

Human Identification Using Hand Radiography

Prof. Arti Tekade
Department of E&Tc,
Pimpri Chinchwad College of
Engineering and Research, Ravet,
Pune, India.
arti.tekade@pccoer.in

Aditya M Deshmukh
Department of E&Tc,
Pimpri Chinchwad College of
Engineering and Research, Ravet,
Pune, India.
aditya.deshmukh_etc2020@pccoer.in

Kountey Wadje
Department of E&Tc,
Pimpri Chinchwad College of
Engineering and Research, Ravet,
Pune, India.
kountey.wadje_etc2020@pccoer.in

Mustafa Baldiwala
Department of E&Tc,
Pimpri Chinchwad College of
Engineering and Research, Ravet,
Pune, India.
mustafa.baldiwala_etc2020@pccoer.in

Prof. Maithili Andhare
Department of E&Tc,
Pimpri Chinchwad College of
Engineering and Research, Ravet,
Pune, India.
maithili.andhare@pccoer.in

Prof. Vijayalakshmi Kumbhar
Department of E&Tc,
Pimpri Chinchwad College of
Engineering and Research, Ravet,
Pune, India.
vijayalakshmi.kumbhar@pccoer.in

Abstract

Biometric radiographs have gained increasing significance in recent times due to the surge in crime and disaster incidents. Presently, authenticating and identifying individuals has become a fundamental component of most computer vision automation systems. Traditional biometric methods such as fingerprints, iris scans, facial recognition, and palm prints fall short when it comes to recognizing individuals whose external biometric features have been compromised due to conditions like rashes, injuries, or severe burns. Ensuring security, robustness, privacy, and resistance to forgery are pivotal aspects of any person authentication system. In such challenging scenarios, utilizing radiographs of the skull, hand, and teeth emerges as effective alternatives. The below research introduces an innovative approach for human authentication based on forensic hand radiographs, employing a deep neural network. The feature extraction from hand radiographs and subsequent recognition tasks are executed through a three-layered convolutional deep neural network architecture. In our experimentation, we analyzed a dataset comprising hand radiographs obtained from subjects of varying age groups, professions, and genders. The algorithm's performance is rigorously assessed through cross-validation accuracy, wherein we systematically vary parameters such as striding pixels, pooling window size, kernel size, and the number of filters. Our experiments unveil the presence of biometric information within hand radiographs, enabling the identification of individuals, particularly in the context of disaster victim identification.

Keywords: Hand Radiography, Human Identification, CNN, Deep Learning, Human X-Rays, Radiography.

I. INTRODUCTION

The fusion of deep learning and hand radiographs presents a highly promising solution in the current era, where accurate and secure identification is of utmost importance across various domains. Through the utilization of deep neural networks, this innovative approach enables the analysis of hand radiographs, generating distinct

representations of individuals' hand structures. These representations serve as reliable biometric markers, finding practical applications in fields such as forensic science, medical diagnostics, and security, including the identification of disaster victims. This project delves into a comprehensive exploration and application of hand radiography as a robust method for identifying individuals in forensic contexts. By capitalizing on the unique structure of the hand, this study aims to unveil the potential of radiographic imaging in establishing dependable biometric markers for human identification. In the face of natural calamities such as tsunamis, earthquakes, and fatal accidents, the biometric features of individuals often suffer damage, posing a significant challenge in identifying them. However, Forensic Radiography emerges as a critical component of forensic medicine, aiding in the identification process. By utilizing post-mortem radiographic (X-ray) images of various body parts, such as the hand, skull, and teeth, Forensic Radiography plays a vital role in determining the identity of individuals. These radiographic images, obtained both before and after death, are referred to as antemortem (AM) and postmortem (PM) radiographs [7], respectively. Typically, postmortem radiographs are compared with stored antemortem radiographs in a database to establish human identification. To achieve this, patient data is stored in a database, and deep learning algorithms are employed to identify the individual.

Radiographic images, commonly referred to as x-rays, possess sufficient energy to liberate securely bonded electrons from atoms, so forming ions. Because of their ability to pass through soft tissues and be absorbed by harder materials like bones, X-rays are important in medical imaging. This allows for the generation of detailed pictures.

Medical imaging tests called hand radiographs, also known as hand X-rays, are utilized to analyze the bones and structures of the hand. These tests are frequently conducted to identify fractures, dislocations, arthritis, infections, and various other ailments that impact the bones and joints of the hand. The process of identifying individuals through hand radiographs



heavily relies on the analysis of bone structure. By comparing radiographs and examining the distinct bone structures of different individuals, identification can be achieved. This principle is exemplified in [2], where various algorithms were utilized to incorporate bone structures for identification purposes. Additionally, [3][7] explores the estimation of a person's age using different methodologies that involve the examination of bone structures.

Joint Spaces: Identifying a human based on joint spaces involves assessing the spaces between bones in various joints, such as the knees, elbows, or wrists. Everyone has unique joint space characteristics that can be analyzed for identification purposes. Radiographic imaging, such as X-rays, can be used to visualize these joint spaces and compare them between individuals. By examining the size, shape, and alignment of joint spaces, along with any abnormalities or pathologies present, experts can potentially distinguish one person from another. This method is particularly useful in forensic or medical contexts for identifying individuals based on their skeletal features [4].

Identification using Dental Radiographs:

The identification of humans using dental radiographs involves the analysis of dental structures, such as teeth, and surrounding bone, to establish individual characteristics. Various algorithms and techniques are employed in this process to aid in accurate identification [6]. These algorithms typically focus on features such as the shape, size, alignment, and unique characteristics of teeth and their associated structures.

Various studies use different methodologies like CNN using deep learning techniques [7], Selective Binary Gaussian Filtering Regularized Level Set (SBGFRLS) [3] used for human identification using teeth. Laplacian Pyramid Decomposition Technique [1].

II. LITERATURE SURVEY

1. Bhat, Anil K., Bhaskar Anand Kumar, and Ashwath Acharya (2011) – Analyzed the role that imaging techniques in knowing the anatomy and pathology of the wrist, A methodical search approach was applied to several databases, including Scopus, MD Consult, Web of Knowledge, PubMed, Ovid Medline, and the Cochrane Library, covering the years 1990 to 2011. Furthermore, a manual search was conducted on the print journals, books, and secondary research materials found in the major article references of the Manipal University Library. Articles about ancillary viewpoints, dynamic studies, and conventional wrist radiography were all included in the inclusion criteria. Both full articles and abstracts were accepted. The information collected was critically reviewed and analyzed to differentiate the role of different imaging modalities in detecting static and dynamic wrist pathologies, thereby forming the basis for investigations.
2. Y Kabbara, A Shahin (2013) – offered a method for detecting hand radiographs, implemented a recognition mechanism based on the k-nearest neighbor (k-NN) method. This approach facilitates the combination of extracted features with our database, which was gathered from 16 adults (32 in total), allowing identification of individuals by identifying nearest neighbors in the feature space through similar measures. The algorithm involves dividing the dataset into training and testing subsets to evaluate its performance. A variety of performance metrics were used, including recognition rate, accuracy, precision, recall, and F1 score. Notably, the specific conditions lead to a 100. Our testing process includes rigorous validation steps to ensure the robustness and reliability of the algorithm. This involves parameter tuning to optimize performance and generalization under different conditions.
3. Frejlichowski, Dariusz, and Robert Wanat. (2013) – presents a method for applying the Laplacian Pyramid Decomposition methodology to improve digital dental radiography pictures, especially pan tomograms. It is well-known for its effectiveness in enhancing other radiographic pictures, such as CT scans and mammograms. The paper explains the effects of both uniform and non-uniform Laplacian pyramid augmentation techniques on important image characteristics, including dental fillings and tooth shapes. Results show how well this technique works to improve image contrast, edge sharpness, and the capacity to identify various dental structures within the radiographs.
4. Pushparaj, V., Gurunathan, U., & Arumugam, B. (2013) - presented a system that uses dental pictures in forensic contexts, for victim identification. The technique uses skeleton representation for shape matching and contour tracing with the SBGFRLS approach for shape extraction. Through the combination of contour-based and skeleton-based methods, the algorithm improves the precision of using dental features to identify people.
5. Pushparaj, V., Gurunathan, U., & Arumugam, B. (2013) – explains Laplacian Pyramid Decomposition technique to enhance digital dental radiographic images for automatic person identification. This technique decomposes the original image into layers, allowing for specific enhancements to be applied to different layers independently. Various contrast equalization and enhancement functions are utilized to improve the visibility of dental fillings, teeth shapes, and trabecular structures in the images. The results show promising improvements in image quality, particularly in regions critical for identification purposes.
6. Iglovikov, Vladimir I., Alexander Rakhlin, Alexandr A. Kalinin, and Alexey A. Shvets. (2018) – presented an analysis by collecting the 2017 Pediatric Bone Age Challenge dataset, which includes 12,600 labeled left-sided X-ray images. Several deep neural network architectures have been selected for application in regression and image analysis tasks. To minimize overfitting, rigorous validation techniques, including cross-validation, were applied during model training. Techniques such as activation maximization and attention mechanisms have been used to elucidate the importance of individual hand bones in automated bone age assessment. Standard regression evaluation metrics such as mean absolute error and root mean square error are utilized to quantify model performance. It provided a comprehensive understanding of its applicability. The results obtained.



through this method include both quantitative and qualitative analysis. Quantitatively, the deep learning method shows superior performance compared to conventional methods.

7. Koitka, Sven, Aydin Demircioglu, Moon S. Kim, Christoph M. Friedrich, and Felix Nensa.(2018) – explored fine-tuning of a pre-trained Faster R-CNN network for detecting ossification zones in children's hand radiographs using COCO dataset. By using 240 annotated radiographs from the RSNA Pediatric Bone Age Challenge dataset, which consists of includes more than 14,000 pediatric radiographs for refinement. Validation on a separate dataset showed impressive results, with the refined model outperforming one trained from scratch. Comparison with expert annotation revealed high accuracy in identifying ossification areas, with an average F1 score of 91, demonstrating the effectiveness of this approach with a relatively small dataset of 240 radiographs.

8. Joshi, Sagar V. (2020) – offered a method consisting of dataset comprising 750 hand radiographs from 150 subjects across various age groups, professions, and genders. The model development phase involves crafting a three-layered convolutional neural network (CNN) for feature extraction from hand radiographs, coupled with extensive hyperparameter tuning. Integration of K-Nearest Neighbors (KNN) and Support Vector Machines (SVM) classifiers enables recognition based on CNN-extracted features. The experimentation involves splitting the dataset for training, validation, and testing, employing cross-validation to gauge accuracy, sensitivity, and specificity. The results are evaluated by comparing the proposed method with conventional biometric methods, highlighting its effectiveness in identifying disaster victims.

9. Heinrich Andreas. (2020) – presented a method which used antemortem and postmortem dental records, focusing on the collection of standard orthophotographs. Experienced dental professionals carefully analyzed these records, comparing tooth samples and dividing the data by age groups to explore. correlations. Statistical analyzes including descriptive statistics, correlation assessment, and reliability measures were applied to interpret the results.

10. Omprakash, N., Radhakrishnan, K., Manesh, M., & Suganya, T. (2021) -Proposed a new method combining deep neural network architecture with fuzzy clustering for forensic radiography-based authentication. The researchers designed a complex convolutional neural network (CNN) to automatically extract features from hand X-rays. Later, adjusted the network weights using the dataset to minimize the difference between the predicted positive label and the actual positive label. Experimental results demonstrate that hand X-rays, when processed by the proposed deep neural network with fuzzy clustering, provide valuable fingerprint information for individual identification.

11. Moniga, B., D. Nandika, P. S. Monica, and V. Roopa. (2021) – investigated the use of biometric X-rays for forensic human authentication. It used a complex convolutional neural network (CNN) architecture. This

deep learning method makes it possible to automatically distinguish hierarchical patterns in X-ray images of the hand. Additionally, a new aspect of fuzzy clustering has been introduced to identify smooth clusters in images, providing an additional layer of detail for the validation process. Then, the validation process itself involves exploiting the features extracted by the CNN and the results of fuzzy clustering. The method was subjected to rigorous testing, evaluating its performance parameters such as accuracy, precision, and recall.

12. Ozdemir, C., Gedik, M.A. and Kaya, Y., (2021) - presents a novel deep learning approach for estimating bone age from wrist radiographs. It introduces a modified InceptionV3 model and evaluates its performance on two datasets, including one created by the researchers. The study aims to improve the accuracy and efficiency of age determination in medical and legal settings. The results show promising outcomes, indicating the potential of deep learning models in enhancing bone age estimation processes.

III. METHODOLOGY

In the proposed methodology, a greyscale image with dimensions 256x256 pixel is given as input to the CNN architecture.

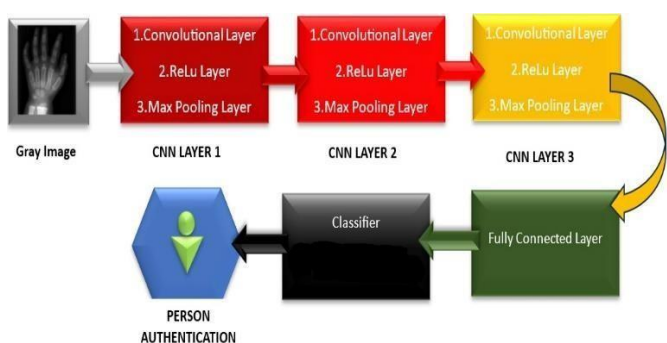


Fig1. Block Diagram of proposed methodology

The Fig1. shows a typical CNN architecture, consisting of three main layers:

Convolutional layers: These layers extract features from the input image. The first convolutional layer (CNN Layer 1) of the image takes a grayscale image of a person's hand as input and extracts low-level features such as edges and lines. The following convolutional layers (CNN Layer 2 and CNN Layer 3) extract higher-level features from the output of the previous layer.

ReLU Layer: These layers introduce non-linearity into the network. They are applied after each convolution layer.

Pooling layers: These layers reduce the dimensionality of the data by down sampling. The Image Pooling Layer (Max Pooling Layer) performs max pooling, selecting the maximum value within a subregion of the input.

The output of the convolutional layers is fed into a fully connected layer, this is a traditional artificial neuron. network layer. The fully connected layer classifies the input into

different types. In case of authenticating a person, the classifier generates a binary value indicating whether the person is authenticated or not.

Detailed description of every layer:

1. Input Layer: This is the starting point where the system receives data for authentication. In this case, the input would be an image, possibly a grayscale image of a person's hand or face.

2. Convolutional layers (e.g. CNN layer 1, CNN layer 2, CNN layer 3): These layers are the core of the CNN architecture. They perform a mathematical operation called convolution, which essentially involves pulling a filter (like a small kernel) over the image. This filter detects specific patterns or features in images. As the filter moves across the image, it creates a feature map that highlights these specific patterns.

2a. First convolutional layers (e.g. layer 1 of a CNN): Layers This typically extracts low-level features of an image, such as edges, lines, and corners. These features form the building blocks for recognizing more complex features in later layers.

2b. Later convolutional layers (e.g. CNN Layer 2, CNN Layer 3): As the network grows Over more convolutional layers, the filters become more complex and begin to identify higher-level features based on combinations of previously detected low-level features. When authenticating people, these layers can start to recognize relevant shapes for faces or hands, or patterns in fingerprints.

3. ReLU layer: These layers, placed after each layer convolution, introduce non-linearity into the network. They essentially act as a threshold, allowing only positive values to pass through. This nonlinearity helps the network learn more complex relationships between features and improve the model's ability to distinguish between different people.

4. Max Pooling layer (e.g. class max-aggregation): This layer reduces the dimensionality of the data, makes the network more computationally efficient, and helps prevent overfitting. There are many different clustering techniques, but one popular method is maximum clustering, which selects the maximum value within a predefined region of the input data. Essentially, this process samples feature maps, summarizing important features in a specific area.

5. Fully Connected Layer: After processing through layers convolution and pooling, the data will be fed into a fully connected layer. This layer is like a traditional artificial neural network layer, in which each neuron is connected to all the neurons in the previous layer. This last layer takes the features extracted from the previous layers and performs the classification task. During live authentication, the classifier generates a probability score indicating whether the input image belongs to the registered person or not.

6. The classifier: which is typically the final layer of a CNN architecture for user authentication, plays an important role in

making authentication decisions. It gets the features extracted throughout the convolutional layers. These features represent a compressed version of the original image, highlighting the most important features for distinguishing different people. The classifier uses machine learning algorithms, e.g. Support vector machine (SVM) or SoftMax regression, to analyze these features and assign class labels to the input. Direct validation leads to a binary classification problem. The classifier generates a probability score. If the score exceeds a predetermined threshold, the system will identify the person as authorized. Conversely, a score below the threshold indicates an illegal attempt. The effectiveness of the classifier depends on the quality of the features extracted by the convolutional layers. Well-trained convolutional layers ensure that the classifier gets the most relevant and discriminative features for accurate person recognition.

IV. FINDINGS FROM LITERATURE SURVEY

From the survey of various techniques of Human Identification using hand radiographs and using deep learning we found the following findings that needed to be concentrated

1. Limited Database availability.
2. Assessing the accuracy and reliability of hand radiography-based identification methods remains a crucial challenge.
3. The reliability of hand radiography-based identification over time, especially in the context of aging, is not well-understood.
4. Hand radiographs can vary significantly due to factors like hand pose, image quality, and patient positioning.

V. DISCUSSION

From the survey done on various techniques used, we found certain gaps that needed to be focused, they are mentioned below:

1. Different databases used were discussed.
2. Models used with some having different accuracies.
3. Due to more processing time, some models had more accuracy but time consuming and some had models had less accuracies depending on classifiers and algorithms used.
4. Parameters (hand, teeth) taken into consideration and which techniques are used were discussed and what are the algorithms used for parameters was discussed.
5. Data augmentation has given better results in a few studies and more discussion was done on data augmentation.
6. Discussed about what model can be used and what its parameters are capable of F1 score, precision.
7. The absence of a fully automated approach.



Sr. No.	Authors & Year	Methodology	Database	Performance
1.	Frejlichowski, Dariusz, and Robert Wanat. (2010)	Laplacian Pyramid Decomposition technique	Digital dental radiographic images	--
2.	Bhat, Anil K., Bhaskaranand Kumar, and Ashwath Acharya (2011).	--	Scopus, MD consult, Web of Knowledge, Pub Med, Ovid Medline, and Cochrane Library	--
3.	Pushparaj, V., Gurunathan, U., & Arumugam, B. (2013).	Selective Binary Gaussian Filtering Regularized Level Set (SBGFRLS)	Dental radiographs and photographs	Accuracy = 87% (Top 3-Ranking) Accuracy = 98.3% (Top 15-Ranking).
4.	Kabbara, Yeiha, et al. (2013). [6]	Phalanges segmentation, Fourier descriptors, k-nearest neighbor.	X-Ray of 16 persons.	Accuracy = 100% (on database used)
5.	Iglovikov, Vladimir I., Alexander Rakhlin, Alexandr A. Kalinin, and Alexey A. Shvets. (2018) [9]	Greulich and Pyle (GP) Method, Tanner-Whitehouse (TW) Method, Active Appearance Model (AAM),	Radiological Society of North America	Mean Absolute Error (MAE) of 4.7 months.
6.	Koitka, Sven, Aydin Demircioglu, Moon S. Kim, Christoph M. Friedrich, and Felix Nensa. (2018) [11]	Pretrained models to compare performance of expert and non-expert annotations.	COCO Dataset	--
7.	Heinrich, Andreas, et al. (2020)	Image processing, feature extraction and algorithm comparison, SURF algorithm	Jena University Hospital.	Accuracy = 100%
8.	Joshi, Sagar V., and Rajendra D. Kanphade. (2020)	KNN, SVM Classifier, Dual Cross Pattern Analysis.	Hand Radiographs.	Accuracy = 99.20%
9.	omprakash N, Radhakrishnan K, Manesh M, Suganya T. (2021)	Fuzzy k-approach, R-CNN, ANN.	--	Accuracy = 99.6%
10.	Moniga, B., D. Nandika, P. S. Monica, and V. Roopa. (2021)	CNN using Deep Learning.	--	--
11.	Ozdemir, C., Gedik, M.A. and Kaya, Y. (2021)	InceptionV3, EfficientNetB4, MobileNetV2, and a modified InceptionV3	4 different hospitals in Kütahya (KCRD), RSNA.	Mean Absolute Error = 5.75 (RSNA) MAE = 4.3 (KCRD).
12.	Pushparaj, Vijayakumari, Ulaganathan Gurunathan, and Banumathi Arumugam. (2013)	Morphological Operations, Spline Isolation.	Dental Radiographs and Images.	Accuracy = 94.4% (Radiographs) Accuracy = 98% (photographs)

IV. CONCLUSION

In addressing the imperative need for secure and efficient human identification leveraging hand radiographic images, this project embarked on the development of a comprehensive system employing Convolutional Neural Networks (CNNs) within a web-based framework. The objective was to create a robust algorithm capable of accurately identifying individuals and extracting medical records from hand radiographic images. Through multiple steps, ranging from data collection and preprocessing to model development and validation, a systematic approach was formulated. The algorithm's architecture was designed to process uploaded images via a user-friendly website interface, employing preprocessing techniques to ensure optimal model input. During model inference, CNN analyzed hand radiographic images, extracting intricate details for individual identification, and retrieving associated medical records. Outputs encompassed identified individual information, including name and unique identification, along with access to relevant medical history, fostering a holistic understanding of the subject.

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