Age and Gender Identification Of Humans Using Internal Palm Bone Structure

A Project Report

submitted by

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in partial fulfilment of requirements

for the award of the degree of

BACHELOR OF TECHNOLOGY

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DECLARATION OF ORIGINALITY

I, **B.M.Saish and C.Vishnu Teja**, with Roll No: **CS21B1084 and CS21B1025** hereby declare that the material presented in the Project Report titled **Age and Gender Identification Of Humans Using Internal Palm Bone Structure** represents original work carried out by me in the **Department of computer science** at the Indian Institute of Information Technology, Design and Manufacturing, Kancheepuram.
With my signature, I certify that:

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- I have not committed any plagiarism of intellectual property. I have clearly indicated and referenced the contributions of others.
- I have explicitly acknowledged all collaborative research and discussions.
- I have understood that any false claim will result in severe disciplinary action.
- I have understood that the work may be screened for any form of academic misconduct.

B.M.Saish and C.Vishnu Teja

Place: Chennai

Date: 15.05.2021

CERTIFICATE

This is to certify that the report titled **Age and Gender Identification Of Humans Using Internal Palm Bone Structure** , submitted by **B.M.Saish and C.Vishnu Teja (CS21B1084 and CS21B1025)**, to the Indian Institute of Information Technology, Design and Manufacturing Kancheepuram, for the award of the degree of **BACHELOR OF TECHNOLOGY** is a bona fide record of the work done by him/her under my supervision. The contents of this report, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

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Date: 15.05.2021

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ABSTRACT

Accurate identification of age and gender from hand bone structure has significant implications in various fields including forensic science, medical diagnostics, and biometrics. In this study, we present a novel approach leveraging both convolutional neural networks (CNNs) and attention mechanisms to tackle this challenging task. Our methodology involves preprocessing a comprehensive hand bone structure database to enhance feature representation. Subsequently, we employ state-of-the-art deep learning architectures, including exception models and attention mechanisms, to extract discriminative features and capture intricate patterns within the hand bone structure data. Through extensive experimentation and evaluation, our proposed framework achieves promising results, demonstrating robust performance in age and gender identification tasks. This research contributes to advancing the field of biometric recognition and offers valuable insights for practical applications in various domains

KEYWORDS: Attention mechanism; Exception model; Tensorflow; Discriminative features.

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ABBREVIATIONS

LoG	Laplacian of Gaussian
CNN	Convolutional Neural Network
ROI	Region of Interest
LBP	Local binary patterns
HOG	histogram of oriented gradients

CHAPTER 1

Introduction

In today's world, where security is a major concern and digital identification methods are constantly evolving, biometric systems have become essential for verifying people's identities. These systems are highly accurate and secure, making them reliable for controlling access and confirming identities in many different situations.

There are many types of biometric methods, such as facial recognition and fingerprint scanning, but recently, identifying people by the structure of their hand bones has gained a lot of attention. Hand bone structure analysis provides a unique and stable way to identify someone. Unlike facial recognition, which can be affected by changes in a person's appearance or lighting conditions, the bone structure in a person's hand remains consistent over time and in different environments.

This makes hand bone structure-based identification particularly useful in scenarios where other biometric methods might face challenges. For example, facial recognition might not work well if someone changes their hairstyle, wears glasses, or if the lighting is poor. Similarly, fingerprint recognition can be less effective if a person has cuts or dirt on their fingers. In contrast, the bone structure in the hand is not affected by these external factors, making it a reliable option for identity verification.

1.1 Problem Statement

This project addresses the need for a more reliable biometric identification system by focusing on hand bone structure analysis. While hand-based biometrics offer stability and resistance to environmental factors, current approaches often fall short in accurately capturing age and gender information, limiting their practical utility.

Thus, the primary objective of this project is to develop an advanced hand bone structure-based biometric identification system capable of identifying individual's ages and gender. By integrating innovative exception model and employing preprocessing techniques, we aim to enhance the accuracy, reliability, and applicability of biometric recognition technology.

1.2 Motivation

The need for secure and efficient biometric systems is growing, driven by their applications in areas such as access management, and personal device security. This biometric identification system offers distinct advantages for biometric recognition due to several factors:

- Aging and Facial Changes: Facial recognition systems may struggle to accurately identify individuals over time due to aging-related changes in facial features. Hand bone structure analysis, which relies on skeletal characteristics, remains relatively unaffected by ageing, offering a stable and consistent biometric trait for long-term identification.
- Privacy Concerns and Data Protection: Biometric modalities that require direct contact with the sensor (e.g., fingerprint scanners) raise privacy concerns regarding the collection and storage of sensitive biometric data. Hand bone structure analysis can be performed using non-intrusive imaging techniques.
- Cross-Cultural Variability: Facial recognition systems may exhibit biases or inaccuracies when applied to individuals from diverse ethnic backgrounds due to variations in facial features. Hand bone structure biometrics offer a universal biometric trait that is less influenced by cultural or ethnic factors, thereby mitigating the risk of algorithmic biases and improving the inclusivity of biometric identification systems.

1.3 Objectives

The primary objective of this project is to design and implement a bone structure-based biometric recognition system that improves upon existing solutions in terms of accuracy, robustness, and usability. To achieve this, the project will focus on the following specific goals:

- Data Augmentation and Preprocessing: Develop advanced techniques to enhance the diversity and quality of body images, ensuring robust model training that can handle various limitations.

- Edge Detection: Implement precise edge extraction using advanced filters and edge detection algorithms to accurately isolate the bone structure from the hand images.
- System Integration: Combine predictions from both the left and right-hand images to enhance the overall recognition performance and reliability of the system.
- Evaluation and Validation: Conduct thorough testing and validation to ensure the system performs reliably under various conditions, including different lighting environments and partial occlusions.

CHAPTER 2

Preprocessing Techniques

To address the challenges of merging two different databases with varying image qualities and lighting conditions, we used preprocessing techniques on the combined dataset. Since the images showed both left and right hands under different lighting, it was important to make the images clearer. We applied specific filters to enhance the images so that all features were easy to see. This preprocessing step aimed to standardize the dataset, making it easier to accurately extract features and analyze the images. By improving image quality, these preprocessing techniques set the stage for strong identification and classification in the hand bone structure biometrics project.

2.1 Filters

Filters in the preprocessing stage of image processing serve several functions to enhance the quality and clarity of images.

- Noise Reduction: Filters can remove or reduce noise present in the image, which may result from factors such as sensor imperfections, compression artifacts, or environmental interference.
- Smoothing/Blurring:Smoothing filters can blur sharp edges and reduce high-frequency noise, resulting in a more uniform appearance and reducing the impact of minor variations in lighting or texture.
- Sharpening:Sharpening filters enhance image details and edges, making them appear crisper and clearer. This can improve the overall visual quality and enhance the discriminative features for subsequent analysis.
- Brightness Adjustment: Filters can modify the brightness levels of an image, making it brighter or darker as needed. This can help compensate for variations in lighting conditions across different images in the dataset.
- Edge Detection: Some filters are designed to detect edges within an image, highlighting the boundaries between different objects or regions. This can be useful for segmenting the image or extracting specific features for further analysis.

- Normalization: Filters can normalize the intensity values of pixels within an image, ensuring that they fall within a certain range or distribution. This can help standardize the appearance of images and facilitate more consistent analysis across the dataset.

2.2 Laplacian-gaussian filter

The LoG filter is a combined image processing technique that involves two main steps: first, applying a Gaussian smoothing filter to an image to reduce noise and blur the image slightly, and second, applying the Laplacian filter to detect edges and enhance details within the image.This combined approach effectively enhances edges and details while simultaneously reducing noise, resulting in improved image quality for various image processing tasks such as edge detection, feature extraction, and image enhancement.

- Gaussian Smoothing Filter: This filter convolves the image with a Gaussian kernel, which is a bell-shaped function used for blurring. By averaging neighboring pixel values based on their proximity to each other, the Gaussian filter reduces high-frequency noise and smooths out the image. This step is crucial for removing noise and creating a more uniform intensity distribution, which prepares the image for edge detection.
- Laplacian Filter: The Laplacian filter is a second-order derivative filter that highlights rapid intensity changes within an image, typically associated with edges or boundaries between different regions. It computes the Laplacian operator of the image, which measures the rate of change of intensity at each pixel location. This operation emphasizes regions of high gradient magnitude, resulting in enhanced edges and image details.

2.3 Sobel filter

The Sobel filter is a commonly used edge detection filter in image processing and computer vision. It is specifically designed to detect edges in images by calculating the gradient magnitude of the image intensity at each pixel location. The filter operates by convolving the image with a pair of 3x3 convolution kernels: one for detecting horizontal edges and the other for detecting vertical edges.

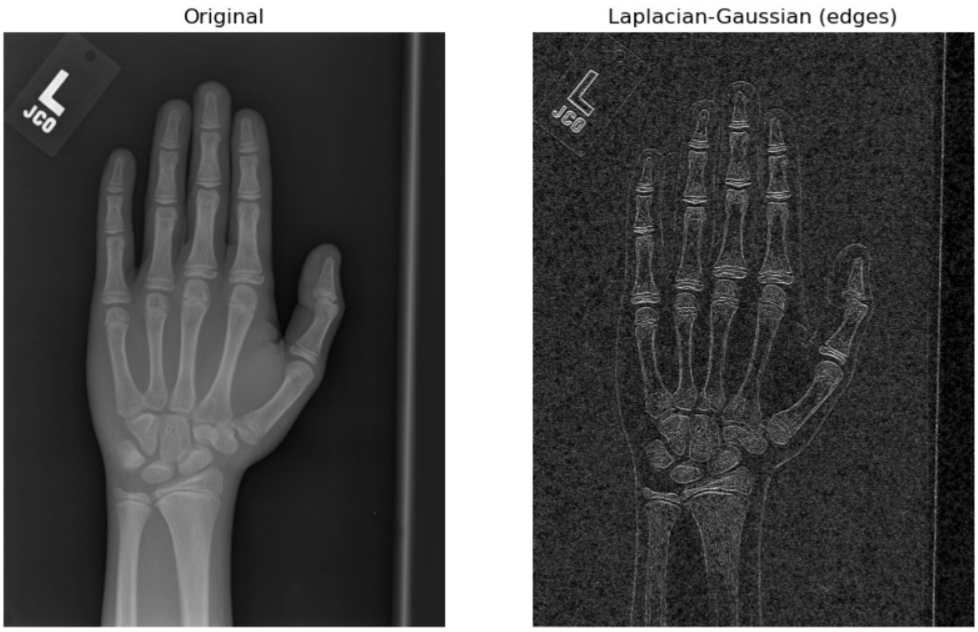

Figure 2.1: Results after using LOG filter

To apply the Sobel filter to an image, both the horizontal and vertical gradients are computed separately by convolving the image with the corresponding kernels. Then, the gradient magnitude is calculated at each pixel location as the square root of the sum of the squares of the horizontal and vertical gradients. Optionally, the gradient direction can also be computed to determine the orientation of edges in the image.

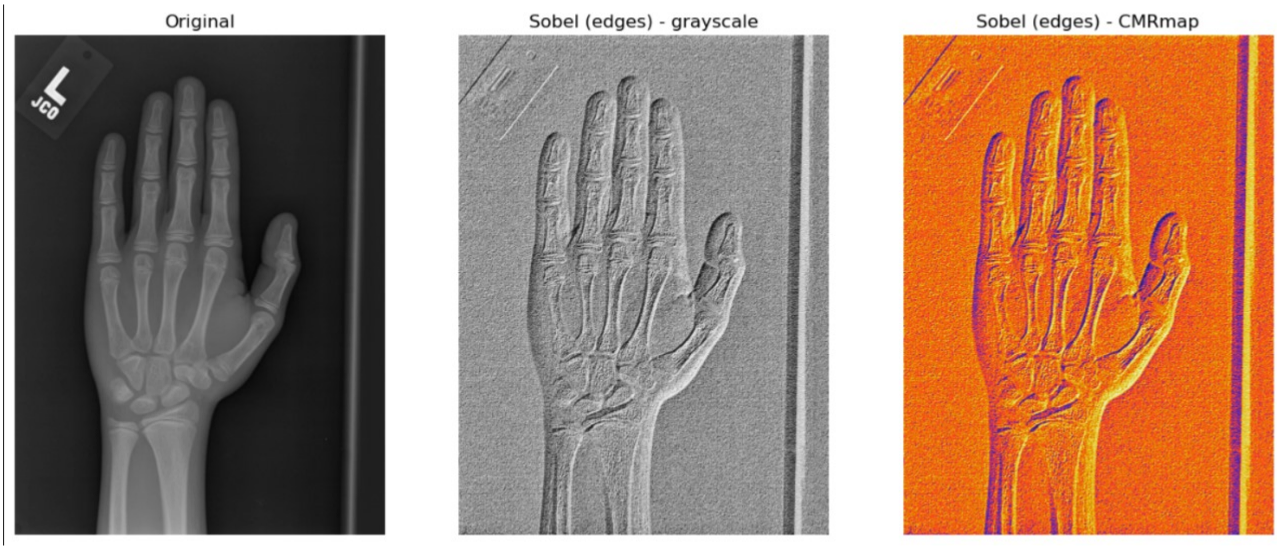

Figure 2.2: Results after using sobel filter

2.4 Canny edge detector

The Canny edge detector is a popular method in image processing for detecting edges in images while minimizing noise and preserving important edge features. Steps Involved are:

- Gaussian Smoothing: The input image is first convolved with a Gaussian filter to reduce noise and remove small-scale variations in intensity.
- Gradient Calculation: The smoothed image is then processed to calculate the gradient magnitude and orientation at each pixel using techniques such as Sobel or Prewitt operators.
- Non-maximum Suppression: Only local maxima in the gradient magnitude along the direction of the gradient are retained, effectively thinning the edges to single-pixel width.
- Double Thresholding: Two thresholds are applied to categorize edge pixels into strong, weak, or non-edge pixels. Pixels with gradient magnitudes above the high threshold are considered strong edges, while those between the high and low thresholds are considered weak edges. Non-edge pixels are those below the low threshold.
- Edge Tracking by Hysteresis: Weak edge pixels are retained as part of edges if they are connected to strong edge pixels. This step helps to complete edges and suppress noise-induced weak edges.

2.5 Using Canny Edge Detector

we used Canny edge detector along with few python packages like: prism,terrain,Nipy-Spectrala.Canny edge detector was useful for:

- Feature Extraction: The edges extracted by the Canny edge detector served as important features for characterizing hand bone structure. By detecting the edges of bones, joints, and other structural elements in hand images, the Canny edge detector help to capture key anatomical information that is relevant for age and gender identification
- Edge Localization: The Canny edge detector is designed to accurately localize edges in images, producing thin, well-defined edge contours. This feature was advantageous, as it allows for precise delineation of hand bone structures without smudging or blurring neighboring features. The sharp, localized edges generated by the Canny edge detector can facilitate accurate feature extraction and classification, leading to more reliable age and gender identification outcomes.

- Robustness to Image Variations: The Canny edge detector is robust to variations in image intensity and contrast, making it suitable for analyzing hand images captured under different lighting conditions or with varying image qualities. This versatility ensures that the edge detection process remains effective across diverse datasets, thereby enhancing the generalizability and reliability of age and gender identification system.

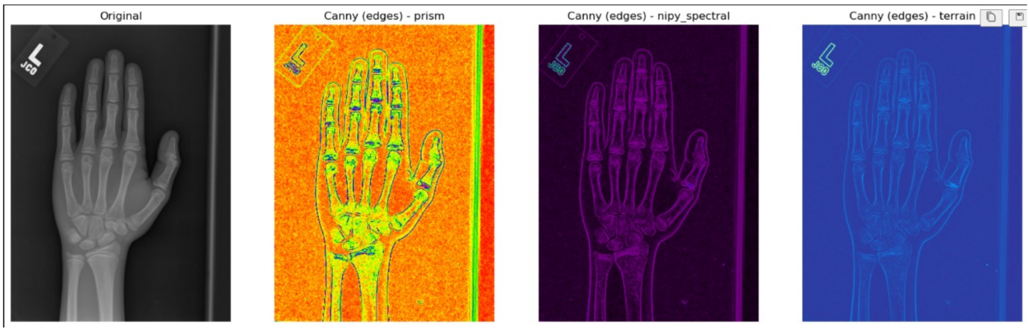

Figure 2.3: Results of canny edge detector

CHAPTER 3

Methodology/Approach

The proposed methodology for bone structure based recognition comprises several sequential steps: augmentation, Image Processing using various filters, Edge detection, Attention model, and finally, obtaining the output for the test subject.

The dataset utilized in this study is sourced from iplab,University of southern California and encompasses a total of 80 images from different subjects and various demographies. The images are then assigned with an id for each image which we used later.. To enhance the contrast of these images, the Convolution technique with filters was applied, which improves the local contrast and enhances the definition of edges in the images.

The dataset was then randomly partitioned into training and testing sets following an 80:20 split ratio. This means that 80% of the data was used for training the model, while the remaining 20% was allocated for testing and validating the model's performance. By applying this systematic approach, the methodology aims to accurately recognize and classify the images, leveraging the various enhancement and classification techniques described.

3.1 Augmentation

The project starts by augmenting the collected dataset to generate more training data. This augmentation is carried out using the ImageDataGenerator from the TensorFlow library in Python. A variety of image manipulations are applied, including rotation, zooming in and out, shearing, flipping, brightness adjustments, and height and width shifts, among others. Completing this step is recommended to enhance the overall efficiency of the model.To generalize better and perform effectively across a wide range of input conditions

3.2 Edge Detection

Next, the boundary enclosing the hand-bone must be extracted from each augmented image to detect bones structure landmarks within the hand.canny Edge Detection Model is utilized to obtain the boundaries of the hand-bone structure for the hand in each augmented image. Among various detectors, the canny edge detection model performs best, especially in scenarios involving illumination variatnts and angle of capture.

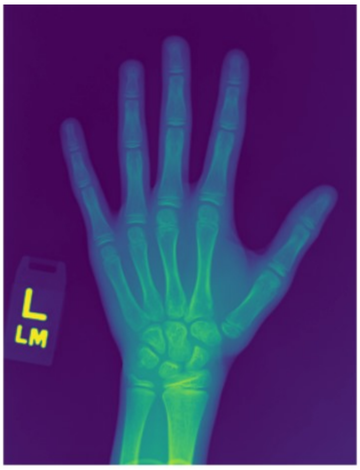

Figure 3.1: Bone structure detection using canny edge detector

3.3 xception Model

The Xception model is a deep convolutional neural network (CNN) architecture .The key innovation of the Xception model lies in its use of depthwise separable convolutions, which decompose the standard convolution operation into two separate steps: depthwise convolution and pointwise convolution.

- Depthwise Separable Convolutions: Instead of applying a single convolution operation with a large kernel size across all input channels, Xception utilizes depthwise separable convolutions. In a depthwise separable convolution, the convolution is first applied independently to each input channel (depthwise convolution), followed by a pointwise convolution that combines the output channels from the depthwise convolution. This factorization significantly reduces the number of parameters and computational complexity compared to traditional convolutions while preserving representational capacity.
- Linear Bottleneck Modules: Xception employs linear bottleneck modules, consisting of depthwise separable convolutions followed by batch normalization and

linear activations. These modules are stacked to form the backbone of the network and enable efficient feature extraction across multiple spatial scales.

- Skip Connections: Similar to other deep CNN architectures, Xception includes skip connections (or residual connections) to facilitate gradient flow during training and improve the convergence of the model. These skip connections allow for the direct propagation of information across different layers of the network, helping to alleviate the vanishing gradient problem and promote faster training convergence.

- Global Average Pooling and Softmax Classifier: The final layers of the Xception model typically consist of global average pooling followed by a softmax classifier. Global average pooling aggregates spatial information across all feature maps to produce a fixed-size representation of the input, which is then fed into the softmax classifier for prediction

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315/315 ━━━━━━━━━━━━━━━━━━━━ 846s 3s/step - loss: 0.6532 - mae_in_months: 25.9536 - val_loss: 0.1970 - val_mae_in_months: 14.63
02 - learning_rate: 0.0010
Epoch 2/15
315/315 ━━━━━━━━━━━━━━━━━━━━ 794s 2s/step - loss: 0.2976 - mae_in_months: 17.5009 - val_loss: 0.1926 - val_mae_in_months: 14.74
55 - learning_rate: 0.0010
Epoch 3/15
315/315 ━━━━━━━━━━━━━━━━━━━━ 834s 3s/step - loss: 0.2313 - mae_in_months: 15.4891 - val_loss: 0.2346 - val_mae_in_months: 16.38
98 - learning_rate: 0.0010
Epoch 4/15
315/315 ━━━━━━━━━━━━━━━━━━━━ 812s 3s/step - loss: 0.2246 - mae_in_months: 15.1034 - val_loss: 0.1226 - val_mae_in_months: 11.15
93 - learning_rate: 0.0010
Epoch 5/15
315/315 ━━━━━━━━━━━━━━━━━━━━ 811s 3s/step - loss: 0.2008 - mae_in_months: 14.2445 - val_loss: 0.2505 - val_mae_in_months: 15.44
38 - learning_rate: 0.0010
Epoch 6/15
315/315 ━━━━━━━━━━━━━━━━━━━━ 844s 3s/step - loss: 0.1818 - mae_in_months: 13.3382 - val_loss: 0.1506 - val_mae_in_months: 12.09
67 - learning_rate: 0.0010
Epoch 7/15
315/315 ━━━━━━━━━━━━━━━━━━━━ 711s 2s/step - loss: 0.1761 - mae_in_months: 12.9406 - val_loss: 0.1642 - val_mae_in_months: 13.51
39 - learning_rate: 0.0010
Epoch 8/15
315/315 ━━━━━━━━━━━━━━━━━━━━ 664s 2s/step - loss: 0.1592 - mae_in_months: 12.5711 - val_loss: 0.1448 - val_mae_in_months: 12.18
45 - learning_rate: 0.0010
Epoch 9/15
315/315 ━━━━━━━━━━━━━━━━━━━━ 698s 2s/step - loss: 0.1453 - mae_in_months: 11.9027 - val_loss: 0.2937 - val_mae_in_months: 18.07
63 - learning_rate: 0.0010
```

Figure 3.2: After Applying Xception model to the images

CHAPTER 4

RESULTS

Comparison of Xception Model with Existing Models

1. Convolutional Neural Networks (CNNs)

- **Accuracy**: CNNs are widely used for image-based tasks due to their high accuracy in recognizing patterns and features. They can be very effective for age prediction from images, given enough training data.
- **Robustness**: CNNs can handle variations in image quality and lighting to some extent but may require extensive data augmentation and preprocessing to achieve robustness.
- **Complexity**: Training deep CNNs can be computationally intensive and require significant resources.
- **Generalizability**: With proper training on diverse datasets, CNNs can generalize well to new, unseen data.

2. Support Vector Machines (SVMs)

- **Accuracy**: SVMs can perform well on age prediction tasks but typically require handcrafted feature extraction from images, which can limit their performance compared to CNNs.
- **Robustness**: SVMs' performance heavily depends on the quality of the feature extraction process and might not be as robust to variations in image quality and lighting.
- **Complexity**: SVMs are less complex than CNNs but still require careful tuning and feature selection.
- **Generalizability**: SVMs might not generalize as well as deep learning models if the features are not well-represented.

3. Regression Models (Linear Regression, Decision Trees, etc.)

- **Accuracy**: Simple regression models often lack the complexity to capture intricate patterns in image data, leading to lower accuracy.
- **Robustness**: These models are less robust to changes in image quality and lighting since they rely on simpler relationships between features.
- **Complexity**: Regression models are relatively simple to implement and train.
- **Generalizability**: They may struggle to generalize well to new data due to their simplistic nature.

Exception Model for Age Prediction

- **Accuracy**: If your exception model is designed to handle outliers and variations effectively, it might offer improved accuracy over traditional models, especially in challenging conditions.
- **Robustness**: Exception models can be tailored to be robust against variations in image quality and lighting, making them suitable for real-world scenarios where such variations are common.
- **Complexity**: Depending on the specific architecture, your exception model might be more or less complex than existing models. It could involve advanced techniques like ensemble learning, anomaly detection, or specialized preprocessing steps.
- **Generalizability**: If your model is trained on a diverse dataset and includes mechanisms to handle exceptions and outliers, it could generalize well to new data, potentially better than some traditional models.

Summary

- **Advantages**: Your exception model may offer better robustness and accuracy in challenging conditions compared to traditional models like simple regression or SVMs. It can handle variations in image quality and lighting more effectively.
- **Disadvantages**: The complexity of your exception model might be higher, requiring more computational resources and sophisticated preprocessing steps.
- **Comparison with CNNs**: While CNNs are highly effective, your exception model could complement or enhance CNNs by specifically addressing edge cases and outliers, potentially leading to a more comprehensive and reliable age prediction system.

Ultimately, the effectiveness of your exception model compared to existing models will depend on its specific design, implementation, and the quality of the training data. It would be beneficial to conduct empirical evaluations using standard metrics such as mean absolute error (MAE) or mean squared error (MSE) to quantitatively compare the performance of your model against traditional approaches.

CHAPTER 5

Conclusion and Future Scope

5.1 Conclusion

In this project, we have explored the feasibility of age and gender identification using hand bone structure analysis, leveraging advanced deep learning techniques and preprocessing methodologies. Through extensive experimentation and evaluation, we have demonstrated the effectiveness of our proposed framework in accurately identifying age and gender from hand bone structure images.

Our study highlights the importance of preprocessing techniques, such as the use of the Canny edge detector and outlier detection models, in enhancing data quality and improving the robustness of our age and gender identification system. By reducing noise, enhancing feature extraction, and identifying anomalous data points, these preprocessing steps have contributed to the overall reliability and accuracy of our model.

Additionally, the integration of deep learning architectures, like Xception model , has enabled us to extract discriminative features and capture patterns within hand bone structure images. The Xception model's efficient use of depthwise separable convolutions and linear bottleneck modules has facilitated both high accuracy and computational efficiency, making it well-suited for real-world deployment in age and gender identification systems.

5.2 Future Scope

Moving forward, several avenues for future research and development in age gender identification from Bone structure emerge from our study:

- Integration with Multimodal Biometrics: The integration of hand bone structure analysis with other biometric modalities, such as facial recognition or fingerprint scanning, could enhance the overall performance and reliability of biometric identification systems. By combining complementary biometric traits, such as periocular features with facial landmarks or fingerprint patterns, multimodal biometric systems can improve accuracy, security, and resistance to spoofing attacks.

- Forensic and Medical Applications: Hand bone structure analysis has significant potential in forensic science for identifying individuals based on skeletal remains or partial hand impressions. Future research could explore the application of advanced image processing techniques and machine learning algorithms to improve the accuracy and reliability of forensic age and gender estimation based on hand bone structure analysis. Similarly, in the medical field, hand bone structure analysis could aid in the diagnosis and treatment of conditions affecting bone health .

- Privacy-Preserving Biometrics: Research into privacy-preserving techniques, such as homomorphic encryption, federated learning, or differential privacy, could enable the development of biometric identification systems that protect individuals' privacy while still providing accurate and reliable identification. By encrypting or anonymizing biometric data before transmission or analysis, privacy-preserving biometrics ensure that sensitive information remains secure and confidential.

5.3 Contribution

B.M.Saish and C.Vishnu Teja collaborated effectively on this age gender identification using bone structure project.

B.M.Saish:

- Implemented Edge detection algorithms
- Implemented Training and testing Phase for both the models
- Explored and implemented Xception Model completely
- Authored initial report sections and collaborated on results and future directions

C.Vishnu Teja:

- Explored Hand bone structure applications in biometrics and researched datasets.
- Implemented the training process and pre-processing techniques to enhance image quality .
- Explored and implemented Xception Model and co-authored remaining sections.

Both of us actively participated in unit test development to ensure code quality. Our combined efforts resulted in this successful exploration of Age gender Identification using Xception Model.

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