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People identification via tongue print using fine-tuning deep learning

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ABSTRACT

Many person-verification systems are critical in security systems for verifying passage through doors opened to specific people using various techniques. People can use electronic payment methods and security apps to generate codes for quick, remote financial transactions. Older systems required precision and speed. Many alternative methods were developed by technology and artificial intelligence to make such operations simple and quick. The identification of tongue prints is discussed in this paper. Tongue prints, like fingerprints, are unique to each individual. The tongue was used in this study because it is unique among such organs. The tongue is protected by the lips. This guards against taking a tongue print by force. Some people distort their fingerprints, making fingerprint recognition systems unable to recognize them. Car accidents cause facial distortion, which distorts the system and prevents it from distinguishing facial prints, so the tongue was used as a fingerprint in this study. A database of 1,104 images for 138 Mustansiriyah University College of Science students yielded an average of eight images per individual. VGG16 was implemented for transfer learning and fine-tuning. In comparison to previous studies, the accuracy achieved was more than 91%.

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1. INTRODUCTION

The tongue is an important internal organ that is protected from the outside world by the oral cavity's protective covering. Individuals and identical twins have noteworthy variances in the tongue's defining characteristics. It is no surprise that the tongue has its network of nerves, muscles, and blood arteries, just like every other organ [1]. It also has taste buds and papillae. Observing the tongue's properties, such as its color and form, is crucial in traditional Chinese medicine for illness diagnosis [2]. Recently, it has seen a rise in use as a biometrics tool. They aimed to create a 3D representation of the tongue that described the texture and form of the tongue images. They constructed a database of 3D tongue images that defined the images' texture and form [3]. Every day, all money transactions and payments are made through the internet. As mentioned above, much other biometrics can be used. To this day, tongue recognition technology is novel in biometrics; authentication is the superior method for providing top-tier security. Some examples of such uses are: biometrics has great potential in many areas, including account access, criminal identification, online banking, automated teller machine use, employee access, personal data access, medical identification, and air travel [4].

Tongue prints are getting much interest as a biometric authentication method. Over the past decade, scientists have worked to perfect a tongue print identification system. Liu *et al*. [5] suggested that it would become standard practice. That is why the tongue's unique ridges and bumps may be used for identification. If employed in conjunction with other robust biometric qualities, such as those found in multi-modal biometric systems, the tongue's characteristics can be invaluable in biometrics applications. Authentication experts have speculated that the tongue's ability to detect subtle differences in texture may one day be used to verify an individual's identification in person [6]. The tongue is considered an internal organ, external when needed, and is covered within the oral cavity. For this to be protected, each tongue is distinct from the other. Each tongue has distinct properties that differ even between identical twins [7]. It is the principal taste organ since its top surface is covered with taste buds. The tongue is a highly delicate organ that relies on saliva for hydration. The mucosa, which is pink and wet, covers the tongue. Papillae are tiny bumps that give the tongue a rough feel. The surface of the papillae is covered with thousands of taste buds [8]. It cannot be created and imitated because it is hidden inside the oral cavity. In identity verification applications, the tongue exhibits geometrical shape and physiological tissue, which are significant pieces of information. The surface texture and general form of each tongue are unique to that particular tongue. It is impossible to examine the tongue without the person's consent. The tongue is a fairly reliable form of human recognition identification and can act as a generic biometric in any given application. The tongue is an essential organ in the human body and has many uses, including moving food for chewing and tasting and helping make speech sounds [1]. A digital device (camera) is used to collect tongue images. The tongue body is taken from the photos, omitting the remainder of the mouth region because the mouth contains more than just the tongue, including the lips, teeth, and other mouth components. Finding the tongue, among other parts of the mouth, is a problem because the colors of the lips, the oral cavity, and the tongue are very close.

Face, iris, fingerprint, palm print, voice, hand shape, and signature are the vast list of behavioral and physiological features researched and applied in such systems. However, it has been a common obstacle challenge for traditional biometrics [9]. Using a false iris can fool traditional biometrics, which is unreliable due to their lack of reliability in such areas. The increased security measures necessitated the use of anti-counterfeiting and liveness-verifying biometrics. Therefore, it is crucial to identify some innovative biometrics that can meet the needs. The tongue might hold the key to deciphering this intricacy, as it possesses features that lend themselves to identity identification and developing an integrated system with other biometric systems.

Zhang *et al*. [10] presented a verification framework and new biometrics based on the tongue-print tongue image database TB06 contains 134 subjects. The method employed extracts the textural features and shape and the Gabor filter. The actual accept rate was 93.3%, while the false accept rate was 2.9%. Lahmiri [11] proposed three different texture analysis methods. They are the Gabor filter, the wavelet transform, spectral analysis, and finding the K-nearest neighbor algorithm (KNN). The database had images of the tongues of 174 people, 33.6% of the women and 66.4% of the men. The experimental findings from a total of 912 photos of the tongue indicate that the false classification ratio is 8.52%, while the correct classification ratio is 92.98%. Choras [12] proposed extracting features from a tongue image using local features such as weber law descriptors (WLD) and steerable filters. Because these features resist specific geometric changes, use a database for the tongue consisting of 30 images. The results show that the texture features of the WLD are robust against rotation and noise. Zhang *et al.* [13] suggested a new automated tongue segmentation method by incorporating the active contour model and a polar rim detector, using a database from 200 images of the typical tongue to test the segmentation results. The suggested approach can correctly and successfully segment the tongue's body as biometrics. According to a quantitative examination, the average true positive is 97.1%, and the normalized mean distance to the nearest point is 0.48%. Sivakumar *et al.* [14] presented a new biometric system for feature extraction and personal identification that utilizes the local binary pattern (LBP) algorithm and linear support vector machine (SVM). An identification accuracy of 97.05% was obtained using a database containing 136 tongue print photos of 34 people. Saharan and Meena [15] proposed many methods for feature extraction and executed them on tongue biometrics. Utilize the histogram equalization technique, the shape feature extraction algorithm, and the Gabor filter for feature extraction on tongue images. The tongue's color may be determined using the hue, saturation, lightness (HSL) model's scale invariant feature transform (SIFT) technique. The mean and standard deviation of every characteristic obtained is calculated and shown. The mean and standard deviation of each of the four Gabor values are then calculated and compared to the values entered into the database; the matching result is shown if all values are the same. Ibrahim and Hindi [7] proposed employing a wavelet transformation algorithm to extract the features. They utilized Bhattacharyya distance to distinguish one person's tongue image from another. Eight images were collected for every participant using a group of tongue images taken from 30 people. Results were a waveleting discriminating rate of 72%, and Bhattacharyya distance people images were identified by 93%.

Traditional biometrics represents a challenge and an obstacle as they can be falsified, and duplicates can be made (iris, face, fingers, signature) or be expensive and rarely used deoxyribonucleic acid (DNA) [16]. The increased security measures called for modern biometrics that is more secure, less expensive, and cannot be falsified. As a result, this paper aims to create a system for distinguishing persons based on their tongue prints. It will contribute to solving many forensic issues and increase electronic security because it has features suitable for identification and distinguishing between people biometrically. This section gives the study's title and its connection to artificial intelligence. The related work is discussed in the next section. The method of work and the tools used are detailed in the third section. The 4th section is devoted to the study of the results and discussions. As for the research conclusions, they are found in the fifth and final section of this paper.

2. RESEARCH METHOD

Feature extraction is a critical function in many image applications. A feature is a property of an image that may capture a certain optical quality globally for the whole picture or specifically for areas or objects. Deferent features such as texture, shape, and color can be disengaged from an image [17]. The surface is the variation of data at different scales. Various techniques have been created for texture extraction, such as VGG 16. They can be extracted from wavelet transform coefficients and co-occurrence matrices [18]. Extracting features from an image and storing them as feature vectors in a feature database is the primary goal of feature extraction. The image's data is discovered by analyzing the value of this feature (or group of values), known as the feature vectors. Images in the database are compared to the query image using these feature vectors. Features are a method used in pattern recognition to differentiate between different types of objects—extraction of features such as shape, texture, and color. When designing an image retrieval system, it's possible for there to be many representations of each feature [19]. Accordingly, the features retrieved at each level are the results of the final layer, resulting in a feature pyramid [20]. The VGG16 model for feature extraction comprises a thousand-node output layer, three dense layers for the FC layer, and sixteen convolutional layers with five max pooling (for 1,000 classes). In the context of this investigation, the top layers (FC and output layers) have been removed [21].

As feature extractors from images, transfer learning algorithms are applied from deep learning (DL). Several studies have used the pre-trained DL model to classify breast cancer based on images from the BreaKHis histopathology. For example, the authors of employ VGG16 as pre-trained DL models to categorize the BreaKHis dataset. The fundamental objective of this research is to investigate whether or not pre-trained deep learning VGG16 can be used effectively as a feature extractor for binary and multiclass breast cancer histopathology image classification tasks once VGG16 has been modified specifically for these tasks [22].

Several considerations are presented: rather than integrating feature extraction and classification inside a single model, it is preferable to use a convolutional neural network (CNN) that has already been trained for feature extraction. Second, the problem of the multiclass sort is complex and requires the input of several experts in their respective fields. Third, a data augmentation approach needs to be implemented to lessen the imbalance in the dataset [23]. Due to the success of CNNs in many areas, there is now a large variety of CNN designs with distinct deep characteristics and learning requirements. Here, we investigated three CNN architectures that are traditional and representational of contemporary feature extractors with potential intermediate representations for capturing complicated visual representations [24]. Figure 1 shows the pre-training of the proposed system. The architectures implemented in this work are:

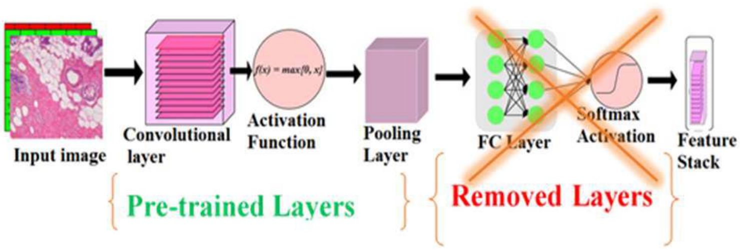

Figure 1. The pre-training of the proposed system

The CNN architectures used here were chosen for their proven success in natural image recognition tasks. It is possible, however, that they are not well-suited for representing and discriminating patterns. Therefore, we used transfer learning to acquire a representation. Transfer learning (TL) is a well-known method that applies learned weights from meaningful broad picture representations by adapting many layers to a particular domain, such as tongue images. The transfer learning with VGG16 (TLk) model (k=VGG16) formally specified the learned image representation as TLk=[F, P(F)], where F is the feature space and P(F) is the marginal probability distribution. In this scenario, the generic picture domain was represented hierarchically with respect to the job at hand by the notation F=[Fi(Fi-1)]. Consequently, the problem's initial definition of classes Dt=[d1,...,dn] was included in the scope of the task Tt (ImageNet). As such, TL's goal was to transform the generic codified learning task Tt into a different task Ts, as Tt=[Dt, Mt]→Ts [Ds, Ms]. Transfer learning (Tt→Ts) is an adaptive, iterative approach that utilizes a relatively modest learning rate and batches from a new domain, in this instance, trained CT slices. Finally, a detailed representation of each CNN architecture was obtained [25].

A process of adapting a pre-trained model on a new task by continuing the training on the new dataset. This is often useful when you have a small dataset and want to leverage the knowledge learned from a larger dataset. For example, you might have a pre-trained model on the ImageNet dataset, a massive dataset with thousands of classes. You can use this pre-trained model as the starting point for a new task, such as classifying a small set of images into a few classes. By fine-tuning the pre-trained model on your new dataset, you can avoid the long training time required to train a model from scratch and still achieve good performance on the new task. Figure 2 shows the block diagram of the proposed methods.

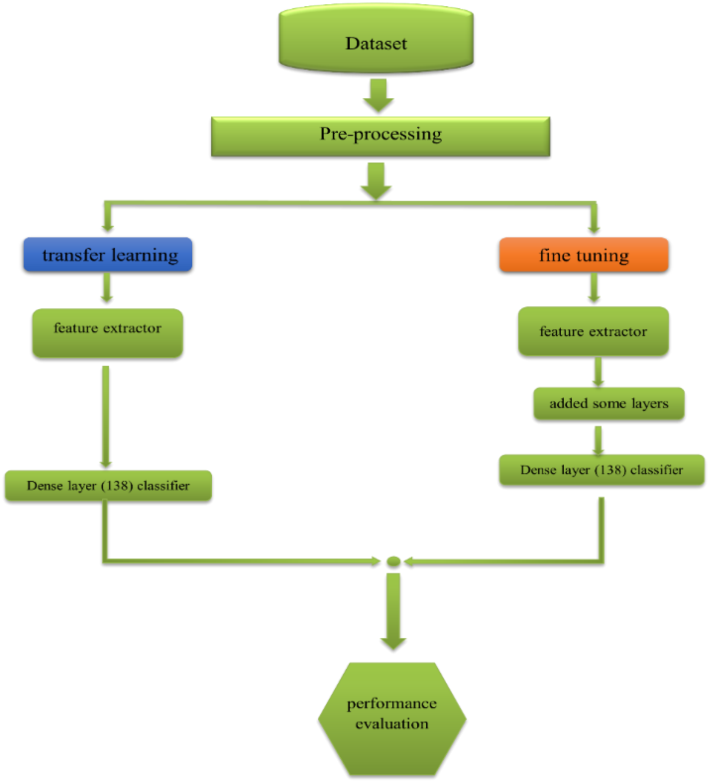

Figure 2. Block diagram of the proposed systems

2.1. Dataset gathering

Before running the system, the image of the own tongue dataset must be loaded. All images are taken for 138 persons, with eight images for the person using an iPhone 12 pro max camera with a resolution (9 Megapixels). We prepare a suitable environment for image capturing. This environment can be made using a box of high-density fiberboard size 45.5×17×27.5 cm^3. The light source was placed from one side with the camera (corresponding to the person). The distance is fixed ±15 cm between the camera and the candidate person. This system is made for the need of the same environment and same conditions for all images in addition to uniform lighting. Figure 3 shows the proposed acquisition image tool.

Samples were taken from different numbers of students of the Department of Physics, College of Science, Mustansiriyah University for the second and third stages of the academic year 2021-2022 after taking their consent to participate in scientific research procedures and to build a biometric database for tongue discrimination. Tongues were taken for 87 females and 51 males, and we got a total of 138 people.

Eight snapshots were taken for each person and 1,104 photos were obtained. Nineteen images were excluded due to the presence of deformation due to the person's movement. The rest are 1,085 pictures of 138 items (person). Figure 4 presents samples of obtained images to build the database.

Figure 3. Proposed acquisition image tool

Figure 4. Samples of the obtained images

2.2. Pre-Processing

The proposed method is applied to specific image data captured for people between 19-23 years. The input image has a JPG format. The image dimensions for all people (classes) are 3,024×3,024 pixels. To proceed to the next phase, all images must be read, cropping region of interest (ROI). The method adopted was to take a window of a fixed size. The resolution was determined at 200×200. This resolution was taken because it is almost suitable for all the images. If more than this resolution is taken, it can contain lip or teeth parts. Finally, this window is automatically passed to all images to get a fixed-size window of all images to be adopted in the extraction features. In the training process, the classification of the intelligent system is learned using the features of the training dataset after normalizing these features. Normalization is another approach to Z-score normalization (or standardization) is scaled the data to a fixed range-typically 0 to 1. In contrast to standardization, the cost of this specified range is that we will end with more minor standard deviations, which can prevent the effect of extreme value.

3. RESULTS AND DISCUSSION

The performance of the designed intelligent classification system must be verified by evaluating the classification accuracy. This evaluation accuracy is performed by implementing the designed classification system on the testing dataset and determining the accuracy between the aggregated class obtained by the designed intelligent system and the pre-defined class of each element in the testing dataset and the second measurement of the relationship among the outputs of the neural network and the targets. Perfect training makes the network outputs and the targets would be the same.

The VGG16 model was used without a fully connected classifier/layers, and the classifier was added to it by adding three blocks (batch normalization 512, global average pooling 2D 512, and Dense 138). In the implementation of the model, it was determined that the number of epochs was 50, the batch size was 32, the loss function was categorical cross-entropy, and the select optimizer was Adam. In order to work with pre-trained weights, the model's parameters must be untrainable; that is important. Figure 5 represents the accuracy of the learning transfer method. It is noticed from Figure 5 that the highest value reached overall accuracy in this model was 90.23%. Also, it is noticed that there is high stability between training and validation accuracy, and there is no overfitting, which indicates that the model is perfect. Figure 6 shows the loss of the learning transfer method. It is noticed that the lowest value we reached in this model is 0.478, which indicates the stability of the model used in VGG16.

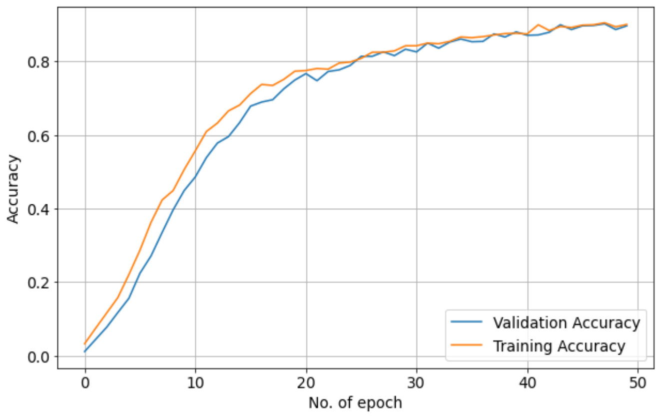

Figure 5. Accuracy of transfer learning method

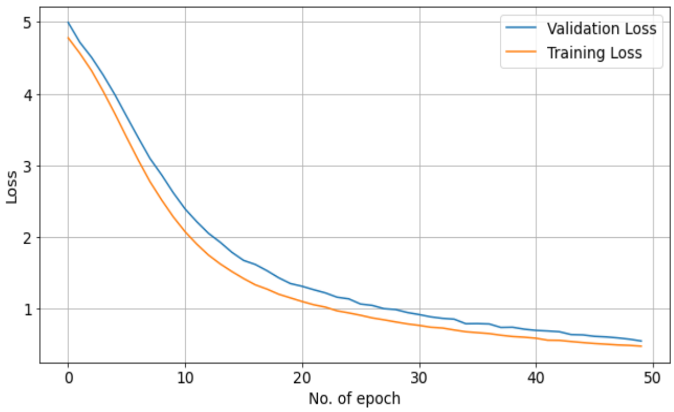

Figure 6. Loss of transfer learning method

In this section, the model has implemented the same (the transfer learning model) as in the previous section, but after adding three blocks (Dense 512, Dense 512, and Dense 256). The parameters were modified, and a model was produced that gave us a higher overall accuracy than the one implemented in transfer learning; it was 91.98%. Figure 7 represents the overall accuracy of the fine-tuning method; it is shown that the highest overall accuracy was 91.98%. This result is higher than in the transfer learning model;

it indicates that the development made to the model gives good results. Figure 8 shows the loss value of the fine-tuning method; the lower value of the loss function, at 0.23, is less than the result in the transfer learning model. It appears that this model gave better results than the transfer learning model. Without any development or fine-tuning of its weight, the ready-made model gave lower values than the model whose layers are modified and other layers are added to increase and improve accuracy and reduce the loss values.

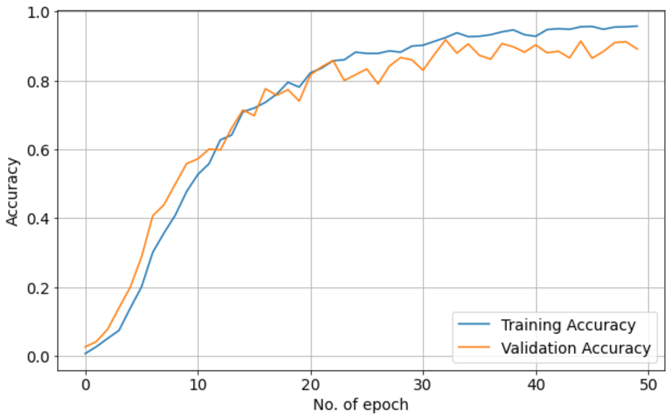

Figure 7. Accuracy of the fine-tuning method

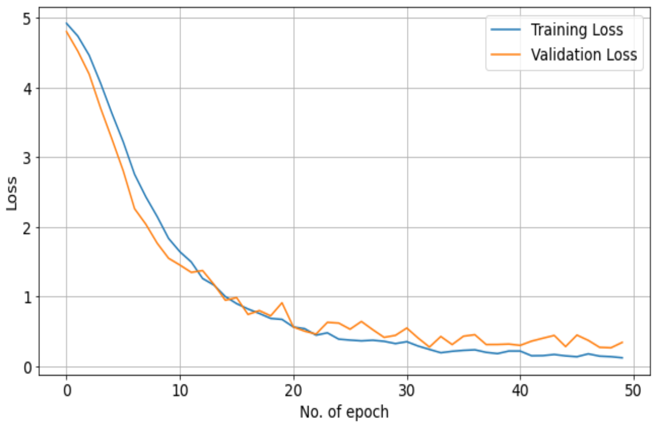

Figure 8. Loss of the fine-tuning method

In conclusion, Table 1 summarizes the findings of many investigations conducted on the tongue image categorization system. The accuracy of the comparison was scored and used as the basis for the evaluation. It is essential to highlight that due to the disparity between the data sets, it is impossible to make direct comparisons (for example, the number of images). However, compared to previous efforts, ours did far better, demonstrating the dependability and robustness of the model provided.

Table 1. Comparison of our proposed model with other studies

Refrence	No. of class	Method	accuracy
Zhang *et al*. [10]	134	Gabor filter	93.30%
Lahmiri [11]	174	k-nearest neighbor algorithm (k-NN)	92.00%
		Gabor filter	83.00%
Sivakumar *et al*. [14]	34	SVM	97.05%
Ibrahim and Hindi [7]	30	Bhattacharyya distance	93.00%
Our work	138	VGG16-transfer learning	90.23%
		VGG16-fine-tuning	91.98%

4. CONCLUSION

In this work, distinct observations and conclusions were obtained, which can be summarized as: the process of distinguishing people through tongue prints has proven effective and accurate, with an accuracy that approaches 92%. It was noticed that the fine-tuning method is better than the learning transfer method. Adding and modifying the model gives better results than using the same model without any development or modification because no ready-made model works with all cases. This study can be improved in the future by Expanding the database to include the most significant number of people. Also, the implementation and testing of work on other age groups are more significant than the ages taken in this work.

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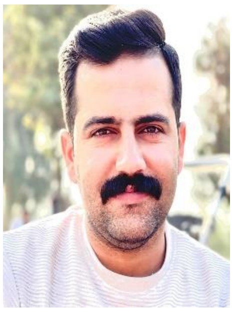

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