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Original Article

Using Convolutional Neural Networks to Detect Races in Human Faces using MATLAB Programming

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Abstract *- Information on race for several purposes is needed, such as the application in determining the forensic problems associated with race. Furthermore, it is important to note that there are four major racial groups in Indonesia, including the Malay Mongolian, Weddoid, Papua Melanesoid, and the Mixed. The objective of this study is to investigate the possibility of using MATLAB programming to build a convolutional neural network (CNN) structure to recognize an image of the human face and detect its race. The model used in this research is a pretrained existing network structure known as ResNet50, commonly used for image recognition. The four races were further trained to determine the accuracy of the CNN. Both image data processing and network training are carried out using simulations based on MATLAB programming. The percentage of detection accuracy for Mongoloid, Weddoid, Papua Melanesoid, and Mixed races against all available images was 87.2%, 98.1%, 95.3%, and 93.2%, respectively. CNNs accurately detect races and can be easily built with MATLAB programming. The detection accuracy was observed to be very good for all the races except for the Malay-Mongoloid, which was only quite good and found to have the lowest value.*

Keywords *- Convolutional Neural Network, MATLAB, Race, Rasnet50.*

1. Introduction

Races recognition is a need for an appropriate system to detect races using only the facial image of a person. Furthermore, it is important to note that there was initially a system capable of detecting races, such as face detection, recognizing a person by recognizing his/her face. The process involves determining the features in images with complex backgrounds using strong and precise schemes. Furthermore, this system was based on the visual and geometric information on the face from image sequences by estimating the skin area depending on the similarity measure of the hue as well as the luminance components of the image in the YIQ (the Y component represents the intensity, while the I and Q components represent the color information) color space[1]. Qing Gu conducted the discovery and separation of the facial images of humans from other unnecessary images, which facilitates the subsequent recognition process[2]. Keil also showed the possibility of recognizing the human face by statistically processing digital images through MATLAB programming[3].

Furthermore, the face detection system was previously designed to detect only images, but it is currently being applied to detect and process moving images. The techniques track a person's real-time movement through facial movements. For example, Jatin showed that 50 human faces were detected and tracked in real-time in a fraction of a second using a modifiedViola–Jones algorithm[4]. Hema and Latha also reported the ability of MATLAB-based programming to assist in designing real-time systems to detect and track human faces using algorithms involving color-based skin segmentation and image filtering. Moreover, face location has been previously determined by calculating the centroid of the detected area[5].

One of the related obstacles associated with this system is the pose of the cameraman's face. Hence, Shengcai tried to resolve this using the Normalized Pixel Difference (NPD) method inspired by the Weber fraction in experimental psychology. This allows the new image to reconstruct the original one[6]–[8]. Moreover, G. Niu tried to solve faces partly covered by certain objects through face-by-frame detection by relying on the lib face detection method and the Gaussian mixture models (GMM) clustering algorithm to train and test the recognition[9].

Hannan used an intelligent system for face detection, recognition, and gender estimation through the local binary pattern histogram (LBPH) and convolutional neural network (CNN) methods to extract features from the images with very low computational complexity[10]. Convolutional neural network (ConvNet/CNN) is a deep learning algorithm that can obtain input images, assign importance, such as learnable weights and biases to various aspects/objects in the image, and distinguish the images from each other. Zhang used a method similar to CNN, known as the deep neural network (DNN) on smartphone devices, to perform face recognition. However, the CNN cascade used as the basis reduces the number of image pyramid levels by exploiting global and local face characteristics due to its limited computational power and memory[11]. Therefore, Hongxin Zhang developed a simpler method by applying a single CNN for the detection and recognition with the geometric transformation matrices studied directly to align the faces that reflect personal identities[12].

The skin characteristics and facial features are required to be detectable for some specific needs, such as accurately determining an individual's identity or skin character as required in the treatment of skin diseases such as acne. Meanwhile, Vats reported that the MATLAB programming language is one of the choices often used in designing face detection systems[13]. The main obstacle associated with the system is the existence of a special color range and texture, which was resolved by Nidhal using the YCbCr (Y, luminance; Cb, chroma blue; Cr, chroma red) face color segmentation method. Moreover, a co-occurrence matrix has also been applied to extract important features representing the skin, followed by using the Tamura texture to remove all non-skin clumps. This algorithm was reported to successfully recognize the faces from blurred images with more than 99% accuracy[14]. Another study by Abdellatif also succeeded in showing the application of color image segmentation on the skin for face and non-face recognition through skin pixel detection and watershed segmentation methods as well as Gabor filters[15]**.** Furthermore, Yadef reported the possibility of combining skin color analysis algorithms such as RGB, YCbCr, and HSV for skin color detection purposes in order to reduce computational complexity. It is also important to note that another study classified the face area based on features, such as eye/mouth hole detection, bounding box, and eccentricity ratio, and achieved an average accuracy of 97.85%[16].

Another technique developed for deeper pattern recognition (emotion) involves the combination of a genetic algorithm (GA) with an artificial neural network (GANN)[17]. This was observed from the findings of Setu that the facial features of lips and eyes provide the greatest information concerning facial emotional changes. The experiment was conducted using GA for the optimization and ANN for the classification of the features, which produced an accuracy of up to 96.42% on the frontal face image[18]. It was also discovered that face images cannot always be taken in frontal conditions in real-time detection. Therefore, Tsai proposed multi-view face training to overcome this problem using the skin filter and entropy rate superpixels (ERSs) as the algorithm to obtain the candidates' faces. Moreover, the angle compensation was performed to increase the accuracy of detection in the in-plane case[19], and this is considered a new detection scheme that involves using deep learning to achieve advanced performance in evaluating the famous FDDB face detection benchmark.

Sun used a more sophisticated method known as the advanced region-based CNN (RCNN) which involves combining several strategies, including feature pooling, hard negative mining, multi-scale training, model pretraining, and precise calibration of key parameters. This method produced the best face detection performance[20]. Furthermore, Venkat currently proved that the computer vision application in MATLAB based on deep learning could provide sophisticated results for different tasks associated with face detection, recognition, and tracking[21]. Vo used CNN to perform race detection experiments for Japanese, Chinese, or Brazilian races with an accuracy of over 90%[37], but race classification with more detailed face segmentation is very beneficial to analyze certain conditions such as ethnic and racial classification. Therefore, Khan proposed a more accurate method known as the deep CNN (DCNN), which was trained on seven face segments, including the nose, skin, hair, eyes, eyebrows, back, and mouth using a probabilistic classification method and creating probability maps (PMs) for each semantic class[23].

The use of AI and deep learning techniques to detect and classify faces has seen significant progress, with researchers developing various algorithms to extract features and identify faces in complex environments[24], [25]. The initial face detection system used visual and geometric information from image sequences, estimating skin area based on hue and luminance components in the YIQ color space. Later works improved this by segregating face images from other images, aiding the recognition process and enabling the system to detect and track moving images in real-time. Some researchers have explored how to handle issues such as camera pose, proposing solutions like the Normalized Pixel Difference (NPD) method.

Researchers have also made strides in face detection, recognition, and gender estimation using methods such as Local Binary Pattern Histogram (LBPH) and Convolutional Neural Networks (CNN). While these methods have shown promise, they can be computationally intensive, leading to the development of simplified methods using single CNNs with geometric transformation matrices[26].

Regarding specific facial feature detection, YCbCr faces color segmentation and co-occurrence matrix have been used to extract key features representing the skin and remove non-skin clumps. These techniques can recognize faces from blurred images with over 99% accuracy. Further research has explored combining skin color analysis algorithms to reduce computational complexity and achieve high accuracy. Deeper pattern recognition techniques have also been developed, such as combining a genetic algorithm (GA) with an artificial neural network (ANN) for emotion detection. For more accurate race detection, some studies have used advanced deep CNN (DCNN) trained on seven face segments, offering a more granular analysis of ethnic and racial classification. The advancements in AI and deep learning[38] have greatly improved the ability to detect, recognize, and classify faces from images, paving the way for a wide range of applications, from security to healthcare.

2. Material and Methods

2.1. Algorithm

A Convolutional Neural Network (CNN)[20], [28] is a type of artificial neural network designed to process structured grid data such as images. CNNs are particularly useful for tasks that handle visual input, such as image and video recognition, though they have also found use in a wide array of other applications. The key innovation of CNNs is that they incorporate convolutional layers, which explicitly consider the spatial structure of the input data. This makes them particularly well-suited to tasks that require understanding spatial hierarchies or structures, such as recognizing objects in images.

In a CNN, each neuron in a layer is connected only to a small region, or "field," of the layer before it, rather than having connections to every neuron in the previous layer as in a fully connected neural network. This field usually spans a square area (e.g., 3x3 or 5x5) and is referred to as the receptive field of the neuron[29], [30]. Biological processes inspired this design, as the connectivity pattern between neurons resembles the organization of the animal visual cortex. The individual cortical neurons respond to stimuli only in a restricted visual field region known as the receptive field.

A Convolutional Neural Network (CNN) is composed of several types of layers that perform different functions. Here, we will discuss the four main types of layers typically found in a CNN: Convolutional, Activation (or ReLU), Pooling, and Fully Connected layers.

- Convolutional Layer: This is the fundamental building block of a CNN. The layer's primary function is to detect local conjunctions of features from the previous layer. In this layer, a set of learnable filters (also known as kernels) are used. Each filter is small spatially (along width and height) but extends through the full depth of the input volume. During the forward pass, each filter is convolved across the width and height of the input volume, computing the dot product between the entries of the filter and the input, producing a 2-dimensional activation map of that filter. As a result, the network learns filters that activate when they see some type of visual features, such as an edge of some orientation, a blotch of some color on the first layer, or eventually entire honeycomb or wheel-like patterns on higher network layers [31].
- Activation Layer: After each convolutional layer, an activation function is applied to introduce nonlinearity into the model, without which the CNN would be equivalent to a simple linear regression model. The purpose of the function is to decide whether a neuron should be activated or not based on whether the relevant information the neuron identified is needed for the given information. The most commonly used activation function is the Rectified Linear Unit (ReLU), which returns the input directly if it is positive; otherwise, it returns zero[32].
- Pooling Layer: This layer progressively reduces the spatial size (i.e., width and height) of the input representation, which helps to decrease the amount of parameters and computation in the network, and hence to also control overfitting. It operates independently on every depth slice of the input and resizes it spatially. The most common approach used in pooling is max pooling which takes the largest element from the rectified feature map. Taking the largest element could also take the average pooling, which takes the average of the elements present in the feature map[33].
- Fully Connected Layer: Fully Connected layers in neural networks are those layers where all the inputs from one layer are connected to every activation unit of the next layer. In most popular machine learning models, the last few layers are fully connected layers that compile the data extracted by previous layers to form the final output. It combines all the learned features from previous layers and finally classifies the image into a particular category.

The composition and order of these layers define a CNN's architecture. Different architectures use different combinations of these layers to achieve the best performance for a specific task. It is also worth noting that modern CNN architectures often include additional layer types not discussed here, such as normalization layers, dropout layers for regularization, and more.

2.2. Research Design

This research developed CNNs with variable depths to evaluate the performance of these models for facial skin recognition. This method's preprocessing activities are lower than other classification algorithms.

Moreover, the filters are usually engineered by hand with sufficient training in primitive methods, and these filters/characteristics can be learned through the ConvNets.

The purpose of our research is to identify races in Indonesia by using CNN based on the MATLAB programming language. The CNN used is a CNN network with Rasnet50 configuration. The type of research carried out is image processing from photos of four races in Indonesia, namely, the Malay-Mongoloid, Weddoid, Papua Melanesoid, and Mixed. The number of images for each race is more than 40. The photo images are from photos of natives taken using makeshift devices such as smartphones, so the face position, lighting, and resolution vary; some are good, and some are not.

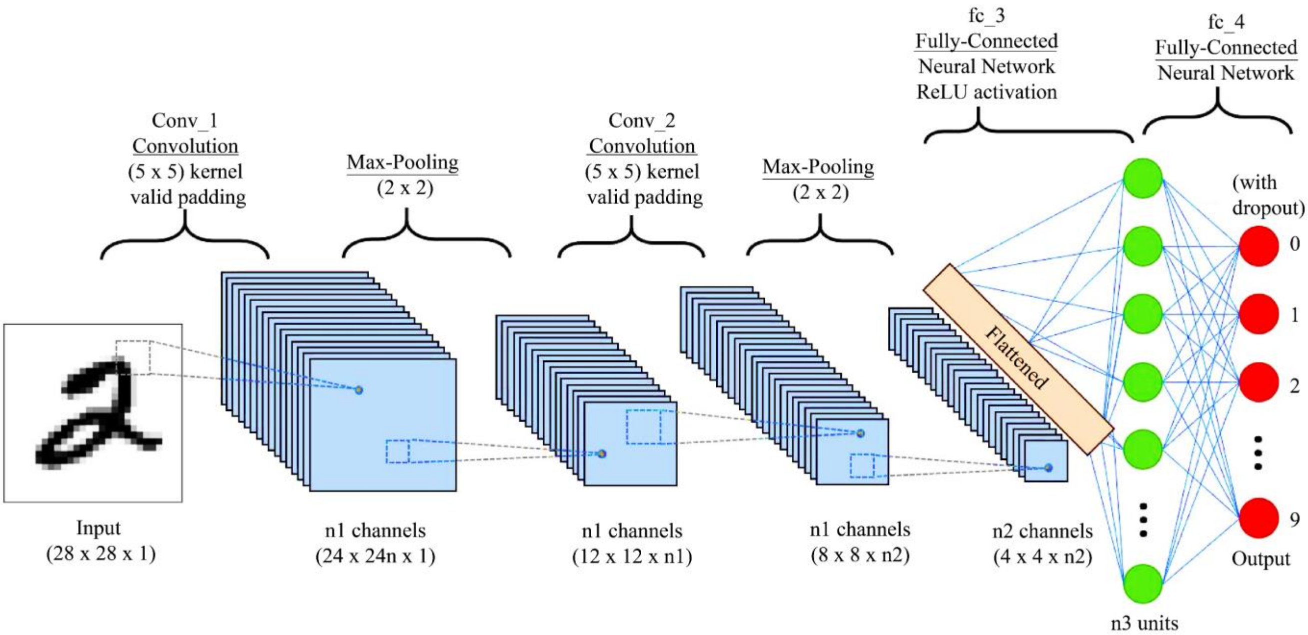

Fig. 1 CNN in classifying the types of numbers from handwriting

2.3. Architecture of CNN

The architecture of the CNN model is analogous to the connectivity patterns of neurons in the human brain and is inspired by the organization of the visual cortex. Individual neurons respond to stimuli only in a limited visual field region known as the receptive field. This set of planes overlaps to cover the entire visual area (Fig. 1).

The races can be recognized from a face image by designing a system based on a convolutional neural network (CNN) which is a simple design that can solve the difficult part of the process. It is also important to note that the most important part affecting the results of race detection is entering the image samples in the correct racial group to produce very high accuracy.

CNN is the most important architecture of deep learning, consisting of neurons, an information level, a yield layer, and different standardization layers. CNN has complete presentations in action declaration, a grouping of sentences, text acknowledgment, expression acknowledgment, object identification, confinement, and picture portrayal. The hidden layer comprises convolutional, pooling, completely associated, and different standardization layers.

Deep learning is a powerful tool for image and video handling, audio preparation, text analysis, speech training, independent frameworks and advanced mechanics, clinical diagnostics, computational science, actual sciences, money and financial matters, network safety, and many more. However, it faces difficulties such as the huge information base, external exposure of impression, energy-productive methods and superior equipment, huge information examination utilizing deep learning, absence of adaptability and performing various tasks learning, and lack of adaptability[34].

According to research by Gaba[34] examines deep learning applications and systems to illuminate zones where deep learning still cannot seem to make huge commitments. Deep learning is a form of machine learning that uses different levels of non-linear planning units to remove features from data. It uses the stochastic point falls approach to search for an ideal, figuring out a fixed point.

This paper reviews deep learning advancements, classifies Convolutional Neural network structures and their models, and gives brief portrayals of noticeable deep learning stages and usage particulars. This is the same as other researchers[35], [36].

2.4. MATLAB Programming Application

Moreover, using MATLAB programming language for the design requires race division in the form of folders depending on the number of races to be detected. The faces in Fig. 2 were placed into four folders of racial groups according to the real conditions. The folder s01 in Fig. 3 is for Malay-Mongoloid race, s02 for Weddoid, s03 for Papua Melanesoid, and s04 for Mixed race. The next stage was the design of an adequate.

2.5. CNN Rasnet50 Training Process

The CNN network structure to detect the images can be achieved manually by considering the simplicity and ease of training or through the use of available network structures to obtain higher accuracy, such as rasnet50, which has been proven to detect different kinds of images (Fig. 4).

The training provided is required to be sufficient. It can be achieved by selecting standard choices from different available training options to conduct the CNN design process and training more easily (Fig. 5).

(a) (b) (c) (d)

Fig. 2 Examples of races: (a) Malay-Mongoloid, (b) Weddoid, (c) Papua melanesoid, and (d) Mixed

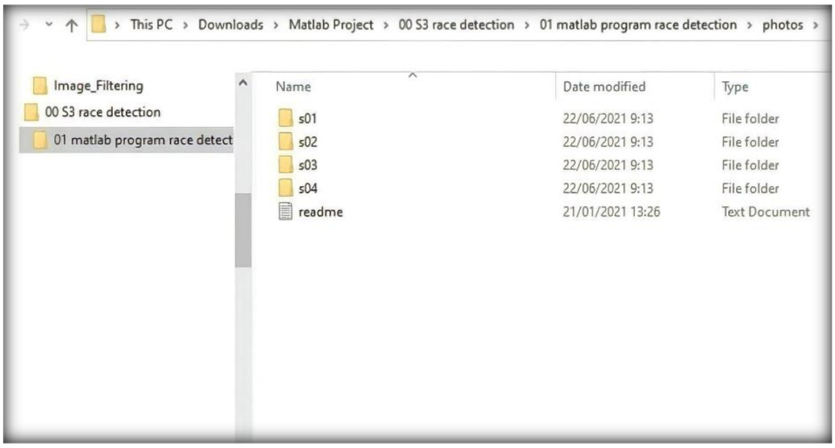

Fig. 3 A collection of face images for four races divided into four folders

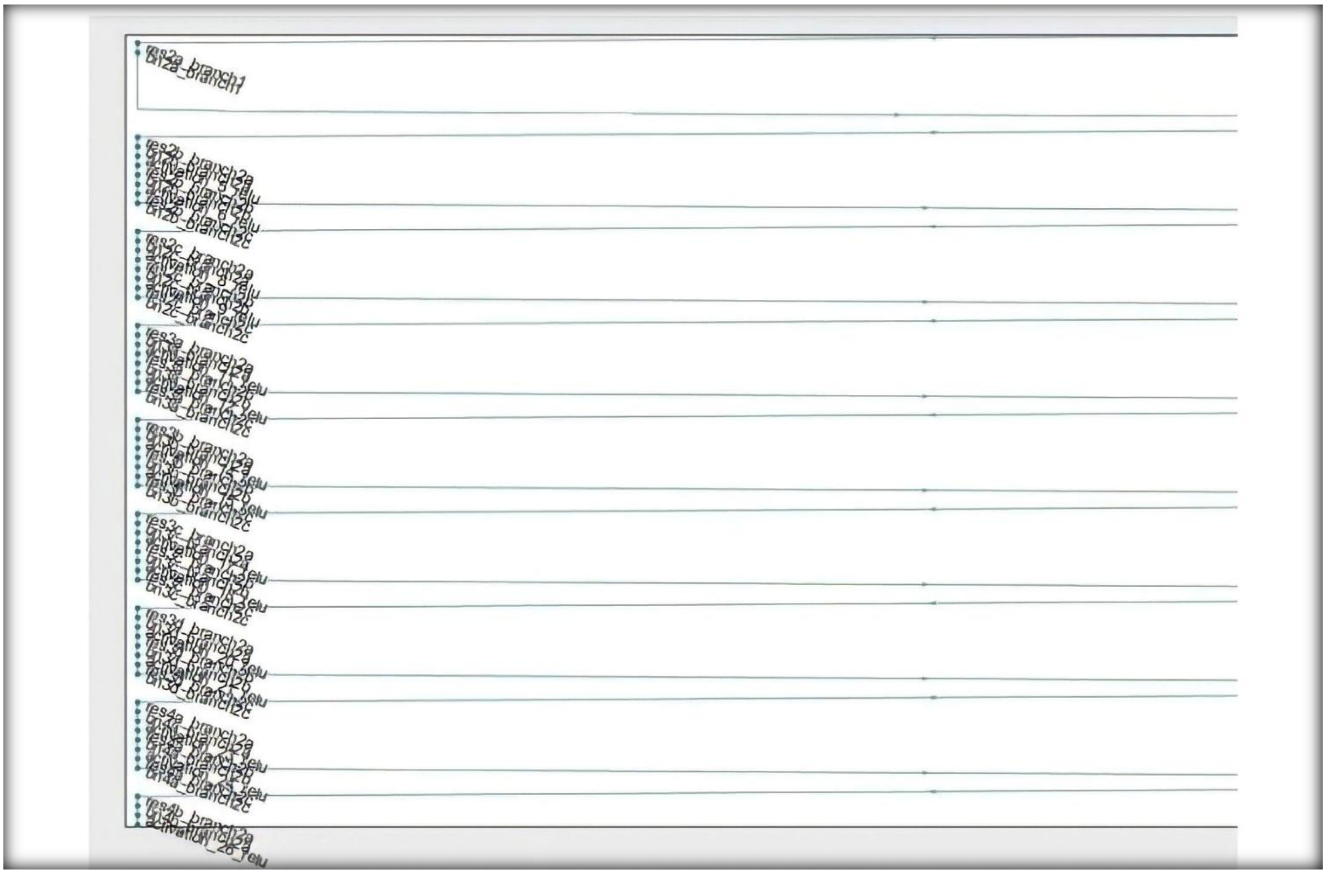

Fig. 4 CNN Resnet50 network structure

Fig. 5 CNN training process

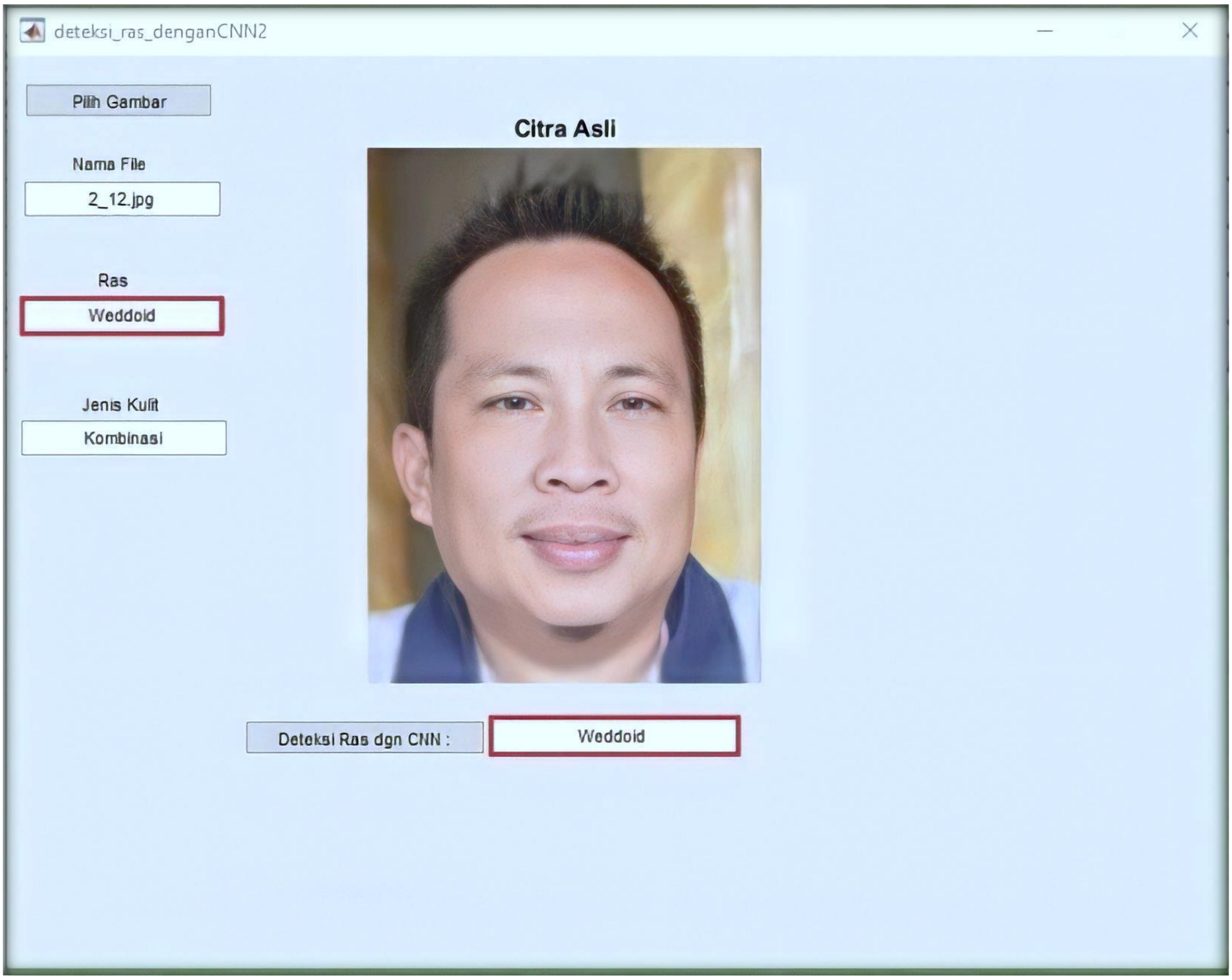

Fig. 6 GUI application for race detection with correct results

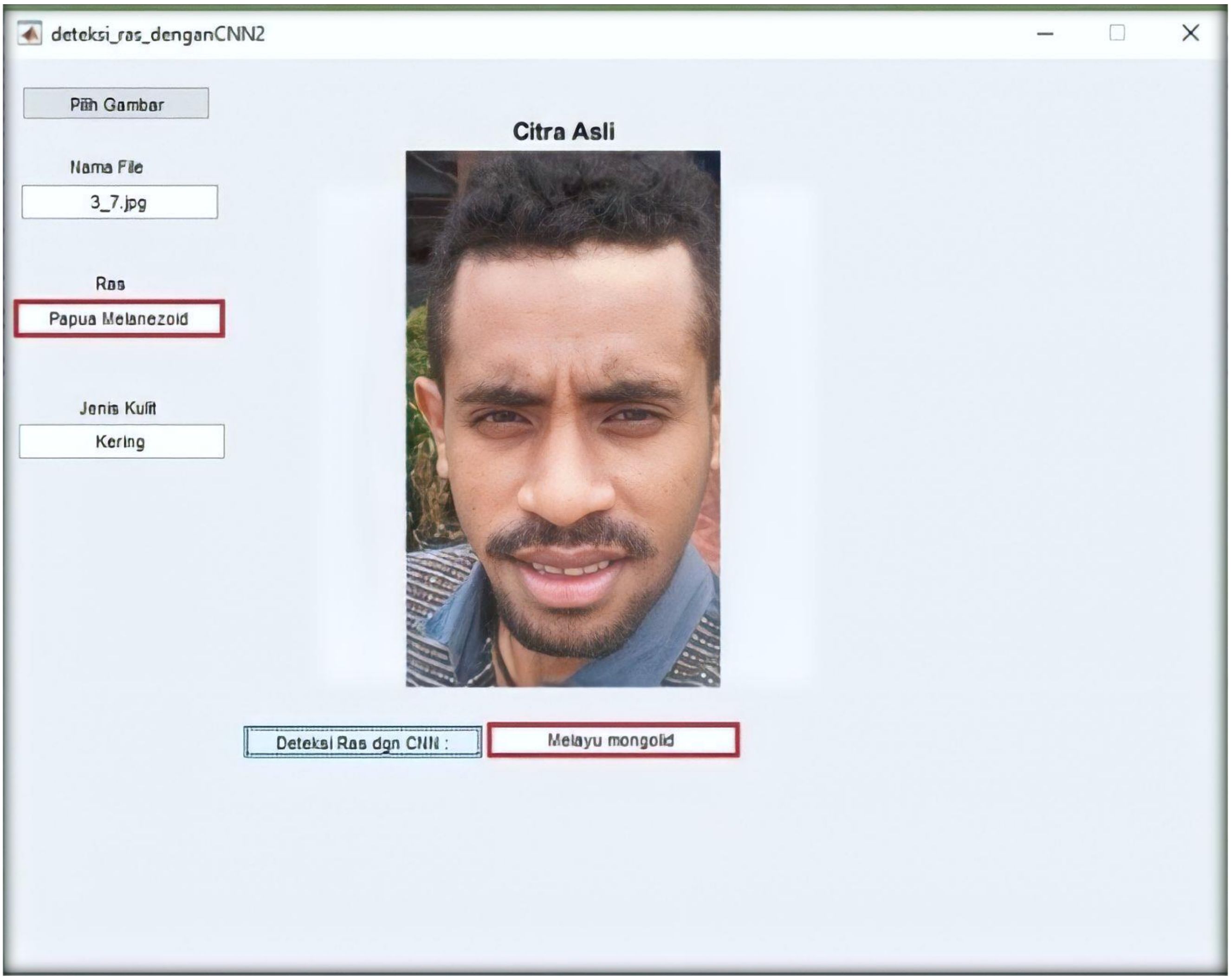

Fig. 7 GUI application for race detection with incorrect results

3. Results and Discussion

The CNN that has been trained is a CNN with a Rasnet50 structure. There are many structures that can be used, some simpler, some more complex. However, Resnet50 has adequate ability to detect and classify image types, namely, faces. The ones from these facial images are then classified into four races.

The training carried out also has many options. The default option was used in this study. There are other options that provide faster training times but with lower accuracy. On the other hand, the other option has a longer training time with higher accuracy. The detection process using the CNN network structure was conducted directly on the images in each folder grouped by race, and the images were observed not to be showing in the overall test considering the fact that there are hundreds of them to be detected, leading to the running of the "Pengujian CNN.m" file.

An application program designed based on the graphical user interface (GUI) can be used in a situation where each of the images needs to be tested. This involves selecting an image from the racial grouping folders at random and using a trained CNN-based detector (with the same CNN used in the overall test) to produce the face image with the information on the races and skin types from the available data. Moreover, the information presented by the CNN in other fields was compared with the displayed data, and the detection process was classified as correct in a situation where the data are the same and incorrect when they are not (Fig. 6 and 7).

The results from the images used as the input data showed that 41 were Malay-Mongoloid, 52 were Weddoid, 43 were Papua Melanesoid, and 45 were Mixed, with many of the detection found to be correct while some were incorrect. Meanwhile, the accuracy of the races detection was calculated using the following equation:

$$Acc \ \sum_{i=1}^{c} \ A_i \frac{1}{c} \qquad (1)$$

where:
Acc = detection accuracy
c = number of images per race
Ai= CNN detection output (1 if true, 0 if false)

The use of CNN to test all the existing data showed the following:

- The accuracy for Malay-Mongoloid race image was 87.1795%.
- The accuracy for the Weddoid race image was 98.0769%.
- The accuracy for the Papua Melanesoid race image was 95.3488%.
- The accuracy for Mixed race images was 93.1818%.

4. Conclusion

The detection accuracy was observed to be very good for all the races except for the Malay-Mongoloid race, which was only quite good and found to have the lowest value. Some of the possibilities associated with the lower value include the following:

- The lower number of images used for the training
- The high similarity of the images for the Malay-Mongoloid race with other races
- Including some images of faces unsuitable for the grouping process into the races folder during the data collection stage.

Therefore, some improvements required to collect data with good quality images for all races include ensuring they have a fairly high resolution, uniform lighting, and frontal view. Moreover, the Malay-Mongoloid, Weddoid, and Papua Melanesoid races need to be pure without mixing with other races.

In contrast, the racial mixtures of the Mixed races need to be explained based on their parental data. CNN, built using the MATLAB programming language, can be built easily and has fairly high accuracy, i.e., above 90%. With a GUI tool also provided by MATLAB, the resulting CNN can be used as an application program to detect races, especially the four races in Indonesia.

Future research can use the same technique with more detail, that is, by paying attention to the T and U areas. However, a much better image quality is needed, so the facial skin's texture can really be extracted.

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