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Convolutional Neural Network for Skull Recognition

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***Abstract*—Automatic skull identification systems play a vital role for forensic law authorities to recognize victim identity. Motivated by potential applications of these kinds of systems, this research aims to apply a pre-trained deep convolutional neural network (CNN) for face skull recognition. Basically, the unknown skull image is fed to a pre-trained CNN network to extract a 1D feature vector, and then it will be matched with photos at database agencies to identify the closest match. To validate the proposed skull recognition system, it has been applied for a total of 13 skulls, and the reported results indicated a good was achieved. In addition, various CNN architectures were investigated, including shallow, medium, and deep CNN models. The best performance was reported from the shallow CNN model with a 92% recognition rate.**

***Keywords*—Deep learning, face skull identification, CNN model**

I. INTRODUCTION

Machine learning models have been widely used for the problem of face recognition. These models include Extreme Learning Machine (ELM) [1], Fuzzy models [2], and Metaheuristic-based models [3], [4], [5]. Recently, deep learning has been successfully used for face recognition [6], [7] [8], [9], [10], [11]. The application of face recognition for the Internet-of-Things (IoT) which is connected to a cloud, was given by Masud *et al*. [6]. In their work, they proposed a tree-based architecture where the unknown input face was passed to a parallel tree of deep residual models. Then the output of these parallel models is combined and fed to another residual network. Their model was evaluated on various benchmark datasets such as ORL, FEI, and LFW. Reported results confirmed the usefulness of the proposed tree architecture in reducing execution time. Further study was investigated by Wang *et al*. [7] for using face recognition in violence detection. The main idea was to encode spatial features using a CNN model, and then these encoded patterns will be classified as normal or abnormal behavior (violence). Reported results on Crow and Hockey datasets showed an accuracy of 92% and 97.6% were achieved on these datasets, respectively. Lin *et al*. [8] utilized deep learning models to perform face alignment. Specifically, they developed a deep transformation model that recovers the input face to the near frontal view. Conducted analysis indicated that their model was able to work effectively even with severe pose variations (with angles of 90 degrees). The application of facial expression recognition in human-computer interaction was studied by Shi *et al*. [9]. Their proposed system consists of three main stages, namely face detection, feature points localization, and facial expression recognition. The deep CNN model has been used to perform both face detection and landmark points extraction. As compared with other approaches, the proposed system in [9] achieved a superior outcome in terms of face feature localization, facial expression recognition, and eye-tracking. The idea of developing a lightweight end-to-end deep learning-based face recognition system was investigated by Gunawan *et al*. [10]. The proposed scheme employs the ResNet model as the backbone network which used for feature extraction. Conducted experiments in [10] showed that their system required around six milliseconds to perform face recognition. Another real-time face recognition system that employs a CNN-based deep learning model was given in [11]. Their system was able to report an accuracy of 98% recognition rate. As compared with the traditional models such as PCA, HOG, Markov Random Fields, and Eigen face; CNN in [11] reports better performances. The potentials of using deep learning models to handle the challenges of face re-identification were overviewed by Cheng *et al*. [12] in their recent review paper. In their finding, deep learning models were recommended to deal with common difficulties in face recognition problems such as low resolution, blurring, pose variation, occlusion, cutters, and poor illumination.

A very limited studies were exist in the ligature that tackle the problem of face recogntion from skull images [13], [14], [15]. In the work of Yang *et al.* [13], they adopted the correlation measure for skull idetenfication. They introduced a novel region fusion strategy that matches unknown input skulls with 3D face images at the gallery database. Their model was evaluated using a database of size 208 skulls captured by a CT scanner. The results showed that the model outperformed other approaches, and it has achieved an accuracy of 94% identification rate. A shared transformation model that matches face and skull images was explained by Singh *et al*. [14]. Their transformer model projects input features to a new common feature space that minimizes the distance between each skull with its corresponding face. Conducted experiments on 464 skull images indicated that the proposed model was able to achieve an accuracy of 51% at rank-1. However, the idea of 3D skull reconstruction was given in [15]. They have suggested the use of the least square canonical dependency technique to reconstruct faces from input skulls. In addition, they have utilized the mutual information technique to compute dependency factors to reconstruct a 3D skull.

Nevertheless, the problem of skull recognition using deep learning models was not investigated in the literature. To fill this gap, this study develops a pre-trained deep learning CNN model to handle this issue. In particular, the unknown input skull is fed to a pre-trained CNN network to extract a 1D feature vector, and then the similarity function is computed to find the best match photo. The remaining part of this paper is organized as follows. The proposed CNN model is given in Section II. The conducted analysis and results are explained in Section III. Section IV overview the conclusion of this study.

II. THE PROPOSED SYSTEM

The basic architecture of the proposed skull recognition system is given in Fig. 1. The main steps of that system are explained as follows.

A. Input Skull Image

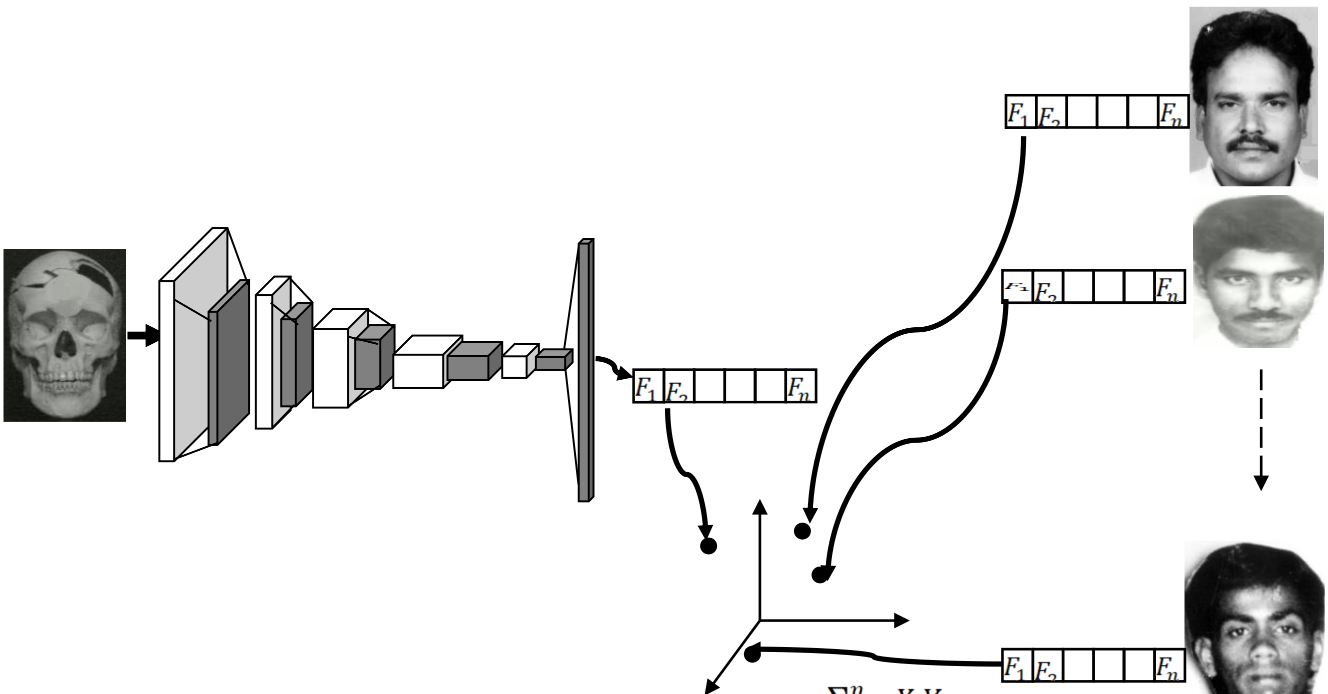
This is the head of CNN, where the unknown input skull image is fed to a pre-trained CNN for feature extraction. At this stage, the input image should be resized according to the architecture of the pre-trained CNN (i.e., 224 x 224).

B. CNN Features

In this study, the pre-trained VGG-face CNN model [16] is employed. The feature extraction stage is responsible for extracting visual features for both skull and photos. These visual features include edges, dots, corners, etc. In particular, CNN has a number of cascaded operations which are executed to extract these features, which are convolutional, activation, and max-pooling operation. These CNN operations will automate the traditional feature extraction, and they are explained as follows.

1) Convolutional

The key idea of the convolutional operation is to convolve the input image with several filters of size 3x3, 7x7, or 9x9. To illustrate this mathematical operation, Fig. 2 illustrates a numerical example. To calculate the convolutional output of one output pixel, the following convolutional formula is applied.

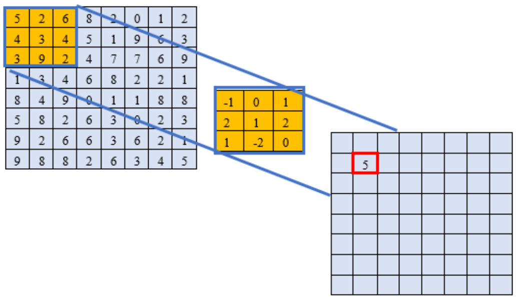


$$Similarity = \frac{\sum_{i=1}^{n} X_i Y_i}{\sum_{i=1}^{n} X_i^2 \ \sum_{i=1}^{n} Y_i^2}$$

Fig. 1. The proposed system

$$y[t] = (x * w)[t] = \sum_{a=-\infty}^{a=\infty} x[a]w[a+t] \tag{1}$$

where y is the output feature map generated by convolutional operation, x is the input image, and w is the convolved CNN filter.



Fig; 2. CNN Convolutional Operation

2) Activation

After performing the convolutional operation, the second operation will be the activation operation. The aim of this operation is to pass only positive numbers resulting from the convolutional stage. This is done using Rectified Linear Unit (ReLU) activation function. Mathematically, ReLU is defined as follows equation.

$$y[t] = \max(x(t), 0) \tag{2}$$

A visual illustration example is given in Fig. 3. As can be seen that all negative values become zeros, and positive values pass without change.

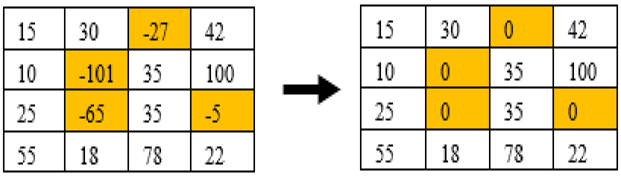


Fig. 3. CNN ReLU activation Operation

3) Max-pooling Operation

The third CNN operation applied is max-pooling, and the main task of this operation is to reduce the dimensionality of the input image. Basically, a 2 x 2 max-pooling operation works by choosing the max value from the 2 x 2 window. A numerical example is given in Fig. 4 that demonstrates how the max-pooling operation is working.

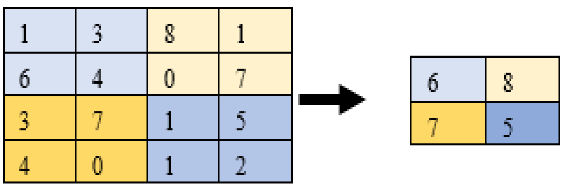


Fig. 4. Max-pooling operation

The last stage of CNN is the flattening layer that covers 2D output to 1D vector. The basic architecture of that 1D vector is given in Fig. 5. The 1D vector has a length of *n* where *n* will depend on the length and the number of CNN filters.

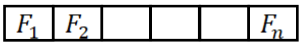


Fig. 5. 1D feature vector

C. Similarity function

The computed 1D feature for the unknown input skull will be compared against the pre-computed 1D vector of face phots stored at the database agency. Then, a similarity function will be computed to find the best match photo. The formula of the similarity function is defined as follows.

$$Similarity = \frac{\sum_{i=1}^{n} X_i Y_i}{\sum_{i=1}^{n} X_i^2 \ \sum_{i=1}^{n} Y_i^2} \tag{3}$$

where X is the computed 1D vector from the input skull, Y is the computed 1D vector from the face photo, and n is the length of the 1D vector.

III. RESULTS

This section aims to evaluate the performances of CNN in skull image recognition. A total of 13 skull images with their corresponding face photo were given by the School of Health Sciences, Universiti Sains Malaysia. It should be noted that each experiment has been conducted ten times, and the mean accuracy is reported in Tables II and III. In addition, the parameter setting of the conducted experiments are given in Table I.

TABLE I. PARAMETERS SETTINGS

Parameter	**Settings**
Skull input size	224 × 224 pixels
1D vector size	512x3x3x512
Shallow CNN	4 convolution layers
Medium CNN	8 convolution layers
Deep CNN	16 convolution layers
Max-pooling window size	2x2

The results of the conducted analysis are given in Table II. As can be seen that the proposed CNN model is able to report an accuracy of 85% rank-1 recognition rate.

TABLE II. RANK-1 ACCURACY

Model	**Accuracy**
CNN	85%

An additional experiment was conducted by computing cumulative matching characteristic (CMC) as given in Fig 6. In CMC, the x-axis shows a ranking range from 1 to 10, and the y-axis shows the skull recognition rate for each rank. As indicated that CNN was able to reach an accuracy of 100% at rank 3.

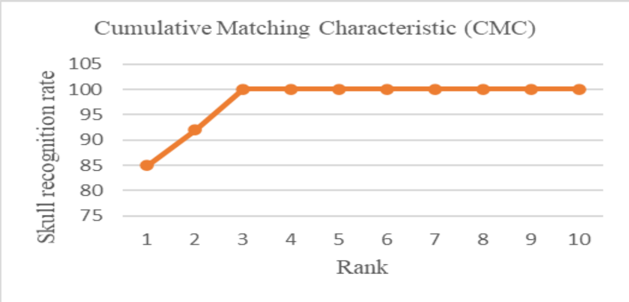


Fig. 6. CMC curve

Further analysis has been analyzed by examining the effect of the number of CNN layers on model performances. Specifically, three different architectures were used, namely shallow, medium, and deep architecture, as given in Fig 7. The results of these models are shown in Table III. As indicated that CNN was able to perform better with the shallow model. This is due to that a deeper CNN model will damage shape and texture features from both skull and face photos.

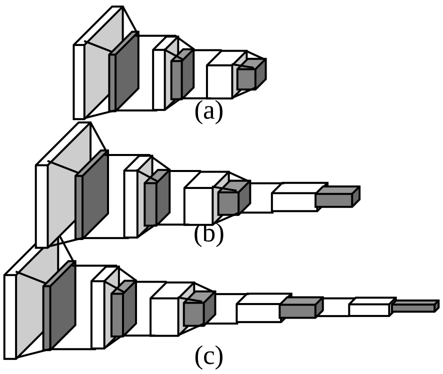


Fig. 7. Different CNN architecture (a) shallow, (b) medium, and (c) deep model

TABLE III. RANK-1 ACCURACY

Model	**Accuracy**
Shallow CNN	92%
Medium CNN	85%
Deep CNN	85%

IV. CONCLUSIONS

This study introduces a CNN-based skull recognition system. The analysis of 13 skull images indicated that CNN could achieve a good performance in accuracy and CMC curve. Further analysis on various CNN architectures showed an accuracy of 92% for a shallow CNN model. This is because small CNN could generalize better and keep critical facial features in both skull and face images.

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