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Revolutionizing Skull Classification: Leveraging Digital Forensics and Deep Learning in Physical Anthropology

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Abstract:
The human skull's dimensions, shape, and physical characteristics differ from person to person. Skull collections need to be handled carefully if physical anthropology collections are to be preserved and kept affordably. For example, the authenticity of collections may be jeopardized if skulls are labelled with printed material or given erroneous names. As manual skull recognition is a tedious process, we propose a deep learning (DL) approach and various feature extraction techniques(Fractal features) and feature combinations, to classify human skulls automatically. Every existing facial bone has unique properties that are important to the skull's physical composition and can be utilized to identify an individual. Consequently, we created a Convolutional Neural Network (CNN)-based system for automatically classifying human skulls that reliably distinguishes them more accurately than conventional classification methods. Our proposed technique achieved 99.98% classification accuracy with a loss of 0.01% for skull classification. Our study contributes to the development of an autonomous system by improving the collection of skull pictures through image augmentation using pre-processing approaches for classification. Archaeologists, anthropologists, and forensic scientists may manage, analyze, and preserve anthropological collections more effectively with the help of this creative framework. It can be used in archaeological research, forensic investigations, museum collections, and medical studies. The results highlight the revolutionary possibilities of incorporating digital forensics and machine learning into anthropological research, providing a powerful instrument for expanding our knowledge of human evolution and cultural legacy.

Keywords: Image Augmentation, Deep learning, Accuracy, Fractal Features, CNN

1. Introduction

Digital forensics researchers frequently work on a number of tasks, such as gathering, looking over, recognizing, and evaluating the digital artifacts needed to gather proof of the legitimacy of physical objects [1]. The administration of skull collections in museums is a common example that will help with future study and instruction. A key element of managing a skull collection is a method for cataloging and retrieving skulls. Skulls in this system that have lost their labels can be identified using an investigative procedure. As part of this procedure, each skull is given a call number, which serves as a label for the collection. This makes it easier to identify the skulls and guarantees that they are part of a certain collection.

For existing collections to be properly documented, developed, maintained, and enhanced, as well as made accessible to curators who wish to use them in accordance with classification criteria, this is equally crucial [2], [3]. However, applying an alphanumeric designation to skulls using ink streaks can compromise the skull's validity as a study tool. Therefore, managing a skull collection requires a specific strategy to preserve the collection's authenticity and prevent harm through the usage of chemicals. Another option is to affix stickers bearing the call number. However, there are disadvantages to this approach as well because stickers have the potential to come free, fall off, and adhere to other skulls. [4], [5].

As a result, the challenges of collecting and storing skulls make it impossible to expand the number of new collections. Skulls that are not attached to the mandible can be included. When it comes to human skulls and other bone collections, labeling errors are a significant issue. At an anthropological forensics laboratory are ink out [6]. Anthropologists and other scholars are currently only able to classify human bones using digital cameras for manual comparison and inquiry. While some earlier research has used automated techniques, such machine learning, to recognize human skulls, most Computerized tomography (CT) scans of live subjects were used to collect the samples. These samples are not very relevant to the examination of deceased subjects' skulls, which is necessary for physical anthropology forensics [6].

The Primary Contributions of this work:

1. Preprocessing techniques like Image Augmentation, noise removal and image restoring are used to have efficient feature extraction.
2. Feature extraction [7] [8] methods, such as GLCM-features [9], Gabor-features, fractal-features, and DWT-features are used to extract the important features for classification process.
3. Existing classifying method based on SVM [10] produces a accuracy of 83.3% [11], which is enhanced by using CNN model up to 96.21% .
4. Integrating SVM in the last layer of CNN [12] architecture increases the accuracy up to 99.98%.

1.1 Motivation and objectives

The main problem for anthropologists and forensic scientists is the time-consuming manual classification of skulls, especially when determining which ones have mandibles and which do not. Collections of skulls frequently fluctuate in size, and anatomical variations among skulls can be subtle and challenging to identify with conventional techniques. Additionally, when researchers are dealing with big datasets that may comprise hundreds or thousands of skull pictures, manual inspection is laborious and prone to mistakes.

To categorize skulls according to the presence of the mandible, an automated, high-performance system is essential. This system should be able to classify skull photos in real time and analyze them with speed and accuracy. Additionally, it should be user-friendly and portable for usage in a variety of research contexts, including lab and fieldwork. It needs to be flexible enough to accommodate different kinds of skulls and tailored to the particular needs of various research initiatives.

The following are important issues to address:

(1)Image Variability: It can be difficult to create a categorization system that works for all skull photos due to variations in quality, orientation, illumination, and anatomical features.
(2)Complexity of Skull Structures: Skull characteristics are complex, and it takes meticulous feature extraction from the images to distinguish between skulls with and without mandibles.
(3)Scalability: The system must be able to process massive amounts of skull images quickly and accurately while handling datasets of various sizes and complexity.
(4)Real-Time Processing: When working on forensic investigations that have a tight timeline, researchers require results virtually immediately. For the system to facilitate prompt decision-making, real-time monitoring must be possible.

By tackling these issues, the suggested solution seeks to get beyond the drawbacks of conventional techniques and provide a quicker, more precise substitute.

The objectives of this research are listed below:

(1)Real time monitoring: To develop an automated system [13] that can identify skulls in real time and provide prompt information on whether or not a skull has a mandible. Forensic scientists need quick input in order to make conclusions in instances that have a tight deadline, hence this goal is essential.
(2)Portability: To ensure that the system is easily deployable in a variety of scenarios, including fieldwork and lab settings. Widespread use is made possible by this goal, particularly in places without access to cutting-edge research facilities.
(3)Customization: To give users freedom by letting them alter the classification criteria to suit their own research requirements. It's possible that various skulls need different traits to be given priority, and the algorithm should account for these differences.
(4)Sustainability: Enhance the classification procedure to decrease errors and lessen reliance on human labor, supporting more environmentally friendly forensic and physical anthropological research methods.

2. Related Works

An autonomous facial recognition system for image classification [14] is becoming more and more necessary. Facial perception and identification have been the subject of several studies. Auto-facial processing is a useful method for facial identification. With these methods, low-cost digital cameras or video recorders generate a useful dataset. Numerous theories also examined human recognition using different body photos taken by cameras.

In recent works they [15] used similarity learning to re-identify people based on several regions by describing the matching using a polynomial feature map. Each feature map was then included into a single framework. This technique was also used by to combine deep CNNs with gait-based person recognition. Numerous scenarios, including cross-walking and cross-view scenarios with various network designs and pre-processing, were investigated. As part of a multimodal approach to person recognition is employed a deep CNN to examine the face and torso.

In further investigation of face recognition, rotated the cheeks, lips, eyes, and nose in addition to employing a Feature extraction and processing using CNN prior to SVM classification. Looking at partial face analysis. identification by matching the local key points with the Gabor ternary patterns utilizing a mixture of robust points. In several studies, CNNs have been used to create face representations and extract complementary facial information from the deep neural network's layers, producing impressively accurate results [16] .

Additionally, a previous study information of facial recognition by analysing skull-objects in various locations. In cases involving missing persons, forensic experts use skulls and bones to rebuild a person's face and determine their sex. Discovering craniofacial superimposition can yield exact identification and forensic proof of a living person's sex.. We can also learn about the food we eat from the structure of our teeth. Skeletal residue serves as the basis for craniofacial superimposition and may produce forensic artifacts prior to identification. Professionals therefore employ the aforementioned techniques for applying the skull overlay [17].

The methodology of digital forensic anthropology is founded on a distinct computational approach Bewes et al.[18] employed NN to infer sex from human skulls [19]. Furthermore, Walker [20] developed an algorithmic categorization technique. The majority of the aforementioned research demonstrate that automatic face recognition mostly concentrates on evaluating data from live individuals, whether they be digital camera or CT images [19], even if facial recognition and computational forensics require physical characteristics. Even though anthropology has investigated gender identification, it appears that there aren't many automated computer systems with powerful facial recognition skills [21]. Therefore, our study promotes the creation of an automated tool by integrating expertise in robust characteristics with machine learning. Transfer learning(TL)approaches [22] and modified deep learning techniques(DLT) [23] can be used to improve this Skull categorization procedure[24] .

3. Method

The approach used in this study adheres to a number of crucial steps meant to effectively categorize skulls using digital forensics methods. Skull photos are first obtained from physical anthropology collections and subsequently preprocessed to enhance their quality. This entails using median filters to minimize noise and shrinking the photos to a consistent 256x256 pixel size. Following A CNN model is created as part of the pre-processing procedure to classify skulls according to their morphological traits. A number of convolutional and pooling layers are incorporated into the CNN architecture in order to extract significant characteristics from the images. On the training dataset, data augmentation methods like rotation, flipping, and scaling are applied to improve the model's dependability and avoid overfitting. Stochastic gradient descent with momentum (SGDM) is used for training, and the model is optimized across 100 epochs at a learning rate-LR of 0.001. A validation dataset-VD is used to assess the system's performance, with an emphasis on measures like F1 score, recall, accuracy, and precision. These findings support the efficacy of the suggested methodology shown in Figure 1. show that it has the potential to greatly improve skull classification in physical anthropology as well as simplify the administration and examination of anthropological collections.

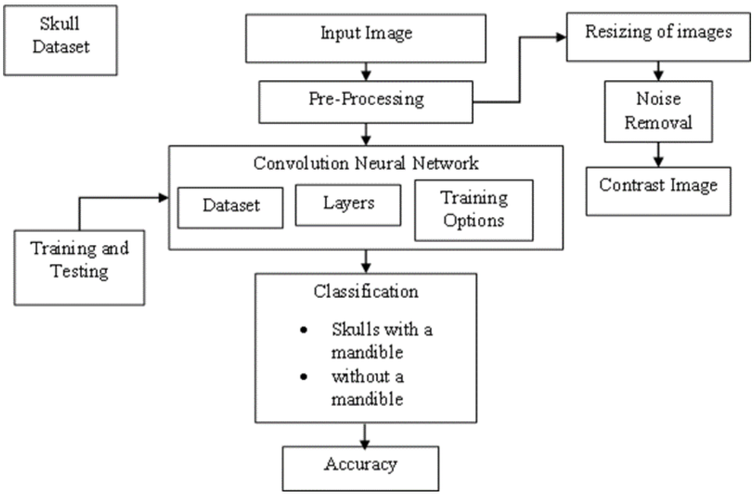

Figure 1: Block diagram of Proposed Method

3.1 Load DATA: Human skulls were grouped in this study according to their mandibles. as illustrated by photos of skulls, for instance The distinct features of the samples (not just skulls with mandibles, but also skulls without one) in Figures 2.a and 2.b were verified and contrasted. In order to produce unbiased research findings, we took into account 24 skulls.Twenty-four skulls without mandibles and twenty-four skulls with mandibles serve as the basis for our classification target classes. The samples were then photographed with the aforementioned digital camera. The skulls were from Airlangga University's Physical Anthropology Laboratory. You can access the original skull photos at http://fisip.unair.ac.id/researchdata/Skulls/.

Skulls were first digitalized by using a digital camera to take pictures of them from different perspectives. This could lead to pictures of the face or the front, left, right, bottom, and top regions. After that, the results were photographed and stored as digital picture files. An image sample's region of interest (ROI) is shown in Figures 2.a and 2.b. A group of pixels in this figure refers to the skull region, and (i,j) indicates a spatial location index in the image.

Figure 2.a: Skull with Mandible

Figure 2.b: Skull without mandilble

3.2 Image Preprocessing Techniques : Image Preprocessing techniques include the following techniques which helps in extracting the important features for enhancing the classification process. Image Acquisition: High-resolution skull images in common file types like PNG, JPEG, or TIFF can be imported. Large dataset processing can be streamlined with support for batch uploads. Image Resizing: Use Python's imresize function to standardize image dimensions to 256x256 pixels. Make sure the resizing process avoids distortion or artifacts while maintaining important visual elements. Reduce noise by using filters like the median filter for salt-and-pepper noise. Gaussian filter for edge preservation and smoothing. Adaptive noise reduction using the Wiener filter. the capacity to manage different datasets noise levels. Image Enhancement: To make important details more visible, use Python's imadjust function to increase contrast. To standardize orientation and eliminate extraneous sections, rotate, flip, or crop photos.

a. Image Resize

In image analysis, resizing images is an essential preprocessing step, especially for applications like feature extraction and machine learning. The imresize function in Python allows you to change an image's size while maintaining important visual elements. Several interpolation techniques, such as nearest-neighbor, bilinear, and bicubic, are supported by this function and dictate how pixel values are updated during scaling. Bilinear and bicubic techniques give smoother results than nearest-neighbor interpolation, which is computationally efficient but may result in blocky artifacts. For classification tasks in particular, consistent resizing guarantees consistent input dimensions across datasets. Python's powerful scaling capabilities preserve the original images' key features and quality, effectively preparing them for further analysis.

b. Noise Removal

By removing undesired distortions brought on by external influences or imaging settings, noise removal is an essential step in enhancing image quality. Analysis and understanding may be hampered by noise, which appears as erratic changes in color or brightness. Gaussian, salt-and-pepper, and speckle noise are examples of common noise types. Pythin offers a variety of noise reduction techniques, including Gaussian filtering, which smoothes images while maintaining edges, and median filtering, which successfully handles salt-and-pepper noise. Adaptive filters, such as Wiener filters, balance noise reduction and detail retention by taking into account local image variance. These methods provide images that are sharper and more accurate, which improves the dependability of later processes like feature extraction and classification. Image processing performance is greatly improved by noise removal as shown in Figure 3.a.

c. Image enhancement and augmentation - In Python image processing, improving picture contrast is a basic operation that is frequently accomplished with the imadjust function. This utility enhances the visual quality of an image by remapping pixel intensity values to a new range. A more balanced and aesthetically pleasing image is produced by brightening low-intensity pixels and stretching or compressing high-intensity pixels. The function enables gamma correction for non-linear changes and permits configurable input and output intensity ranges. This is especially helpful for repairing photos that have low contrast because to bad lighting or deterioration over time. Applications include photographs with uneven illumination, satellite imagery, and medical imaging. Sharper and more detailed images are produced by imadjust, which accentuates important features and improves visibility by redistributing pixel values to make the most of the available intensity range as shown in Figure 3.b. Image augmentation technique helps in creating the images in different angles 45^0, 90^0, -

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45^0, -90^0, front and back as shown in the Figure 3.c.

Figure 3.a: Noise removal

Figure 3.b: Restored Image

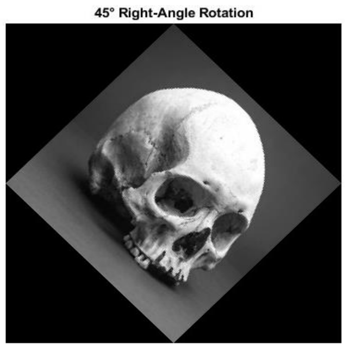

Figure 3.c: Augmented Image

3.3 Convolution Neural Network :

In the discipline of deep learning, convolutional neural networks, or CNNs, are essential, particularly when processing visual data. They use layers to gradually extract and learn hierarchical patterns from raw pixel data, simulating the organization of the human visual brain. CNNs are incredibly efficient at tasks like object detection, picture classification, and segmentation because of these features, which range from edges and textures to complicated structures.

The Deep Learning Toolbox, which offers pre-defined layers, data augmentation tools, and visualization features, makes it easy to create CNNs in Python. Python's environment is quite flexible for researchers and practitioners alike, supporting preprocessing, augmentation, and real-time monitoring. CNNs are essential to the development of autonomous systems to medical diagnostics. The intricacy of the application and the dataset can affect a CNN's design. While more complicated designs with many layers are required for huge, complex datasets, simpler networks with a few convolutional layers may be adequate for grayscale images or smaller datasets. Regression models need a regression layer, but a softmax layer and a classification layer are used in networks intended for classification.

a. Image Input Layer:

A neural network's image input layer is where picture data enters the system. This layer in python is essential for getting input photos of different sizes and formats ready for training. It guarantees compatibility with the network's structure and makes it easier to consume augmented datasets. Additionally, this layer supports preprocessing processes, which improves how well later layers learn important information. It is essential for creating python-based deep learning models due to its adaptability and integration features, which greatly streamline the management of various datasets.

b. Convolutional Layer

The important layer of a CNN is the Convolutional Layer, which extracts localized features from 2D input data by applying sliding filters. Every filter is a collection of weights that travels across the input image. A bias term is then added when a convolution operation is completed by computing the dot product between the filter weights and the relevant input region. The network can identify crucial patterns like edges, textures, and spatial relationships thanks to this mechanism.

Filters and stride - The size of the area in the input image that is being analyzed is defined by filters. The step size that the filter uses to traverse across the image both vertically and horizontally is referred to as stride. While greater strides give faster processing at the expense of granularity, smaller strides allow for overlapping regions, capturing finer data. The resolution and richness of the feature maps produced are determined by the parameters of the Convolutional Layer, such as the stride, number of filters, and filter size. The following layers, which gradually hone and interpret the retrieved features for classification or other tasks, are built upon these maps. The step size at which the filter traverses the input is referred to as the stride. The size of the steps the filter takes while navigating the input is known as the stride. The local regions to which the neurons are linked may overlap as a result of specific stride values and filter sizes.

Feature maps - As the filter runs over the input, it applies the identical set of weights and bias to each convolution, resulting in a feature map. Each feature map represents the result of a convolution with a distinct set of weights and a different bias. A convolutional layer's total number of parameters is determined by (h∗w∗c+1), where the bias term is 1. The filter height is denoted by h, the width by w, and the number of channels by c.

Padding - Both vertical and horizontal padding of the input image's borders can be applied using the 'Padding' name-value pair option. In order to enhance the input's dimensions, padding inserts additional values around it. The size of the output that the layer produces can be controlled by varying the amount of padding. The input in the sample image is scanned by a 3x3 filter with size 1 padding. The upper map displays the result, and the lower map displays the input.

c. Batch Normalization Layer - These layers are often placed between nonlinear layers such as ReLU and Convolutional layers. The input is shifted by a learnable offset β\betaβ and scaled by a learnable scale factor, both of which are changed during training. Batch normalization helps with optimization by normalizing activations and gradients during training. Higher learning rates, quicker convergence, and a decreased requirement for regularization techniques like L2 or dropout may result from this. To fully benefit from the regularizing effect of batch normalization, it is advised to shuffle the training data prior to each epoch for best results.

d. ReLU Layer - A ReLU (Rectified Linear Unit) layer applies a threshold operation to each input element, setting all negative values to zero. To add nonlinearity, a ReLU layer is usually added after a convolutional or batch normalizing layer. The ReLU layer improves the model's capacity to recognize intricate patterns by guaranteeing that every input value that is less than 0 is assigned to 0.

$$f(x) = \begin{cases} x, & x \geq 0 \\ 0, & x < 0 \end{cases} \tag{1}$$

The ReLU layer does not alter the input's size. Positive numbers remain constant while any input value below zero is set to zero when it performs a threshold action.

e. Softmax Layer - A softmax layer applies a softmax function to the input. To construct a softmax layer, use SoftMax Layer. A classification layer computes the cross-entropy loss for classification and weighted classification problems with mutually exclusive classes. To create a classification layer, use classificationLayer. For classification tasks, a softmax layer and a classification layer usually come after the last fully linked layer. The output unit's activation function is the softmax function:

$$y_r(x) = \frac{e^{a_r(x)}}{\sum_{j=1}^{k} e^{a_j(x)}} \quad (2)$$

The activation function in output unit that comes at last is completely linked layer in multi-class classification scenarios is referred to as the softmax function.

f. Fully Connected Layer - A fully connected layer multiplies the input by a weight matrix and then adds a bias vector. The convolutional (and down-sampling) layers are followed by one or more fully linked layers. The last fully linked layer incorporates the attributes to classify the images. This explains why the output Size argument of the network's last fully linked layer equals the number of classes in the data set. Additionally, you may modify the regularization parameters and learning rate for the fully connected layer by using the corresponding name-value pair arguments when creating it. If you choose not to change the global training parameters, trainNetwork uses the ones that are supplied by the training Options function. for more on global and layer training options.

3.4 Experimentation

As previously mentioned, we looked at two distinct digital pictures of skulls: one with mandibles and one without. We first used each feature extraction filter separately in order to have a thorough grasp of the factors influencing the trial results. After that, all of the feature extraction filters were combined. The steps in using CNN for classification can be seen below:

Step1. Preparing the Data: First, a dataset of pictures of skulls with and without mandibles must be created. To make sure the photos are in a format that works with the model, they are pre-processed and given the appropriate labels. This entails normalizing pixel values for consistent input and scaling all photos to a given dimension. The pre-processing techniques used are Image Noise removal, Image restoration and Image Augmentation.
Step2. Design of the CNN Model: A CNN model is made to automatically extract features from pictures. Several convolutional layers and pooling layers, which lower the spatial dimensions while preserving crucial information, are commonly included in the architecture. The edges, forms, and textures of the skull and mandible regions are captured by these layers. Following feature extraction, the model classifies the images as either "with mandible" or "without mandible" using fully connected layers. The features extracted are GLCM features, Wavelet feature, Gabor features and Fractal Features.

Step3. Training: Using optimizers such as Adam, the CNN is trained on a labelled dataset with binary cross-entropy loss. To make the model more robust, data augmentation methods like flipping and rotation are applied.
Step4. Evaluation: After training, the model's ability to classify skulls is evaluated on a validation set using metrics like as recall, accuracy, and precision. By using this method, CNNs can efficiently categorize photos of skulls according to whether the mandible is present or not.

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4. Results and Discussions

Accuracy of the CNN model is calculated using below equation. The sum of true negative-TN and True positive-TP, classification ratio to the total instants.

$$\text{Accuracy} = \frac{True_{positives} + True_{negatives}}{True_{positives} + False_{positives} + True_{neagtives} + False_{negatives}} \tag{2}$$

Accuracy is evaluated for testing data using SVM algorithm and CNN algorithm and also for different number of test images. And its different instances are discussed below. The confusion matrix(CM) for classification of skulls with and without mandibles using SVM is given in Figure.4 with an accuracy-0.8333. The CM for classification of skulls with and without mandibles using SVM is given in Figure.5 with an accuracy-0.1

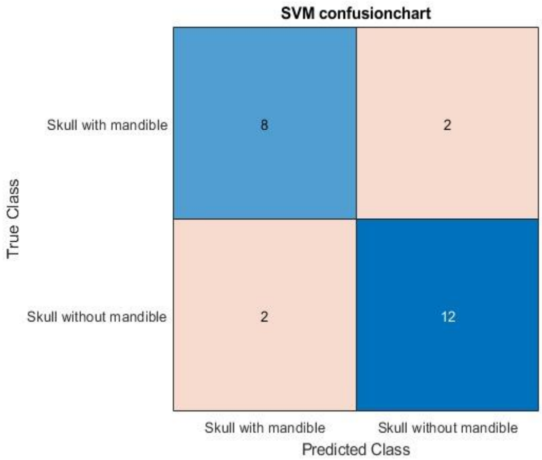

Figure 4. CM for SVM.

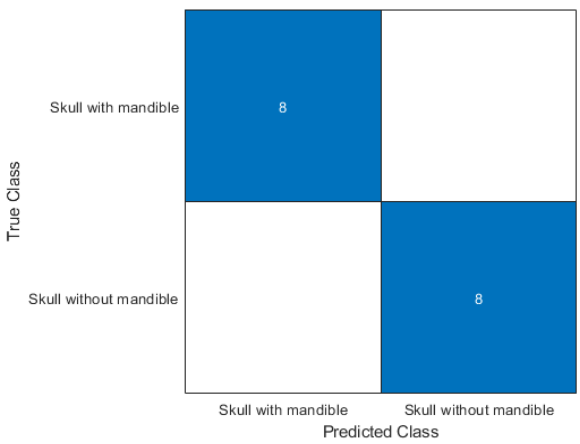

Figure 5. CM for CNN.

The Accuracy and Loss plot for classification of skulls with and without mandibles using CNN is given in Fig.6 with an accuracy-0.1 and loss -0.0 for 100 epochs on Testing data

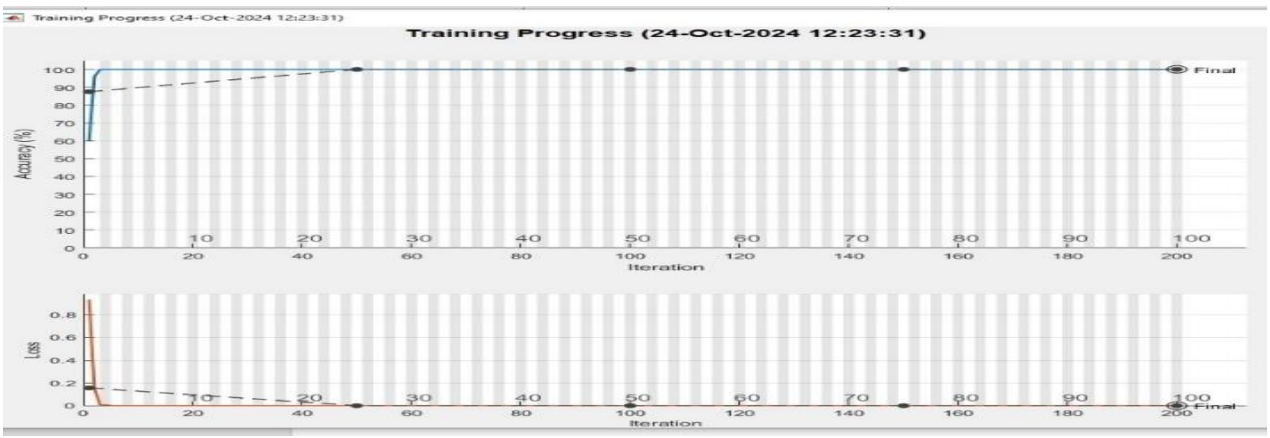

Figure 6. Accuracy and Loss Plot for Testing data

The performance of proposed model with its objective, method approached and accuracy rate is compared with previous existing works and it is detailed in the table, Table.1

Table.1. Comparison with the previous works:

Previous work	**Objective**	**Method approached**	**Accuracy %**
[3]	Live human face[LHF]	PCA(Principle Component Analysis)	97.60
[4]	LHF	Dual-tree complex wavelet transform(DT-CWT)	94.67
[5]	LHF	PCA, PSO(Practical swarm optimization) –SVM	98.0
[7]	LHF	Euclidean Gaussian mixture-EGM	97.04
[8]	LHF	CNN	98.43
[6]	Dead Human Skull	SVM & CNN	83.33 & 99.50
Our Research	Dead Human Skull	CNN with 4 specific Features	99.98

The accuracy of predictions is influenced by the quantity of training and testing data. For instance, we achieved an accuracy rate of 83.33% using the GLCM filter using just one training data item. On testing data, however, the accuracy rate was 99.98% when we employed 100 epochs. Therefore, a higher accuracy will be obtained with more used training data. Accuracy rate for when 1,2,3,4 & 5 number of images used for testing is detailed in Table.2. and visualized in Figure.7.

Table.2. SVM vs CNN accuracy rate for

No. of Images	**1**	**2**	**3**	**4**	**5**
SVM	83.33	83.33	83.33	83.33	83.33
CNN	99.68	99.98	99.72	99.98	99.01

different number of test images

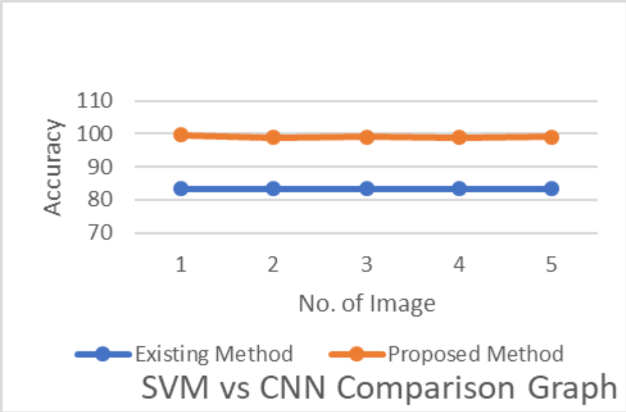

Figure.7. Accuracy rate SVM (Blue) and CNN (Red).

5. Conclusion

Using feature extraction in conjunction with a CNN, we created an automated computerized digital forensics method for identifying human skulls. We classified human skulls with and without mandibles using a digital forensics framework. Four distinct feature extraction filters were examined, and the results showed varying classification accuracies. Using Gabor and fractal feature-derived characteristics, GCLM obtained the highest accuracy (>99.98%). Conversely, DWT characteristics produced identification prediction accuracies of less than 99.72%. For skulls with and without mandibles as accuracy of >99.98%. As a result, each human skull has distinct characteristics that can be utilized to identify it in forensic applications, particularly in the management of physical anthropological collections.

Future study on skull identification can go in a number of areas. Future studies must refine the combined feature extraction and classification approach and explore other feature extraction and classification strategies for performance comparisons. The primary goal of such future studies may be to use more skull data while applying the transfer learning approach. Additionally, figuring out the age and gender of the Human-skulls will be very helpful to researchers in identifying people who vanished as a result of natural catastrophes or who were the targets of criminal activity.

Refrences

[1] M. Pollitt, M. Caloyannides, J. Novotny, and S. Shenoi, “Digital Forensics: Operational, Legal and Research Issues,” 2004, pp. 393–403. doi: 10.1007/1-4020-8070-0_28.

[2] J. Wei, Z. Jian-qi, and Z. Xiang, “Face recognition method based on support vector machine and particle swarm optimization,” *Expert Syst Appl*, vol. 38, no. 4, pp. 4390–4393, Apr. 2011, doi: 10.1016/j.eswa.2010.09.108.

[3] G. Benitez-Garcia, J. Olivares-Mercado, G. Sanchez-Perez, M. Nakano-Miyatake, and H. Perez-Meana, “A sub-block-based eigenphases algorithm with optimum sub-block size,” *Knowl Based Syst*, vol. 37, pp. 415–426, Jan. 2013, doi: 10.1016/j.knosys.2012.08.023.

[4] H. Hu, “Variable lighting face recognition using discrete wavelet transform,” *Pattern Recognit Lett*, vol. 32, no. 13, pp. 1526–1534, Oct. 2011, doi: 10.1016/j.patrec.2011.06.009.

[5] K. Gautam, N. Quadri, A. Pareek, and S. S. Choudhary, "A Face Recognition System Based on Back Propagation Neural Network Using Haar Wavelet Transform and Morphology," 2014, pp. 87–94. doi: 10.1007/978-81-322-1817-3_10.

[6] I. Yuadi, M. D. Artaria, Sakina, and A. Taufiq Asyhari, "Digital Forensics for Skulls Classification in Physical Anthropology Collection Management," *Computers, Materials & Continua*, vol. 68, no. 3, pp. 3979–3995, 2021, doi: 10.32604/cmc.2021.015417.

[7] J. Olivares-Mercado, K. Toscano-Medina, G. Sánchez-Pérez, M. Nakano-Miyatake, and H. Pérez-Meana, "Modifications to the Eigenphases Method for Face Recognition Based on SVM," *Ingeniería, Investigación y Tecnología*, vol. 17, no. 1, pp. 119–129, Jan. 2016, doi: 10.1016/j.riit.2016.01.011.

[8] C. Ding and D. Tao, "Robust Face Recognition via Multimodal Deep Face Representation," *IEEE Trans Multimedia*, vol. 17, no. 11, pp. 2049–2058, Nov. 2015, doi: 10.1109/TMM.2015.2477042.

[9] A. Kuha, J. Ackermann, J.-A. Junno, A. Oettlé, and P. Oura, "Deep learning in sex estimation from photographed human mandible using the Human Osteological Research Collection," *Leg Med*, vol. 70, p. 102476, Sep. 2024, doi: 10.1016/j.legalmed.2024.102476.

[10] S. Shahshikiran, N. Srinivas Babu, S. Pramanik, and Sathwik, "A Modified Deep Learning Architecture for Detecting MalariaInfected Cells," in *2024 International Conference on Knowledge Engineering and Communication Systems, ICKECS 2024*, Institute of Electrical and Electronics Engineers Inc., 2024. doi: 10.1109/ICKECS61492.2024.10617005.

[11] D. Chen, Z. Yuan, B. Chen, and N. Zheng, "Similarity Learning with Spatial Constraints for Person Re-identification," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, IEEE, Jun. 2016, pp. 1268–1277. doi: 10.1109/CVPR.2016.142.

[12] S. S. and S. H. D., "Malaria cell identification using improved machine learning and modified deep learning architecture," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 34, no. 3, p. 2078, Jun. 2024, doi: 10.11591/ijeecs.v34.i3.pp2078-2086.

[13] Y. Duan, J. Lu, J. Feng, and J. Zhou, "Topology Preserving Structural Matching for Automatic Partial Face Recognition," *IEEE Transactions on Information Forensics and Security*, vol. 13, no. 7, pp. 1823–1837, Jul. 2018, doi: 10.1109/TIFS.2018.2804919.

[14] A. Elmahmudi and H. Ugail, "Deep face recognition using imperfect facial data," *Future Generation Computer Systems*, vol. 99, pp. 213–225, Oct. 2019, doi: 10.1016/j.future.2019.04.025.

[15] H.-Q. Nguyen, T.-N. Nguyen, V.-D. Tran, and T.-T. Dao, "A Deep Learning Approach for Predicting Subject-Specific Human Skull Shape from Head Toward a Decision Support System for Home-Based Facial Rehabilitation," *IRBM*, vol. 44, no. 1, p. 100724, Feb. 2023, doi: 10.1016/j.irbm.2022.05.005.

[16] Md. A. Uddin *et al.*, “Deep learning-based human activity recognition using CNN, ConvLSTM, and LRCN,” *International Journal of Cognitive Computing in Engineering*, vol. 5, pp. 259–268, 2024, doi: 10.1016/j.ijcce.2024.06.004.

[17] B. R. Campomanes-Álvarez *et al.*, “Computer vision and soft computing for automatic skull–face overlay in craniofacial superimposition,” *Forensic Sci Int*, vol. 245, pp. 77–86, Dec. 2014, doi: 10.1016/j.forsciint.2014.10.009.

[18] J. Bewes, A. Low, A. Morphett, F. D. Pate, and M. Henneberg, “Artificial intelligence for sex determination of skeletal remains: Application of a deep learning artificial neural network to human skulls,” *J Forensic Leg Med*, vol. 62, pp. 40–43, Feb. 2019, doi: 10.1016/j.jflm.2019.01.004.

[19] M. Nijiati *et al.*, “Deep learning on longitudinal CT scans: automated prediction of treatment outcomes in hospitalized tuberculosis patients,” *iScience*, vol. 26, no. 11, p. 108326, Nov. 2023, doi: 10.1016/j.isci.2023.108326.

[20] P. L. Walker, “Sexing skulls using discriminant function analysis of visually assessed traits,” *Am J Phys Anthropol*, vol. 136, no. 1, pp. 39–50, May 2008, doi: 10.1002/ajpa.20776.

[21] Z. Wu, Y. Huang, L. Wang, X. Wang, and T. Tan, “A Comprehensive Study on Cross-View Gait Based Human Identification with Deep CNNs,” *IEEE Trans Pattern Anal Mach Intell*, vol. 39, no. 2, pp. 209–226, Feb. 2017, doi: 10.1109/TPAMI.2016.2545669.

[22] J. Yang, Y. Xu, H. Cao, H. Zou, and L. Xie, “Deep learning and transfer learning for device-free human activity recognition: A survey,” *Journal of Automation and Intelligence*, vol. 1, no. 1, p. 100007, Dec. 2022, doi: 10.1016/j.jai.2022.100007.

[23] A. De Rosa *et al.*, “Deep learning algorithms for the recognition of human movements in work activities,” *Gait Posture*, vol. 114, pp. S20–S21, Oct. 2024, doi: 10.1016/j.gaitpost.2024.08.040.

[24] J. Heimer, M. J. Thali, and L. Ebert, “Classification based on the presence of skull fractures on curved maximum intensity skull projections by means of deep learning,” *Journal of Forensic Radiology and Imaging*, vol. 14, pp. 16–20, Sep. 2018, doi: 10.1016/j.jofri.2018.08.001.