resulted in the emergence of new architectures such AlexNet, VGGNet, GoogLeNet, ResNet, DenseNet, EfficientNet, among others[20]. The current research uses the VGG-19 (Visual Geometry Group-19) convolutional neural network architecture for the purpose of classifying facial shapes. The VGG-19 architecture is comprised of 16 convolutional layers employing the Rectified Linear Unit (ReLU) activation function, along with 3 fully connected layers that also utilise the ReLU activation. The architectural design of VGG-19 is depicted in Figure 4, titled "VGG-19 Architecture." Based on the provided figure, it can be observed that VGG-19 necessitates input images with dimensions of 224×224 pixels [21]. These images thereafter undergo a series of convolutional operations, which are organised into five distinct blocks. Every block serves the purpose of extracting features. Following the completion of each convolutional block, the picture performs a pooling operation, resulting in a reduction of its size by half. Upon reaching the fully connected layer, the dimensions of the image are reduced to 7×7 pixels.

Before accessing the fully linked layer, the image gets a flattening procedure, reducing the multidimensional image into a one-dimensional representation [22]. After that, the input data proceeds to the fully connected layer, which means each node in the layer is associated with the output classes present in the dataset. The completely connected layer, also known as a dense layer, is a form of neural network layer in which every node from the preceding layer is connected to every node in the subsequent layer. Utilisation of the softmax activation function is the final step in converting the output from the fully connected layer into probabilities that represent the class. This helps the process of multiclass classification [23].

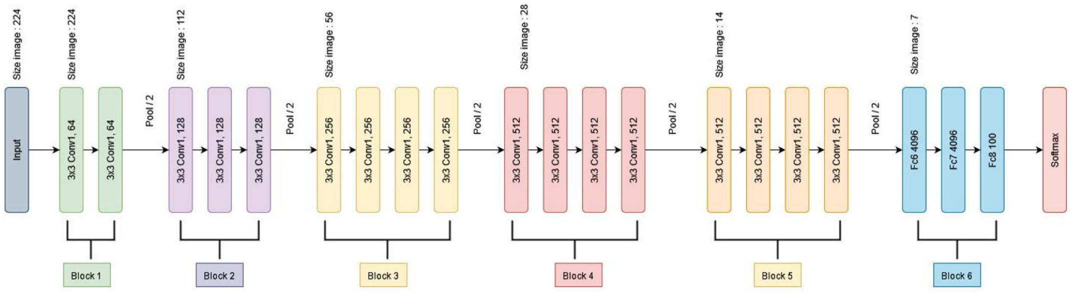

Figure 4. VGG-19 Architecture Model by Khattar [24]

2.4 Testing and Evaluation

This study uses metrics that are based on accuracy, precision and recall. The measures utilized in this study is based on [25] were designed to assess test results based on the four aforementioned indicators. The initial statistic, accuracy, denotes the frequency at which the model accurately classifies instances in its entirety. The equation for accuracy is shown as equation (4), in which TP denotes true positive, TN represents true negative, FP signifies false positive, and FN denotes false negative [26].

$$accuracy = \frac{TP + TN}{TP + FP + FN + FN} \tag{4}$$

The second metric under evaluation is precision, which can be used as a means to evaluate the model's efficacy in predicting positive values and the frequency with which these predictions are accurate [27]. The equation can be observed in equation (5).

$$precision = \frac{TP}{TP + FP} \tag{5}$$

The third statistic, recall, is used to quantify the model's ability to accurately identify all positive instances within the dataset [28]. Recall refers to the capacity of the model to identify and retrieve a maximum number of positive examples. The definition of the concept can be expressed mathematically using equation (6), that let TP represents the number of true positive instances and FN is the number of false negative instances.

$$recall = \frac{TP}{TP + FN} \tag{6}$$

3. Result and Discussion

3.1 Comparation Result of CNN Architecture

This component of the deep evaluation focuses on doing a complete comparison of metrics such as accuracy, precisioin and recall across many models, including examining various CNN architectures. In this study, we investigate the performance metrics of various architectures, namely the VGG-19 Architecture, InceptionV3 Architecture, MobileNetV3 Architecture, a bespoke CNN model, and the VGG-19 Architecture without image contrast enhancement. The objective of this systematic analysis is to offer a comprehensive comprehension of the merits and constraints of each architectural approach, thereby illuminating their efficacy in the domain of facial form classification.

a. Comparison of metrics using the VGG-19 Architecture

Table 1.
VGG-19 Accuracy Comparation

No	Optimizer	accuracy	precision	recall
1	Adam & ReLU	79.6	80.8	78.4

No	Optimizer	accuracy	precision	recall
2	Adam & SeLU	79.6	81.2	78.9
3	RMSprop & ReLU	74.4	77.2	72.7
4	RMSprop & SeLU	73.1	76.1	71.1
5	Nadam & ReLU	79.8	81.7	77.9
6	Nadam & SeLU	79.4	81.5	78.1

Based on the findings presented in Table 1, the VGG-19 model demonstrated varying levels of accuracy when different combinations of the Nadam optimizer and ReLU activation function were used. Particularly, the combination of the Nadam optimizer and ReLU activation function yielded a testing accuracy of 79.8%, surpassing the accuracies attained by other combinations. In contrast, the utilization of the RMSprop optimizer combined with the SeLU activation function resulted in the lowest accuracy, measuring at 73.1%.

b. Comparison of metrics using InceptionV3 architecture

Table 2.
InceptionV3 Accuracy Comparation

No	Optimizer	accuracy	precision	recall
1	Adam & ReLU	71.1	72.3	70.1
2	Adam & SeLU	71.1	71.9	69.8
3	RMSprop & ReLU	70.7	72.0	69.4
4	RMSprop & SeLU	68.0	69.0	67.2
5	Nadam & ReLU	71.4	72.8	70.0
6	Nadam & SeLU	71.9	74.1	70.0

According to the findings presented in Table 2, the InceptionV3 model demonstrated the highest level of testing accuracy, reaching 71.9%. This outcome was observed while employing the Nadam optimizer in conjunction with the SeLU activation function. In contrast, the utilization of the RMSprop optimizer in conjunction with the SeLU activation function resulted in the lowest recorded accuracy of 68.0%.

c. Comparison of metrics using the MobileNetV3 architecture

Table 3.
MobileNetV3 Accuracy Comparation

No	Optimizer	accuracy	precision	recall
1	Adam & ReLU	49.6	65.7	19.6
2	Adam & SeLU	46.5	63.1	21.1
3	RMSprop & ReLU	44.2	62.9	12.4
4	RMSprop & SeLU	30.8	36.5	17.6
5	Nadam & ReLU	52.3	67.4	27.7
6	Nadam & SeLU	49.6	65.7	19.6

According to the findings presented in Table 3, the Nadam optimizer combined with the ReLU activation function gave the highest accuracy rate of 52.3% for MobileNet. In contrast, the utilization of the SeLU activation function in conjunction with the RMSprop optimizer resulted in the lowest accuracy rate, specifically 30.3%.

d. Comparison of metrics using the custom CNN

Table 4.
Custom CNN Accuracy Comparation

No	Optimizer	accuracy	precision	recall
1	Adam & ReLU	72.7	73.2	72.6
2	Adam & SeLU	78.2	79.1	77.6
3	RMSprop & ReLU	77.1	77.7	75.8
4	RMSprop & SeLU	78.2	78.5	77.6
5	Nadam & ReLU	77.5	77.6	77.3
6	Nadam & SeLU	77.2	77.7	76.6

According to the data presented in Table 4, the accuracy comparison for the Convolutional Neural Network (CNN) shows the presence of two identical accuracy values, both recorded at 78.2%. The previous level of accuracy was attained by using the Adam optimizer paired with the SeLU activation function, as well as by utilizing the RMSprop optimizer alongside the SeLU activation function. In contrast, the minimum accuracy observed was 72.7% when employing the Adam optimizer combined with the rectified linear unit (ReLU) activation function.

e. Comparison of metrics using the VGG-19 architecture without image contrass enhancement

Table 5.
Architecture Comparation Without Histogram Equalization

No	Arsitektur CNN	Optimizer	accuracy
1	VGG-19	Adam & ReLU	71.44
2	InceptioinV3	Nadam & SeLU	38.98
3	MobileNetV3	Nadam & ReLU	20.22
4	Custom CNN	Nadam & ReLU	70.24

3.2 System Implementation on Mobile

The study involved the use of the Flutter framework for the frontend and the FastAPI framework in Python for the backend in order to develop the mobile application [29][30]. Figure 5 illustrates the implementation of histogram equalization through the utilization of the Python programming language.

```python
def enhance_contrast_histeq(self, image):
    img = image.copy()
    gray = cv2.cvtColor(img, cv2.COLOR_BGR2GRAY)
    resized_gray = cv2.resize(gray, (250, 190))
    enhanced_image = cv2.equalizeHist(resized_gray)

    cv2.imwrite("./static/result_upload2.jpg", enhanced_image)
    cv2.imwrite("./static/temporary/result_upload2.jpg", enhanced_image)

    return enhanced_image
```

Figure 5. Histogram Equalization with Python

Figure 6, titled "Main Menu Display," displays the graphical user interface of the main menu upon launching the application, wherein users are presented with a selection of two menu selections. The initial choice grants users permission to choose photographs from the gallery, whilst the following choice allows the taking of images directly from the camera.

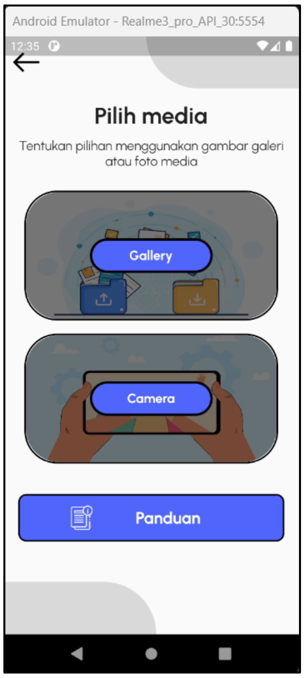

Figure 6. Main Menu Screen

The result of the face shape classification is shown in Figure 7, titled "Result Display." This display demonstrates a pair of images: the unaltered original image and the image subsequent to the application of histogram equalization. The application utilizes the most effective model from prior tests, specifically VGG-19, with the Adam optimizer and ReLU activation function. While previous research predominantly focused on the identifying suitable techniques for recognizing human facial shapes, this study represents a notable advancement in the fields, this study incorporates a direct integration into a mobile application. This aspect has frequently been disregarded in previous research endeavors. As the result in the system implementation experiment, which involved testing on 10 images, the system demonstrated a success rate in recognizing facial shapes. Specifically, 7 images were accurately identified while 3 images were wrongly classified.

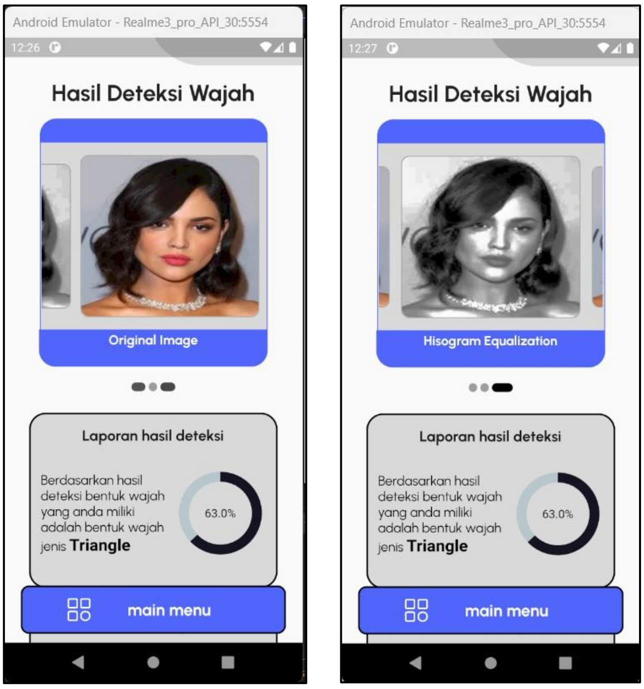

Figure 7. Face Classification Result Screen

4. Conclussion

The present study developed an algorithm for classifying facial shapes. The algorithm employed a dataset consisting of 4979 samples, which were categorized into 5 distinct output groups. To achieve this classification, various designs of convolutional neural networks and histogram equalization algorithms were utilized. Significant advancements were made through the integration of the Adam optimizer and Rectified Linear Unit (ReLU) activation function with the VGG-19 Convolutional Neural Network (CNN) model. This combination yielded an exceptional accuracy rate of 79.84%, surpassing alternative CNN architectures and datasets that do not incorporate image enhancement techniques. By improving the accuracy of facial shape classification, this research makes a substantial contribution to the field and has applications in the fashion and facial recognition technologies industries. Nevertheless, there are certain limitations that need to be acknowledged in this study. One such limitation pertains to the representativeness of the dataset used. Additionally, it is important to note that the study primarily focuses on specific methods, which may restrict the generalizability of the findings. Future research attempts might involve an exploration of a multitude of image enhancement techniques, including the investigation of three prominent methods such as Histogram Equalization, Contrast Stretching, and Sharpening Filters, the utilization of more expansive datasets with more classes, specifically encompassing diverse face shapes such as heart-shaped and long faces, and the development of real-time applications. These efforts would serve to augment the algorithm's practicality across diverse sectors.

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