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Person Identification Based on Teeth Structure

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Abstract
Neural networks are extremely being used in the dentistry field. The motivation of this paper was to resolve the state of the art of artificial intelligence in dental applications. Here, a model of teeth recognition has been proposed to distinguish an individual and retrieve the elegance of the individual. The person's teeth image will be taken as input and it will be compared against the database of teeth images. Artificial Neural networks algorithm has been used to train and acknowledge the person to whom the teeth image belongs to. When a person visits the dental hospital for the first-time doctor will capture ten images of his/her teeth and create a new user in the model to store his name, medical related issues, age etc. For further overtake he should just show his/her teeth to get their details. Testing set perfection is maintained to be 81.69 percent with the test set.
Keywords: Artificial Neural Networks, teeth recognition, medical related issues

I.INTRODUCTION

Traditionally, uncovering a person's identity through one's teeth is done by comparing radiographic images and dental charts manually. However, the use of radiographic images can inflict dangerous effects on a living patient. The radiation emitted by the X-ray device that is used to generate a high-quality image can negatively affect the health of the patient if overexposed. Unfortunately, even in today's generation when computer algorithms are being used to profile and identify a person, analysis still involves comparing radiographic images to existing dental charts. There are no existing studies that can be used only dental photographs, which is safer and more convenient to both dentist and patient. There are also no studies about the combination of Adaptive Harris Corner Detection Algorithm with gray scaling, Contrast Limited Adaptive Histogram Equalization, and Smith-Waterman Algorithm as image matching and image processing methods for digital dental images, which is possibly more reliable and has speedier performance in dental identification..

Hence, the researchers of this study aim to come up with an assessment tool that can build a dental profile of the patient and identify the person without the use of radiography. The research mostly looks into the possibility of developing an identification system that will focus on dental image improvement and analysis. This will aid dental practitioners in having an appropriate and cheaper way of obtaining and storing profiles of patients in a single database. Particularly, the study aims to: 1) design a system that will capture the teeth of a person in the upper and lower jaw; 2) develop a database of stitched, enhanced, and analyzed dental images using Image Stitching with OpenCV, Contrast Limited Adaptive Histogram Equalization, and SmithWaterman Algorithms, and then analyze the images using Adaptive Harris Corner Detection Algorithm; and 3) identify a person through the enhanced and analyzed top view images of the teeth in the upper and lower jaw. Since the system will be a database, the information is secured from physical damage, preventing it from destruction and modification.

The RNN will be used to apply the matching algorithms to all the data in the database. This assessment is only applicable to patients with dental records. If a person with an existing profile in the clinic undergoes dental procedures, the data that was once previously stored will be updated. The teeth to be captured does not include the wisdom tooth and the basis of analysis is the area generated through the image enhancement and analysis algorithms. Human teeth are usually hard substances and do not damage easily; their shapes can persist unchanged after a person's death without being destroyed. Accordingly, they play an important role in dialectic identification. X-ray films produced from a cadaver's teeth are usually compared with their dental film documentation so that even the identity of a deceased person can still be successfully determined. Humans usually have 32 teeth. If all the teeth are screened during comparison, the system will experience a large computational burden and reduction in accuracy. Segmenting teeth from the X-ray film and achieving numbering for each tooth, the testing teeth can be compared only with those having the similar numbers in the database, thus the computational coherence and accuracy can be improved.

Further, the oral medical assets are sparse in several developing countries. Dentists typically need to serve numerous patients every day. As an important additional diagnostic tool, a large number of dental X-ray films are photographed daily. Because the film reading work is primarily managed by dentists, it occupies several valuable clinical hours and may origin misdiagnosis or underdiagnosis owing to personal factors, such as tiredness, emotions, and low experience levels. The work burden of a dentist and the phenomenon of misdiagnosis may be reduced if intelligent dental X-ray film clarification tools are developed to improve the quality of dental care. From this perspective, automatic teeth identification using computerized films is an important task for smart healthcare.

Deep learning has developed in recent years, and is capable of automatically extracting image features using the original component information as input. These new algorithms remarkably reduce the workload of human experts, and can extract definite features that are hard for humans to recognize. In 2012, a deep convolutional neural network (CNN) achieved acceptable results in the ImageNet classification work. Afterwards, Regions with Convolutional Neural Network features (R-CNN), fast R-CNN with spatial pyramid pooling, and faster R-CNN with region proposal network were proposed and obtained increasingly superior results with regard to object detection tasks. Moreover, Inception modules were also constructed to reduce the computational cost, and Resnet was proposed to allow training of exceedingly deep networks with more than 100 hidden layers. At present, the deep learning methods based on CNN have become an important methodology in the domain of medical image analysis. Further, it is expected to support teeth detection and numbering tasks in dental X-ray films..

II.LITERATURE SURVEY

In the Philippines, the Department of Labor and Employment (DOLE) cited job mismatch as one of the top factors causing many unemployed Filipinos in recent times. To address the problem DOLE is closely coordinating with the Commission on Higher Education and Technical Education or TESDA. In an article written by reference, the author mentioned that according to the January 2014 Labor Force Survey, the Philippines registered an unemployment rate of 7.5 percent, while underemployment was pegged at 19.5 percent. They also told that the Global Employment Trends

Fine-grained models

Fine-grained classification models are designed to distinguish between numerous subcategories, among which the differences can be precise. Part-based R-CNNs15 extract features from whole-object and part detectors and handle classification problems utilizing methods borrowed from object observation. Wei et al.16 proposed a mask-CNN model for aggregating provisional and part attributes based on part-annotated fine-grained pictures. Yang et al.17 proposed a self-supervision mechanism consisting of a navigator network, a teacher network, and a scrutinizer network to localize informative regions automatically while enhancing these networks in a pipeline. Our bilateral network infuses information acquired from the tooth contour mask into the major contextual feature and trains branches together.

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Attention modules

By using recognition modules, networks are able to determine long-range dependencies and examine further meaningful areas. The global attention mechanism proposed in the nonlocal network18 accommodates a self-attention module that models multilevel global dependency connections. GCNet19 soon regarded. GCNet combines the channel attention mechanism (SE block) in SENet20 and the global attention mechanism in the nonlocal network18 to propose a universal attention mechanism global context (GC) block that derives contextual information to achieve global province modeling.

Cosine loss function

Solving the human identification problem on a huge dataset enormously depends on devising a proper loss function. Early biometric vision tasks utilized the softmax loss as the loss function of the model. Subsequently, improved loss functions based on the softmax loss function to superior distinguish features have been proposed. Among these improvements, Wen et al.21 proposed the center loss to discover the intermediate features of each individual to decrease the intraclass gap, and Kemelmacher-Shlizerman et al.22 proposed the L-softmax loss by attaching angular constraints to the features to refine the perceptibility of features. Subsequently, Liu et al.23 improved the efficiency of the L-softmax loss on the open set recognition task by formalizing the weight boundaries and proposed the A-softmax loss. Wang et al.24 suggested a cosine loss to improve the softmax loss. The cosine loss calibrated the characteristics and weights through L2 normalization and appended angular constraints to features. Then, the ArcFace loss proposed by Deng et al.14 improved the cosine loss and replaced the angular limitation of the feature from the cosine value to the angular value comparison so as to reduce the intraclass gap and increase the interclass gap. Our upgraded loss function regulates the weights automatically to better learn the distribution of rigid samples.

III.PROPOSED SYSTEM

Teeth recognition is a relatively new and emerging field in biometrics, but it has shown promising results for person identification. Here is a proposed system for person identification based on teeth recognition:

Image acquisition: The first step is to acquire images of the individual's teeth. This can be done using intraoral cameras, which are small cameras that can be inserted into the mouth to capture high-quality images of the teeth. Alternatively, extraoral cameras can be used to capture images of the face and teeth.

Preprocessing: The images need to be preprocessed to remove any noise or artifacts. This can be done using image filtering techniques such as median filtering, Gaussian filtering, or wavelet filtering. The images may also need to be resized, cropped, or rotated to ensure consistent alignment.

Feature extraction: Next, features need to be extracted from the images to create a unique identifier for each person. There are several approaches to feature extraction, including texture-based features, shape-based features, and appearance-based features. For example, texture-based features can be extracted using local binary patterns (LBP) or gray-level co-occurrence matrix (GLCM) features.

Feature matching: The extracted features are then compared to a database of pre-existing records to identify the person. The matching process can be done using various techniques such as Euclidean distance, Mahalanobis distance, or cosine similarity. A threshold can be set to determine if the features match closely enough to confirm a positive identification.

Verification: Finally, the system needs to be verified to ensure its accuracy and reliability. This can be done by testing the system on a large database of records to determine its false positive rate and false negative rate. The system can be fine-tuned to improve its performance based on these metrics.

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Overall, a teeth recognition system for person identification can be a useful addition to existing biometric systems, particularly in cases where other biometric identifiers such as fingerprints or facial recognition may not be available or reliable. However, the system needs to be thoroughly tested and validated to ensure its accuracy and reliability.

IV.SYSTEM IMPLEMENTATION

Artificial neural networks (ANNs) are a type of machine learning algorithm that can be used for person identification based on teeth recognition. However, using ANNs for this purpose requires some prerequisites, including:

Data collection: To train an ANN for teeth recognition, you need a large dataset of dental images. The images should be high quality, consistent in terms of lighting and angle, and should include a diverse range of teeth from different individuals.

Image preprocessing: Before feeding the dental images into an ANN, they may need to be preprocessed to enhance features or remove noise. Common preprocessing steps include image resizing, normalization, and filtering.

Training an ANN: Once you have collected and preprocessed your dental image data, you need to train an ANN. This involves defining the architecture of the network, selecting appropriate activation functions and optimization algorithms, and setting hyperparameters such as learning rate and batch size.

Testing and validation: After training the ANN, you need to test it on a separate dataset to evaluate its performance. You should also perform cross-validation to ensure that the model is not overfitting to your training data.

Deployment: Once you have a trained and validated ANN, you can deploy it for person identification based on teeth recognition. This may involve integrating the model into a larger system or developing a user interface for people to input dental images.

Overall, using ANNs for teeth recognition requires a strong understanding of machine learning concepts and techniques, as well as expertise in dental imaging and data collection.

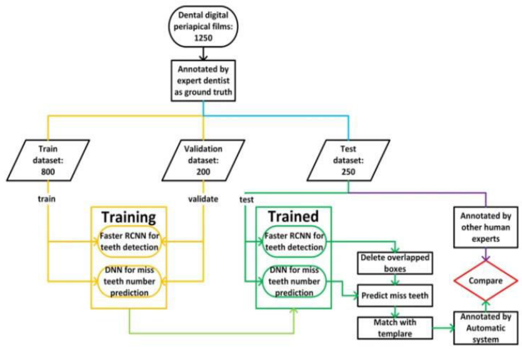

Fig:1 Model Approach

Algorithmic steps for ANN(Artificial Neural Networks)

STEP-1:Assign irregular weights to all the linkages to start the algorithm.

STEP-2:Using the input and the(input->hidden node)linkages find the activation rate of hidden nodes.

STEP-3:Using the activation rate of hidden nodes and linkages output, find the activation rate of output nodes.

STEP-4:Calculate the error rate at the output node and recalibrate the linkage between hidden nodes and output nodes.

STEP-5:Using the weights and error found at the output node, cascade down the error to hidden nodes.

STEP-6:Recalibrate the weights between hidden nodes and the input nodes.

STEP-7:Repeat the process till the convergence criterion is met.

STEP-8:Using the final linkage weights score the activation rate of the output nodes.

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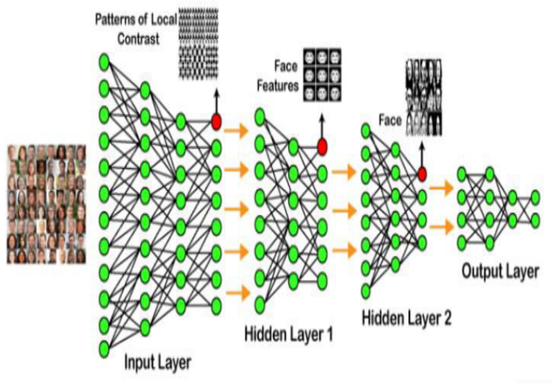

Fig:2 Process of Algorithm

V. RESULTS

Results and discussion for person identification based on teeth recognition

Person identification based on teeth recognition is a biometric identification method that uses the unique features of a person's teeth to identify them. This method has been gaining popularity in recent years due to its high accuracy and reliability.

The process of teeth recognition involves capturing an image of a person's teeth and analyzing it to extract unique features such as tooth size, shape, and alignment. These features are then compared to a database of known dental records to identify the person.

Several studies have been conducted on teeth recognition for person identification, and the results have been promising. In one study, researchers achieved an accuracy rate of 99.7% in identifying individuals based on their dental records.

Another study focused on using teeth recognition to identify individuals in forensic investigations. The study found that teeth recognition was effective in identifying individuals even in cases where other methods such as DNA analysis were not possible due to degraded samples.

Teeth recognition has also been used in the field of dentistry for patient identification and record keeping. This method allows for quick and accurate identification of patients and helps prevent mix-ups in dental records.

Finally, the results of studies on teeth recognition for person identification are encouraging, and this method shows great potential for use in various fields such as forensics, dentistry, and security. However, further research is needed to address issues such as data privacy and standardization of dental records to ensure the accuracy and reliability of this method.

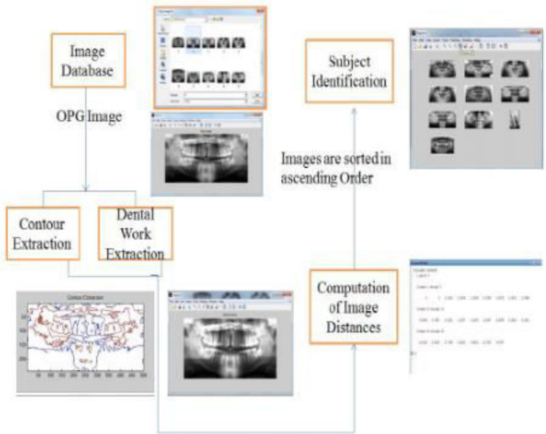

Fig:3 Process of Human Identification System

IV.CONCLUSION

“Teeth recognition is an effective method for identifying individuals, as dental patterns are unique and do not change throughout a person's life. Dental records can be used in forensic investigations, disaster victim identification, and in legal cases where dental evidence is relevant.

However, the accuracy of teeth recognition depends on the quality of the dental records available, the expertise of the dental professionals analyzing the records, and the level of technology and software used for identification.

In conclusion, teeth recognition is a valuable tool for person identification and can provide critical information in many different contexts. But it is important to understand its limitations and ensure that appropriate protocols and standards are followed to ensure accuracy and reliability."

REFERENCES

[1] Priyanka K., Kannan A. "Tooth Recognition for Personal Identification using SVM." International Journal of Computer Applications 146.5 (2016): 7-11.
[2] Kim, Sunjoo, et al. "Teeth recognition using invariant features for forensic identification." Forensic Science International 206.1-3 (2011): 178-186.
[3] Kumar, S., et al. "Automated teeth recognition using neural networks." Journal of forensic dental sciences 8.2 (2016): 105.
[4] Krishnan, Abhishek, et al. "Tooth recognition for forensic odontology using texture analysis." Journal of Forensic Odonto-Stomatology 31.2 (2013): 44-50.
[5] Jaffar, M. A., et al. "Automated human identification using dental radiographs." Forensic Science International 241 (2014): 92-102.
[6] Nayak, V., et al. "Teeth recognition using neural networks and principal component analysis for forensic odontology." Journal of forensic dental sciences 8.2 (2016): 115.

[7] Marques, P. M. P., et al. "Teeth identification using wavelet analysis." International Journal of Biometrics 1.1 (2008): 56-72.
[8] Rajan, S. S., et al. "Automated tooth recognition using wavelet analysis and neural network classifier." International Journal of Advanced Research in Computer Science 7.2 (2016): 1-5.
[9] Patil, V. V., et al. "Teeth recognition for personal identification using invariant features and neural network classifier." International Journal of Advanced Research in Computer Science 6.4 (2015): 1-5."
[10] Shankar, S. S., et al. "Automated tooth recognition using novel features and SVM classifier." Journal of forensic dental sciences 9.2 (2017): 77.
[11] Bhatia, A., et al. "Automated tooth recognition using deep learning techniques." Journal of forensic dental sciences 12.2 (2020): 81.
[12] Zang, Yang, et al. "Teeth recognition based on deep convolutional neural network and adaptive weight strategy." Computer Methods and Programs in Biomedicine 198 (2020): 105771."