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Postmortem Panoramic Dental Radiography: Human Identification Based on Convolution Neural Network and Contourlet Transform

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Abstract
Human identification is crucial in forensics for the investigation of large-scale disasters such as fires, epidemics, earthquakes, and tsunamis. Even though biometric identification using panoramic dental radiography (PDR) has been the subject of several studies in the literature, further study remains a necessary and challenging issue. In this research, a human identification system was developed based on a convolutional neural network (CNN) and contour transform (CT). The proposed system was implemented on a total of 1540 PDR from 302 individuals. The preprocessing applied to PDRs for enhancing and taking the Region of Interest (ROI). The features were extracted using CT transform. These features were fused with features extracted from the CNN to perform identification. Various models with different numbers of layers were applied as a try and test for the proposed system. Data augmentation is used to enhance the system's results. The experimental results illustrate that the best accuracy is 98.9% achieved by implementing the PDRs of size 224*224 using 16 layers (VGG16) with data augmentation of batch size 64*64 and 200 epochs. The prediction time of the proposed system to test PDR was just 3.1 sec. per image. The proposed system can be used to generate candidate images for critical issues. It will likely help with criminal investigations and people identification in large-scale disasters.

Keywords: Human Identification, Convolution Neural Network, Contourlet Transform, Postmortem, Panoramic Dental Radiography (PDR)

التصوير الشعاعي البانورامي للأسنان بعد الوفاة لتحديد هوية الإنسان بناءً على الشبكة العصبية التلافيفية والتحويل المحيطي

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الخلاصة
يعد التعرف على هوية الإنسان أمرًا بالغ الأهمية في الطب الشرعي للتحقيق في الكوارث واسعة النطاق مثل الحرائق والأوبئة والزلازل وأمواج تسونامي. على الرغم من أن تحديد الهوية البيومترية باستعمال التصوير الشعاعي البانورامي للأسنان (PDR) كان موضوعًا للعديد من الدراسات في الأدبيات، إلا أن إجراء مزيد من الدراسة يظل مسألة ضرورية ومليئة بالتحديات. في هذا البحث، تم تطوير نظام تحديد هوية الإنسان على أساس الشبكة العصبية التلافيفية (CNN)والتحويل المحيطي (CT). تم تنفيذ النظام المقترح على إجمالي 1540

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PDR من 302 فردًا. يتم تطبيق المعالجة المسبقة على PDRs لتعزيز منطقة الاهتمام (ROI) وأخذها. تم استخراج الميزات باستخدام تحويل CT. تم دمج هذه الميزات مع الميزات المستخرجة من CNN لإجراء عملية تحديد الهوية. تم تطبيق نماذج مختلفة بأعداد مختلفة من الطبقات كمحاولة واختبار للنظام المقترح. يتم استعمال زيادة البيانات لتعزيز نتائج النظام. أوضحت النتائج التجريبية أن أفضل دقة هي 98.9% تم تحقيقها من خلال تطبيق PDRs بحجم 224*224 وباستعمال 16 طبقة (VGG16) مع زيادة البيانات بحجم الدفعة 64*64 و200 epochs. كان وقت التنبؤ للنظام المقترح لاختبار PDR 3.1 ثانية فقط لكل صورة. يمكن استخدام النظام المقترح لإنشاء صور مرشحة للقضايا الحرجة. ومن المرجح أن يساعد في التحقيقات الجنائية وتحديد هوية الأشخاص في الكوارث واسعة النطاق.

1. Introduction

Over the last ten years, there has been a concerning increase in both criminal and tragic incidents [1]. The significant increase in criminal and violent activity in today's world has made the use of contemporary techniques in criminal investigations necessary [2]. Furthermore, new and effective techniques for mass disaster victim identification are required due to the current occurrence of casualties connected to mass disasters (MD), including travel and transport accidents, terrorism, and exceptional meteorological circumstances. Forensic medicine is a legal field that uses medical information to identify victims. A catastrophe must meet one or more of the following requirements in order to be included in the database: 10 or more persons reported murdered; 100 or more people reported impacted; proclamation of a state of emergency; or a demand for international aid [3, 4]. The Latin word forensic refers to a public forum or marketplace that addresses legal matters. Since every person's dentition is different, forensic odontology is one of the main methods of identification [1]. The process of identifying persons usually involves comparing the ante-mortem (AM) and post-mortem (PM) data that are available. Based on their degree of confidence, forensic specialists can determine the person's identity from this comparison [5]. The image structure of the PM dental radiographs should mimic that of the AM radiographs for successful comparison [6, 7]. Dental biometrics automatically identifies human remains by using information about dental anatomy. The approach is primarily used to identify those affected by large-scale disasters. Deep learning is currently essential for application tasks that are difficult and require a significant amount of time for experts to complete [8].

Deep learning techniques have advanced quickly and are currently being used for object identification, image classification, and pattern recognition in dental work and medical imaging diagnostics [9]. Convolutional Neural Network (CNN) is an effective method in the image domain that uses the image as an input and is very helpful in identifying patterns for image identification, including radiological applications in general medicine [10]. This approach, which is currently useful in forensic odontology and has attracted interest from forensics, is particularly beneficial for disaster victim identification using PDR [11]. Nowadays, some research has been performed comparing DPR images to teeth for human identification using a convolutional neural network. To this date, few studies have fully detected all dental human identification that currently exists, including the identification of teeth as a foundation for disaster victim identification using a convolutional neural network [12].

This research aimed to construct an identification model that has been researched in the forensic science domain. The proposed method was designed for the identification of disaster victims and criminal investigations based on forensic medicine.

2. Related Work

Enomoto et al. in 2023 [13] employed a deep learning technique using CNN to create an autonomous identification system utilizing Panoramic Radiographs (PRs). A total of 1663 people who had different PR image features changed as a result of different dental treatments. In their research, the authors used a data set consisting of 4966 PRs from 1663 individuals to train the CNN model. They used various CNN models that have different layers, such as VGG16, VGG19, EfficientNet, ResNet50, and ResNet101. The test set involves 1663 PR images. Each model has its own accuracy rate precision. The best and highest accuracy rate of the five implemented models is the VGG16. The VGG16 achieved a precision rate of 90% using 200 epochs. The learning time for the model is about 3–6 hours.

In 2022, H. Kim et al. used a total of 2760 DPRs from 746 individuals with 2–17 DPRs with different image features collected as a result of different orthodontic treatments [14]. The most recent DPR for each individual (746 images) was included in the test data set, while the remaining DPRs (2014 images) were utilized to train the model. The authors use a modified VGG16 model that has two fully connected layers for human identification. In rank 5, this model had an accuracy rate of 92.23%. The proposed model took an average of 60.9 s per epoch to train, and the 746 test DPRs had a prediction time of about 3.2 s/image. The proposed methods will be expected to help specialists identify objects more quickly and accurately.

G. Ortiz et al. in 2021 [15] proposed an automated personal identification system using a deep neural network. The system employs a private radiological service database with 200 panoramic radiographs from 100 patients, 50 of whom were male, and the other 50 females were chosen at random. An expert first made 14 measurements of the radiographs, both linear and angular. To simulate a semiautomated personal identification process, radiographs from the same patients were matched using a statistical method with eight ratio indices that were obtained from the original data. After that, measurements were produced automatically by modeling a completely automated personal identification process through the use of a deep neural network for image recognition. The results of this research show that approximately 85% of the radiographs were accurately matched using an automated personal identification technique.

In 2020 [16], F. Fan et al. proposed a modified CNN model for automated human identification. They named their proposed system DENT-net. The data set used in their research included 15,369 PDRs from 6300 individuals. Before applying the proposed system, the preprocessing was used. The preprocessing was represented by histogram equalization and affine transformation. The input image size used has a 128*128 dimension with 7 square patches. The proposed CNN model achieved human identification with a Rank-1 accuracy of 85.16% and a Rank-5 accuracy of 97.74%. The outcomes of this study showed that CNN can quickly and accurately identify humans from PDRs.

3. Contourlet Transform (CT)

The contourlet transform (CT) is represented by the combination of the Laplacian Pyramid (LP) with the Directional Filter Banks (DFB). The CT uses a double filter bank structure to obtain the smooth contours of images. Do and Vetterli invented it in 2002 [17]. It highlights singularities by utilizing a Laplacian Pyramid (LP) to break down a 2-D image into low-pass and high-pass sub-bands. This is an effective way to describe image structure. To capture single points spread along similar directions, apply a DFB to the high-pass subbands. CT is effective for capturing images' geometric structures and smooth curves. The receptive fields of the visual cortex have band-pass, localized, and oriented properties as seen from the viewpoint of the Human Visual System (HVS). Consequently, the CT's acquired characteristics may be used to represent aspects of visual perception [18–20]. Figure (1) illustrates the structure of Contourlet transform filters.

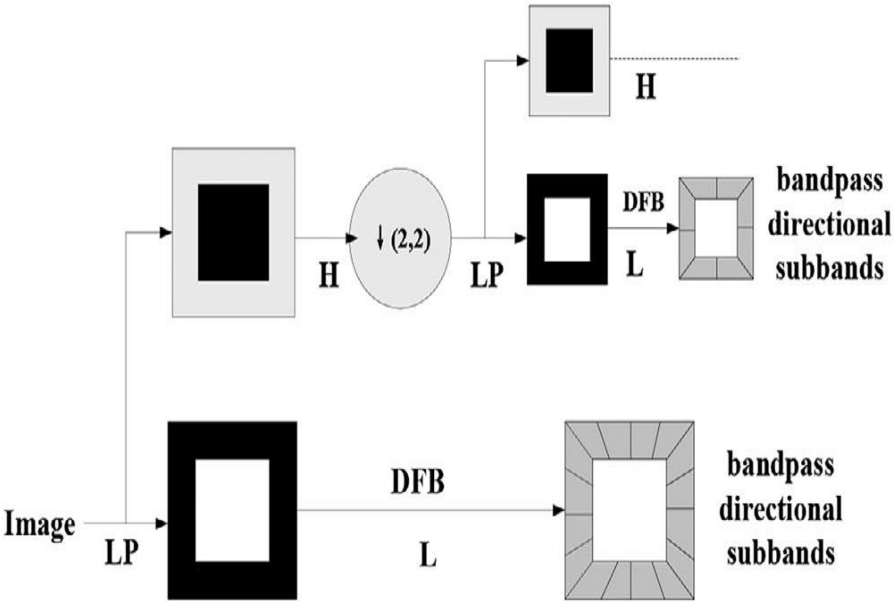

Figure 1: The CT structure Illustrations [18]

4. Convolution Neural Network

One popular type of feedforward learning algorithm is referred to as convolutional neural networks, or CNNs. The CNNs are ideal for image classification because of their primary approach to operation, which involves transitioning from minimal features to global ones [21]. Nowadays, CNNs have been trained for magnetic resonance imaging (MRI) and medical images, including C-scans, X-rays, and PDRs [22]. The CNN model is considerably easier to train and has more successful generalizations in deep learning [2 .[3However, CNN is faster to process complicated medical image analysis [24]. Instead of employing manually generated features, which might identify a few undetected correlations and patterns, it can automatically learn task-relevant characteristics [25 .[26 ,The great efficiency, processing speed, and accuracy of the CNN model make it an effective method in both clinical care and forensic age estimation. CNN's success has raised expectations for PDRs to automatically identify persons [27]. The idealistic CNN comprises alternate batches of convolutions, max pooling, and fully connected layers. The arrangement structure of convolutional layers is as follows [28]. A component of the previous layer is multiplied component-wise by a portion of the filter after it has passed through a tiny matrix known as the filter; the output of these multiplications consequently produces the next layer. Every successive convolutional layer extracts more complicated characteristics than the one before it since convolutional layers have been designed for feature extraction. The pooling layers produce a feature size reduction. The max pooling layers gather a few pixels and either return their maximal value (max pooling) or their average value (average pooling) [29]. Finally ,the fully connected layers are the final type of layers used in CNNs; their primary goal is to provide a class determination using the features that were extracted from all of the prior levels. Figure (2) depicts the main schemes of the CNN model .

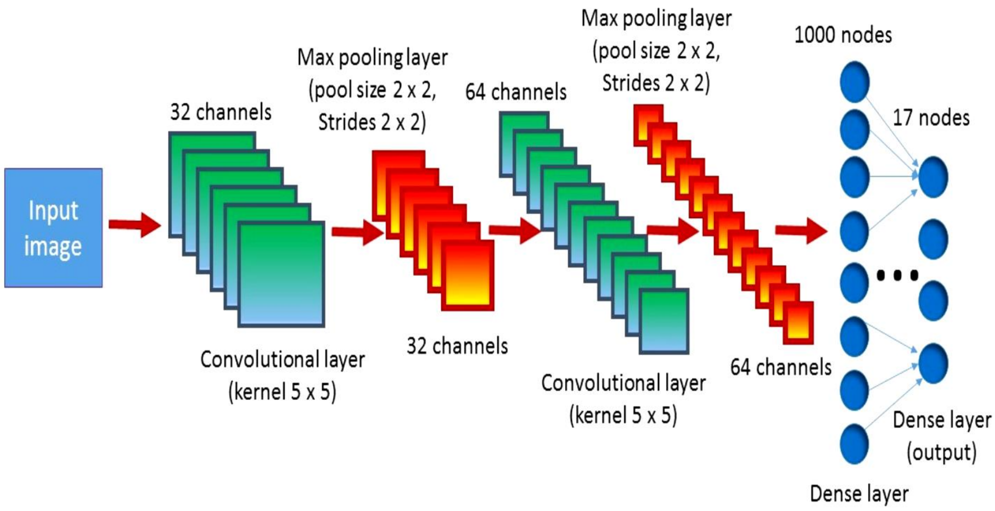

Figure 2: The main schemes of CNN model [29].

5. Materials and Methods

This study presents a method for postmortem human identification using the CT transform and CNN model, which combines the extracted input image feature from the CT transform with the CNN features to enforce the CNN classification. The following steps illustrate the proposed human identification algorithm:

STEP 1: Datasets

The data set used in this research, including 1540 PDRs obtained from 302 individuals, had been acquired for training and testing the proposed identification system. Each person has at least four PDRs in various situations. Every image was kept in the size of 256*256 grayscale JPEG format. The PDRs were obtained from the Dental Implantology Hospital in Chengdu, West China. The RDRs were taken using two panoramic devices from different manufacturers, including Veraviewepocs (Tube energy 65–70 kV) and Cranex3 panoramic (Soredex Co. Helsinki). Our database has a wide range of circumstances, including caries, defects, implants, impaction, and bridges, as well as large time intervals.

STEP 2: Preprocessing

The preprocessing step consists of four processes for the image, including:
1- Remove noise.
2- Histogram equalization
3- Rotate.
4- Cropping the Region of Interest (ROI).

The use of an enhancement process (remove noise and histogram equalization) is to reduce the impact of noise and improve the appearance of the image. The proposed method uses the median filter to enhance the image and eliminate noise. Furthermore, the proposed method employs histogram equalization to improve the appearance of the image, as it increases the dynamic range, thereby enhancing contrast. The rotate process is implemented in order to adjust the tooth contours. The possible cause of the problem could be the patient turning their head while capturing the PDR image. This is done by rotating the teeth's image at an angle relative to the image center. The last process will involve cropping an image to its most significant area, including segmenting for ROI. Figure 3 illustrates the preprocessing steps.

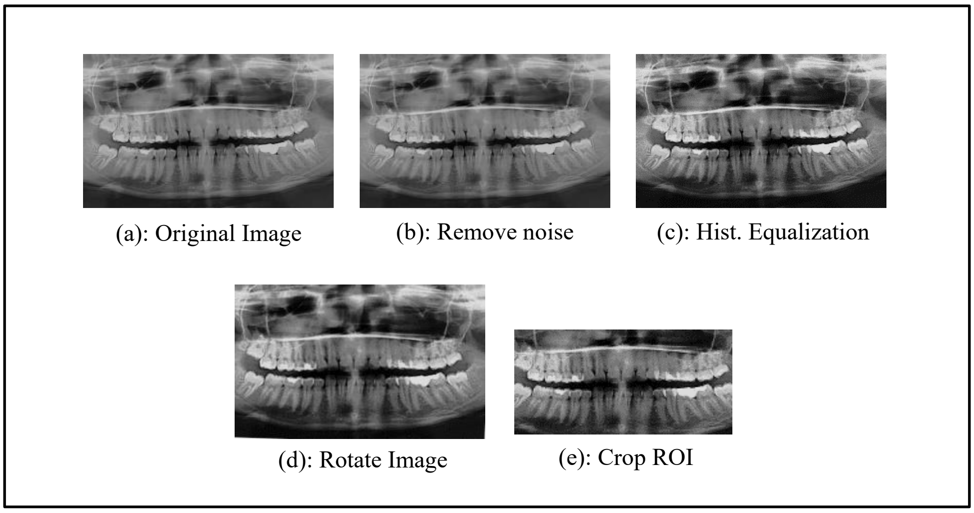

Figure 3: Preprocessing dental image

STEP3: Data Augmentation

Data augmentation is used to increase the amount of data in the training set of deep learning. The amount of data training is a critical factor in the CNN model's success. The augmentation method allows for training the model in a more resilient network by reducing overfitting. The amount of data for deep learning is increasing, and this includes the manipulation of images through contrast, zooming, brightness, and the addition of a square white mask. The square white mask will be added randomly in the middle of the image along the horizontal axis. This manipulation will ensure the feature's uniqueness when extracted from an image. Figure 4 illustrates the data augmentation process.

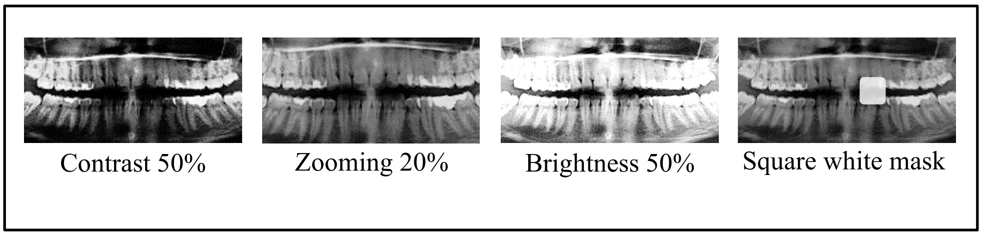

Figure 4: Data augmentation process

The training set after applying the augmentation process will have increased four times due to the four processes of the augmentation.

STEP 4: Feature Extraction

This step involves applying the contourlet transform for the input image for feature extraction, whereas, in biometrics, feature extraction allows the important details from the biometric input to be extracted to provide a unique characterization of the input. It is used to minimize the number of possible values that are compared or fed into the system at a later stage. The contourlet transform (CT) provides two further properties, including directionality and anisotropy, which help in feature extraction. The whole important relevant extracted features from the CT will be passed to the CNN model to be fused with its extracted features.

STEP 5: Convolution Neural Networks

In this step, the CNN model will be applied to the entire dataset. The proposed identification system performs human identification based on two steps: training and testing. The PDR sizes will be downsampled to 224*224 after the preprocessing process to be input for the CNN model. The downsample was applied to match the entered sample size with the neural network training. The CNN model comprises two parts: the feature extraction part and the classification part. Each PDR image will be implemented by the CNN model. The CNN PDR features will acquire further features (adding features) extracted from the CT in step 4 and pass to the CNN classification part. In the classification part, the added features from the CT will be fusion with the CNN features.

The CNN comprises convolution layers and fully connected layers. The CNN model uses the ReLU as its activation function. The convolution layers and max pooling represent the feature extractor part, while the fully connected layers represent the classifier part. The purpose of the second fully connected layer is to acquire deeper significant features, so the extracted features from the CT will be passed to the second fully connected layer. The CT features will be added to CNN feature vectors. The CNN model produces an identification score between 0 and 1 for the image. This score indicates the probability that the input image is part of a single individual's image data. Figure 5 depicts the block diagram for the proposed human identification system as observed below.

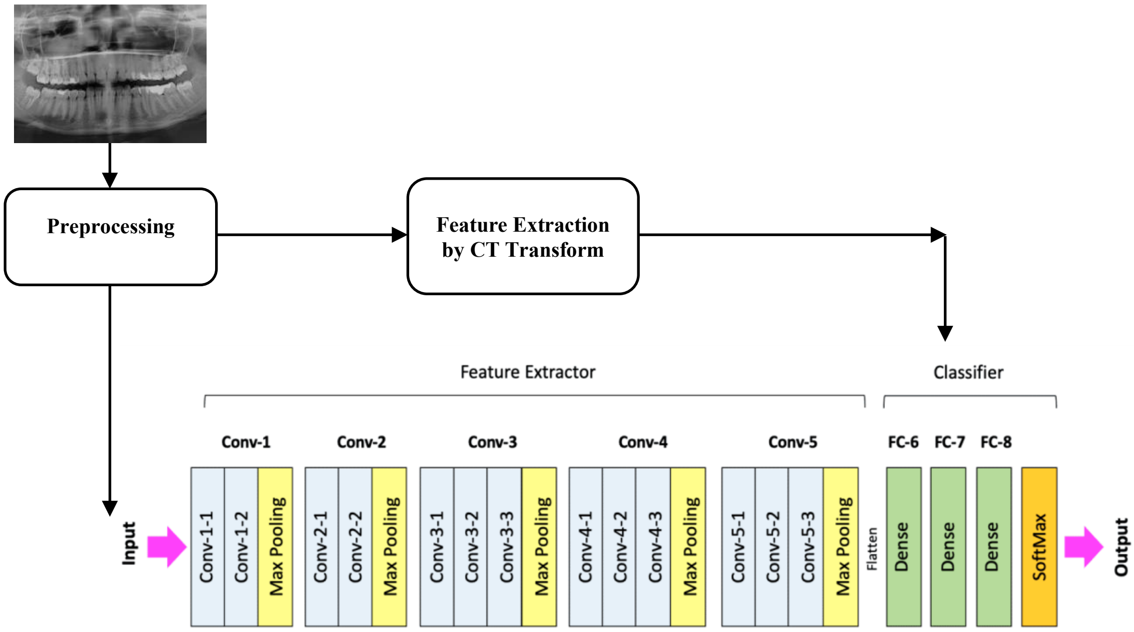

Figure 5: Block diagram for proposed human identification system

6. Evaluation performance

The proposed identification system was implemented using MATLAB 2020b on a computer that has an AMD Ryzen 9 processor. The Graphical Processing Unit (GPU) RTX 3070 and 32 G DDR4 RAM. The proposed system performance was assessed by implementing the metric that calculates the detection precision of the model. The true prediction (TP) represents the correct indication, and the false prediction (FP) represents the false indication. The overall system is predictive, including all TP and FP, so the accuracy rate precision will be determined by Eq. (1) as follows:

$$AR = TP/\ TP+FP \qquad \text{.... (1)}$$

All test data sets (302 individuals) were examined, and the model performance exhibited a good individual identification rate.

7. Experimental Results

The experimental results of the proposed identification system are achieved by using a 1540 PDR image data set taken from 302 persons, and every person has at least about 4 PDRs. The taken PDR images are divided into two sets (80:20). The training set represents 80%, including (1232) from all PDR images, and the test set, including (302) represents about 20% of the PDRs. The identification results are obtained from many configuration structures, which are built as trials and tests to achieve higher and optimal results. Table 1 illustrates the best seven configuration models. The seven models were applied using different CT levels, feature extraction, and a fixed batch size of 64. All the proposed models utilize the same number of 200 epochs to maintain consistent learning conditions. The best number of epochs is chosen according to the observation for the best accuracy results.

Table 1: The Configuration proposed Models

Model No.	No. of layers	CT Levels	Image size	Batch size	Augmentation	Accuracy
A	16	1 Level	224*224	64	No	95.4
B	16	2 Level	224*224	64	No	95.8
C	16	3 Level	224*224	64	No	94.7
D	14	1 Level	224*224	64	No	93.1
E	14	2 Level	224*224	64	No	93.6
F	14	3 Level	224*224	64	No	92.8
G	10	1 Level	224*224	64	No	86.4

The results obtained from Table 1 indicate that model B (VGG16) has the highest results, 95.8 without augmentation. Increasing the CT level beyond 2 will result in a decrease in the concentrated extraction of important features. By using the augmentation for the same configuration model from A to G, the results are increased. Table 2 displays the accuracy results for the same seven models, both without and with augmentation.

Table 2: The Accuracy without and with Augmentation

Model No.	Accuracy Results	
	Without Augmentation	With Augmentation
A	95.4	98.3
B	95.8	98.9
C	94.7	97.2
D	93.1	95.8
E	93.6	96.1
F	92.8	95.2
G	86.4	89.1

Table 2 shows that using augmentation contributed to increasing the model accuracy results for the same number of epochs (200). The use of augmentation enhances the output results by improving the training set, which gives better identification results. The augmentation effects are depicted in Figure 6.

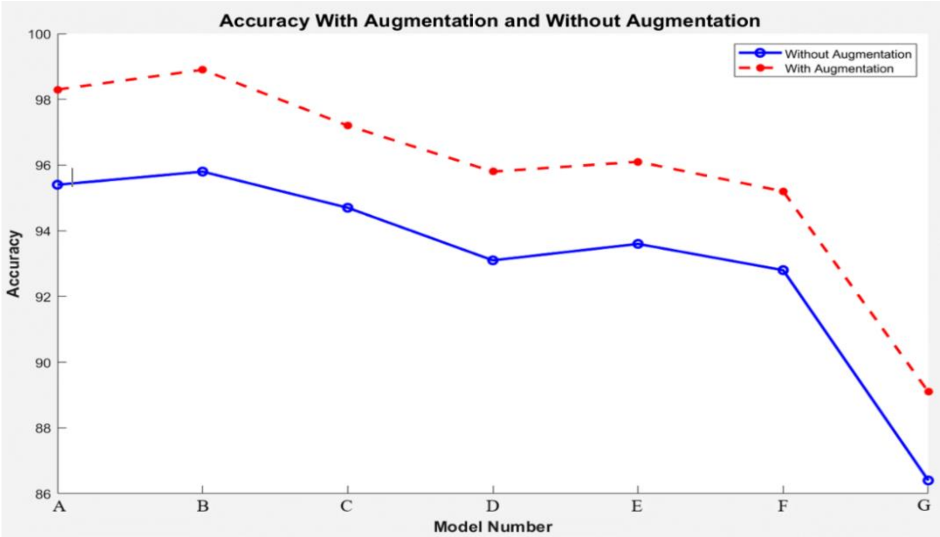

Figure 6 : The augmentation effects on accuracy results

The plot diagram in Figure 6 depicts that the augmentation has an obvious effect on the accuracy results of the proposed model. The results values are increased when applying data augmentation, so the model has higher efficiency.

8. Discussion

This research proposed an identification system based on CNN with CT transform; it tries on the various kinds of CNN models that differ in the number of layers. The preprocessing is used to enhance the images and make them less complex in the learning model. The CT transform is a mathematical tool used for image feature extraction. It is obvious from this research that the CNN model is very effective when fusion of their feature with the extracted CT feature. An increase in the number of hidden layers resulted in a higher recognition rate score. The use of data augmentation enhances the accuracy of results in addition to the exploitation of the batch size. The proposed developed identification model compares antemortem and postmortem PDRs using the CNN model. In this research, the proposed CNN model was compared with other similar studies; it is compared with [13, 16, 14, 30, 31, 32]. The proposed identification model obtains the highest accuracy rate of 98.9 compared with other studies. Table 3 compares the accuracy rate of the proposed system with other nearby studies, arranging the accuracy rates in a descending order.

Table 3: The comparison of accuracy rate

Studies	Test image	Accuracy
Present proposed system	295	98.9 %
[32]	144	97.91%
[16]	499	97.74%
[14]	746	92.23%
[13]	1663	90 %
[30]	206	81 %
[31]	200	80.2 %

Table 3 indicates that the proposed system has a higher accuracy rate due to feature fusion and data augmentation. In spite of the fact that the proposed system results are better, it is recommended to implement a batch size greater than the used one and use another transform type.

9. Conclusions

In forensic informatics, human biometric identification based on PDR photographs is a crucial topic today. In the present study, a proposed identification system was developed based on deep CNN and CT transform. The accuracy result of the system is relatively high (98.9) compared with other close studies. The high result was obtained due to the use of some factors represented by the feature fusion between CT transform and CNN, the number of layers 16, data augmentation, and batch size. These four factors yielded more successful results, represented by more precise identification scores. Future studies will consider the 3D upper jaw separately from the lower jaw.

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