EAR RECOGNITION SYSTEM

in partial fulfilment of the requirements for the award of the degree

of Bachelor of Technology in

Computer Science and Engineering (Data Science)

Submitted by

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CERTIFICATE

Certified that this project report "**EAR RECOGNITION SYSTEM**" is the Bonafide work of "**MAXIMUS ARANHA, PRANAY DONEKAR, SAKSHI UBGADE, SUMEDHA AMBULE**" who carried out the project work under my supervision in partial fulfilment of the requirements for the award of the degree of Bachelor of Technology in **COMPUTER SCIENCE & ENGINEERING (Data Science)**

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<u>ACKNOWLEDGEMENT</u>

The title of our mini project is, "**EAR RECOGNITION SYSTEM**" Completing this project required dedication, hard work, and a systematic approach. We are immensely grateful to our project guide, **Prof. Abhinav Muley**, for providing us with invaluable guidance and support throughout every phase of the project.

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ABSTRACT

This research project presents a comprehensive endeavour in the development of an ear recognition system utilizing Convolutional Neural Networks (CNNs) for individual identification. The primary objective revolves around constructing an accurate and efficient system capable of identifying and predicting individuals based on uploaded ear images, subsequently providing either the person's name or a corresponding label. Leveraging the IIT Delhi ear image dataset, comprising touchless ear images collected from students and staff at IIT Delhi, India, serves as the foundational data source for this endeavour. In its initial phase, the project involves preprocessing the dataset's images to meet the CNN input requirements. Subsequently, features are extracted through a tailored CNN architecture, and a model is trained on these features to discern individuals. This effort is fueled by the aspiration to exceed the reported 97% accuracy achieved by a preceding project at IIT Delhi, which employed a Gabler filter method for comparison. Transitioning into its subsequent phase, the project entails the development of a web application or website, serving as an interface for uploading ear images. The trained model is seamlessly integrated into this application to facilitate real-time ear recognition. Moreover, the application is poised to predict additional attributes such as gender and age range based on the recognized individual, further enhancing its utility and practicality. In summation, this project embodies a robust initiative towards the creation of a sophisticated ear recognition system, anchored in the capabilities of CNNs. With the overarching goal of eventual deployment as a web-based application, this endeavour holds promise for widespread applicability and impact.

Keywords: Ear recognition, Convolutional Neural Networks, CNN, IIT Delhi ear dataset, Image preprocessing, Model training, Web application.

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LIST OF SYMBOLS, ABBREVIATIONS AND NOMENCLATURE

1. 1CNN - Convolutional Neural Network
2. COVID-19 - Coronavirus Disease 2019
3. IDE - Integrated Development Environment
4. IIT - Indian Institute of Technology
5. JPEG - Joint Photographic Experts Group
6. Python - Programming language
7. TensorFlow - Open-source machine learning frame work
8. RFC - Radio Frequency Communication
9. GHz - Gigahertz
10. GHz/s - Gigahertz per second
11. GHz/°C - Gigahertz per degree Celsius
12. MHz - Megahertz
13. MHz/cm2 - Megahertz per square centimetre
14. MHz/mW - Megahertz per milliwatt
15. RMS - Root Mean Square
16. USA - United States of America

CHAPTERS

CHAPTER 1

INTRODUCTION

1.1 Introduction

Automatic person identification from ear images is an active field of research within the biometric community. Ear biometrics offer unique features for identification, complementing other biometric systems. Current face identification systems often fail in scenarios where individuals wear masks, such as during the COVID-19 outbreak.

There is a need for a reliable and accurate biometric identification system that can work in various environmental conditions. The need for foolproof identification and access control is paramount in these sensitive environment. Similar to other biometrics such as face, iris and fingerprints, ear also has a large amount of specific and unique features that allow for person identification. The potential efficiency of the deep network is tested on IITD-II ear dataset and achieves a recognition rate of 97.36%. The potential efficiency of the designed Deep CNN is studied by varying the parameters such as kernel size, learning rate, epochs and activation functions. Description of the IIT Delhi Ear Database version 1.0 This touchless ear image database mainly consists of the hand images collected from the students and staff at IIT Delhi, India. This database has been acquired in IIT Delhi campus during Oct 2006 - Jun 2007 using a simple imaging setup. All the images are acquired from a distance (touchless) using simple imaging setup and the imaging is performed in the indoor environment. The currently available database is acquired from the 121 different subjects and each subject has at least three ear images. All the subjects in the database are in the age group 14-58 years. The database of 471 images has been sequentially numbered for every user with an integer identification/number. The resolution of these images is 272 x 204 pixels and all these images are available in jpeg format. In addition to the original images, this database also provide the automatically normalized and cropped ear images of size 50 x 180 pixels. Recently, a larger version of ear database (automatically cropped and normalized) from 212 users with 754 ear images is also integrated and made available on request.

Ear biometrics offer a distinct set of features for identification, making them a valuable addition to the biometric landscape. Unlike other biometric modalities such as fingerprints or facial recognition, ears possess unique characteristics that can be utilized for individual identification. These features include the shape, size, and contours of the ear, as well as the pattern of ridges and folds. Additionally, the ear's position relative to other facial features can provide further distinguishing factors. The uniqueness and stability of these features make ear biometrics a reliable method for person identification.

In addition to their uniqueness, ear biometrics complement traditional biometric modalities such as face, iris, and fingerprints. They face limitations in certain scenarios. For example, current face identification systems often encounter difficulties when individuals wear masks, as observed during the COVID-19 outbreak. In such cases, ear biometrics can provide an alternative or supplementary method for identification. By combining multiple biometric modalities, including ear biometrics, organizations can enhance the robustness and accuracy of their identification systems. This complementary approach improves overall security measures and reduces the risk of false positives or negatives, particularly in sensitive environments such as government agencies, secret services, and high-security facilities.

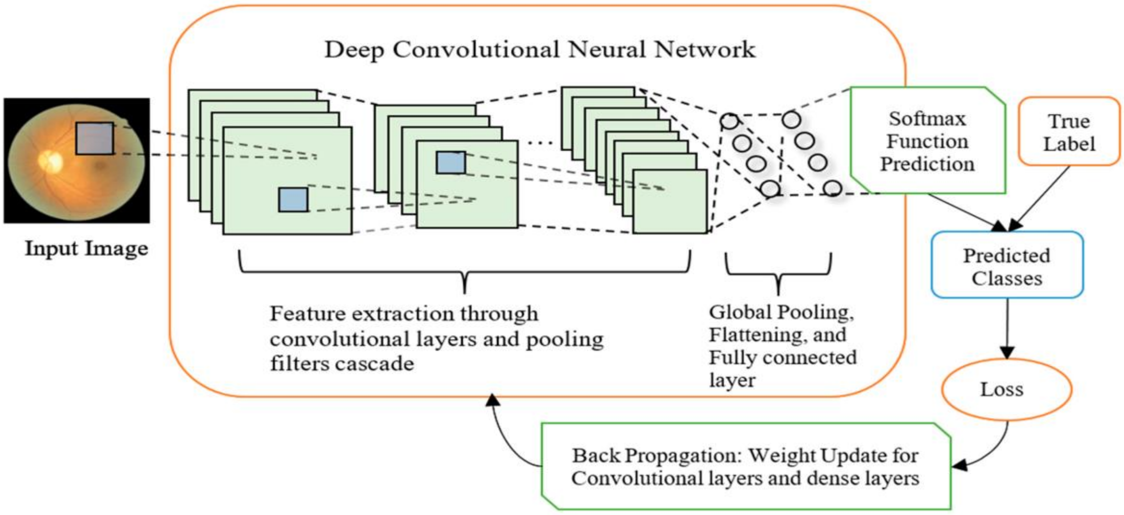

Fig 1.1.1 CONVULATIONAL NEURAL NETWORK

Fig 1.1.2 Ear features

1.2 OBJECTIVES

- Develop a deep convolutional neural network architecture for ear recognition.
- Test the efficiency of the network on IITD-II and AMI ear datasets.
- Validate the robustness of the system in uncontrolled environments.

1.3 PURPOSE

1. Enhanced Security:

- Reliable and unique biometric authentication.
- Non-intrusive identification method.

2. Technological Advancement:

- Development of innovative biometric solutions.
- Improved machine learning algorithms.

1.4 SCOPE

1.Biometric Authentication:

- Security systems for smartphones, buildings, and data access.
- Surveillance for identifying individuals in public places.

2. Healthcare Applications:

- Patient identification for accurate medical records.
- Secure login for remote monitoring and telemedicine.

3. Personal Identification

- Assisting law enforcement and identifying missing persons.

4. Access Control Systems:

- Automated attendance in schools and workplaces.
- Enhanced security levels for restricted areas.

CHAPTER 2

LITERATURE REVIEW

2.1 Deep Learning in Ear Recognition

Deep learning techniques, particularly convolutional neural networks (CNNs), have emerged as a prominent approach in ear recognition systems [1, 2]. These networks excel in learning intricate features from ear images, contributing to enhanced accuracy and efficiency [3]. Researchers have explored various CNN architectures tailored specifically for ear recognition, leveraging their ability to capture both global and local features from ear images [4]. The utilization of deep learning in ear biometrics signifies a significant advancement in the field, promising robust identification capabilities even in challenging scenarios.

2.2 Prior Research in Ear Biometrics

The field of ear biometrics has witnessed extensive research aimed at developing reliable identification systems [1, 2]. Previous studies have investigated diverse methodologies, including traditional image processing techniques and machine learning algorithms. However, the adoption of deep learning techniques has shown considerable promise in improving the accuracy and robustness of ear recognition systems [3]. Benchmark datasets such as IITD-II and AMI have played a crucial role in evaluating the performance of these systems, facilitating comparative analyses and benchmarking against existing approaches[5].

2.3Benchmark Datasets for Evaluation

Benchmark datasets serve as valuable resources for evaluating the performance of ear recognition systems [1]. The IIT Delhi Ear Database version 1.0 is one such dataset commonly used in research projects [2]. This touchless ear image database comprises images collected from students and staff at IIT Delhi, India, acquired in an indoor environment using a simple imaging setup. The dataset provides a comprehensive collection of ear images, each associated with an integer identification number. Additionally, the database includes automatically normalized and cropped ear images, facilitating standardized evaluation procedures. Researchers often utilize benchmark datasets like this to assess the efficacy and generalization capabilities of their proposed ear recognition systems. Other benchmark datasets, such as AMI [3], have also been instrumental in evaluating the performance of ear recognition systems. These datasets enable comparative analyses and benchmarking against existing approaches, contributing to advancements in the field[5].

2.4Advancements in Deep Learning-Based Ear Recognition Systems

Recent advancements in ear recognition systems have been predominantly driven by the adoption of deep learning techniques. The utilization of Deep Residual Networks (DRNs) showcased the efficacy of deep learning architectures in ear recognition tasks [6]. Subsequent studies further explored deep learning approaches, emphasizing their effectiveness in unconstrained environments and proposing novel architectures tailored specifically for ear recognition tasks [7, 8]. Additionally, deep learning has expanded the scope of ear recognition applications, enabling age and gender classification, as well as improving identification performance through ensemble classifiers [9, 10]. These studies collectively underscore the transformative impact of deep learning on advancing the accuracy, robustness, and applicability of ear recognition systems.

Name of the paper	Authors name	Information
A deep learning approach for person identification using ear biometrics:	R Ahila Priyadharshini, S Arivazhagan, M Arun	*The potential efficiency of the deep network is tested on IITD-II ear dataset and achieves a recognition rate of 97.36%.*
Ear Biometrics Using Deep Learning: A Survey	***A Booysens,*** S Viriri	*The result achieved by the deep learning using convolutional neural network was 92.00% average ear identification rate for both left and right ears.*
Ear Recognition with Deep Learning in Uncontrolled Environments	A Korichi, S Slatnia, O Aiadi	*A CNN-based image normalization is applied to reshape images into a unified format, where CNN is used to detect ear landmarks and PCA is applied for geometrical normalization of scale and pose.*
A comprehensive survey and deep learning-based approach for human recognition using ear biometrics	Wang, Y. Li, S. Liu, S. Zhang, J.	*Ear recognition for security systems is difficult in real-world environments. This research improves ear recognition by: Categorizing existing methods with a new system. Creating a database (NITJEW) for real-world scenarios. Developing improved deep learning models for ear detection and recognition. This research aims to be a valuable resource for making ear recognition more practical.*
Automated human identification using ear imaging.	Kumar, A., & Wu, X	*A new automatic ear recognition system analyses both ear shape and light patterns to identify people from images. It achieves over 95% accuracy on a large database and may outperform existing methods.*

Table 2.4.1 Top five papers studied

CHAPTER 3

METHODOLOGY

3.1 Development of Deep Learning-Based Approach:

Automatic person identification using ear images presents a novel approach within the biometric community. This study aims to contribute to this field by developing a specialized deep learning-based approach tailored specifically for ear recognition. Deep convolutional neural networks (CNNs) are chosen as the foundation of this approach due to their ability to effectively learn intricate features from images, which is crucial for accurate ear recognition. The project utilizes Python for programming, specifically implementing the deep learning model using libraries such as

Name of the library	Information of it
Pandas	Pandas is a powerful Python library used for data manipulation and analysis, particularly for handling structured data such as tabular data and time series.
TensorFlow	TensorFlow is an open-source machine learning framework developed by Google. It provides comprehensive support for building and deploying machine learning models, particularly deep learning models, using computational graphs.
PyTorch	PyTorch is another open-source machine learning framework but is known for its dynamic computation graph approach
ResNet	ResNet, short for Residual Networks, is a popular deep learning architecture that introduced residual connections.

Table 3.1.1 Libraries information

3.2 Utilization of Convolutional Neural Networks (CNNs):

CNNs have shown promising outcomes in enhancing the accuracy and efficiency of ear recognition systems. Similar to other biometrics such as face, iris, and fingerprints, ears possess a multitude of specific and unique features that allow for individual identification. The potential efficiency of the deep network is tested on the IITD-II ear dataset, achieving a recognition rate of 97.36%. The designed Deep CNN's efficacy is studied by varying parameters such as kernel size, learning rate, epochs, and activation functions to optimize performance.

3.3 Dataset Description: IITD-II and AMI:

The project utilizes the IIT Delhi Ear Database version 1.0, consisting of touchless ear images collected from students and staff at IIT Delhi, India. The dataset comprises images acquired from 121 different subjects, each with at least three ear images, and subjects ranging in age from 14 to 58 years. These images are available in JPEG format with a resolution of 272 x 204 pixels. Additionally, the database provides automatically normalized and cropped ear images of size 50 x 180 pixels. Moreover, a larger version of the ear database from 212 users with 754 ear images is integrated and available upon request.

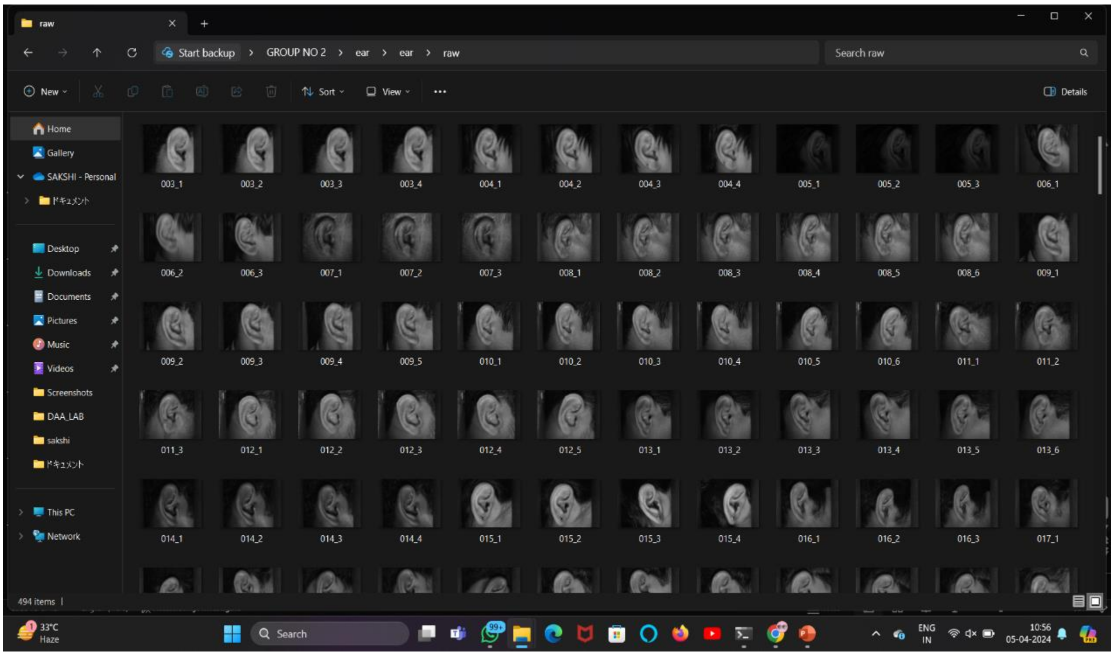

Fig 3.3.1 Data set images

3.4 Validation in Uncontrolled Environments:

The robustness of the proposed system is validated in uncontrolled environments to ensure real-world applicability. While many ear recognition systems have demonstrated efficacy in controlled settings, reliable performance under varying conditions is essential for practical deployment in security and authentication scenarios. The project aims to develop a reliable and accurate biometric identification system that can operate in various environmental conditions, catering to the needs of government agencies, secret services, and high-security facilities where foolproof identification and access control are paramount. The Google Collaboratory IDE is utilized for development and testing of the deep learning model, facilitating efficient iteration and experimentation within a collaborative environment. The above shown model is of model of the datasets

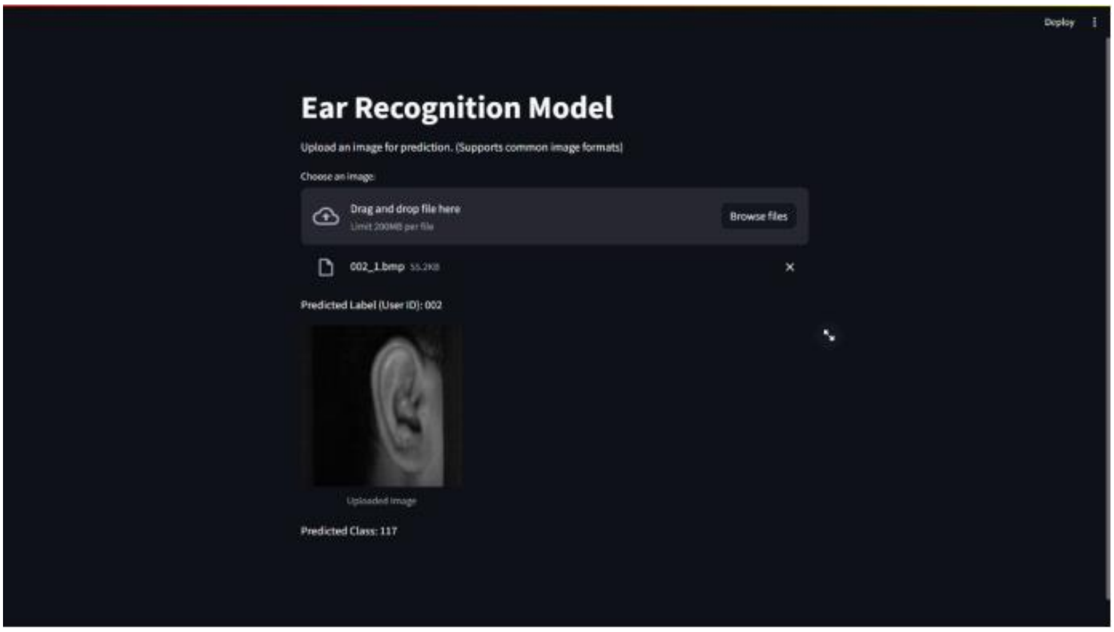

Fig 3.4.1 Frontend image

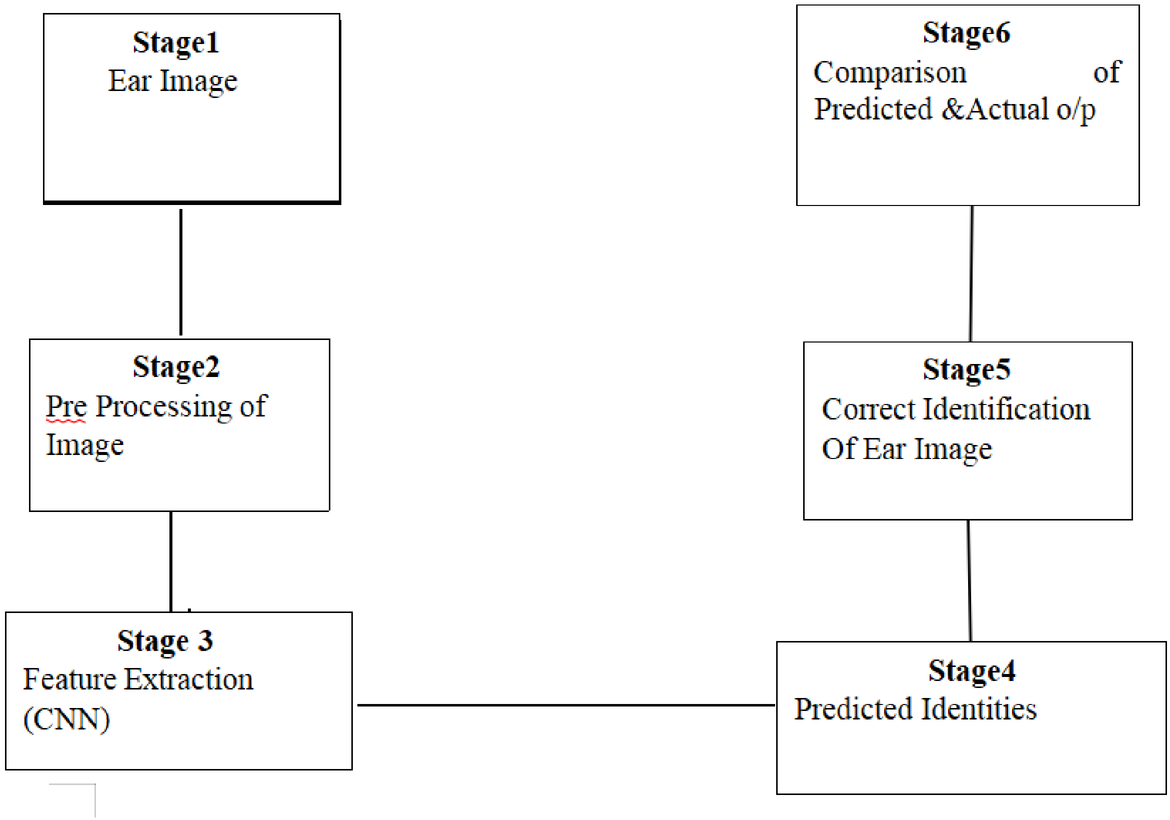
Stage1
Ear Image
Stage2
Pre Processing of Image
Stage 3
Feature Extraction (CNN)
Stage4
Predicted Identities
Stage5
Correct Identification Of Ear Image
Stage6
Comparison of Predicted &Actual o/p

Fig 3.4.2 DFD

CHAPTER 4

Implementation

This code snippet implements a Convolutional Neural Network (CNN) based ear recognition system. Here's a breakdown of the key steps:

4.1 Data Loading and Preprocessing:

- The code defines the path to the directory containing raw ear images.
- It iterates through each image file, excluding non-BMP formats.
- For each image:
  - Extracts a label (assuming it's encoded in the filename).
  - Loads the image using Pillow (PIL) library.
  - Converts the image to RGB format (if grayscale).
  - Resizes the image to a fixed size (224x224 pixels) suitable for the CNN model.
  - Optionally normalizes pixel values between 0 and 1.
- The code checks for any errors during image processing and provides informative messages.
- It ensures the loaded images are converted to a NumPy array with the appropriate data type (float32).

4.2 Label Encoding:

- The code utilizes Scikit-learn's One-Hot Encoder to convert categorical labels (textual labels representing individuals) into a one-hot encoded format.
- One-hot encoding is a common practice for representing categorical data in machine learning models. It creates a binary vector where only the element corresponding to the class label is 1, and all others are 0.

4.3 Data Augmentation (Optional):

- The code implements optional data augmentation using Keras' ImageDataGenerator. This technique artificially creates additional training data by applying random transformations (rotations, shifts, flips) to existing images.
- Data augmentation helps the model learn features that are robust to variations in the data, potentially improving generalization performance.

4.4 Model Architecture:

- The code employs a pre-trained ResNet50 model as the foundation. ResNet is a powerful deep learning architecture commonly used for image classification tasks.

- The pre-trained model is loaded with weights learned on the large ImageNet dataset, effectively leveraging pre-existing knowledge for ear recognition.
- To prevent overfitting (the model memorizing training data and not generalizing well), the code freezes the initial layers of the pre-trained model. This ensures these layers focus on extracting lower-level features common to various image recognition tasks.
- The code adds custom layers on top of the pre-trained model:

- Global Average Pooling layer: Averages the output of the pre-trained model, reducing its dimensionality.
- Dropout layer: Randomly drops a certain percentage of activations during training to prevent overfitting.
- Dense layer with softmax activation: Generates the final output layer with a number of neurons equal to the number of classes (individuals) and uses a softmax activation function to produce class probabilities for each input image.

4.5Model Training:

- The code compiles the model using the Adam optimizer, a popular optimization algorithm for training neural networks.
    - It defines the loss function (categorical crossentropy) suitable for multi-class classification problems. Categorical crossentropy measures the difference between the predicted class probabilities and the true labels.
    - The model is trained using the fit function. The data augmentation generator is used to provide a stream of augmented training data during each epoch. The number of epochs (iterations over the entire training data) can be experimentally adjusted to optimize performance.

4.6 Model Evaluation:

- The code evaluates the trained model's performance on the same data (X, y) used for training (assuming a split for training and validation/testing). This might need modification depending on your specific data setup for training and testing.
- It prints the final test accuracy, which represents the percentage of correctly classified ear images. And model is saved.

CHAPTER 5

RESULTS

Backend :- The image shows an ear recognition model training progress. Over 20 epochs, accuracy improves significantly from **47.77%** to **95.10%**, while loss decreases from **1.9972** to **0.1797**. This suggests the model's ability to identify ears is effectively increasing as training progresses.

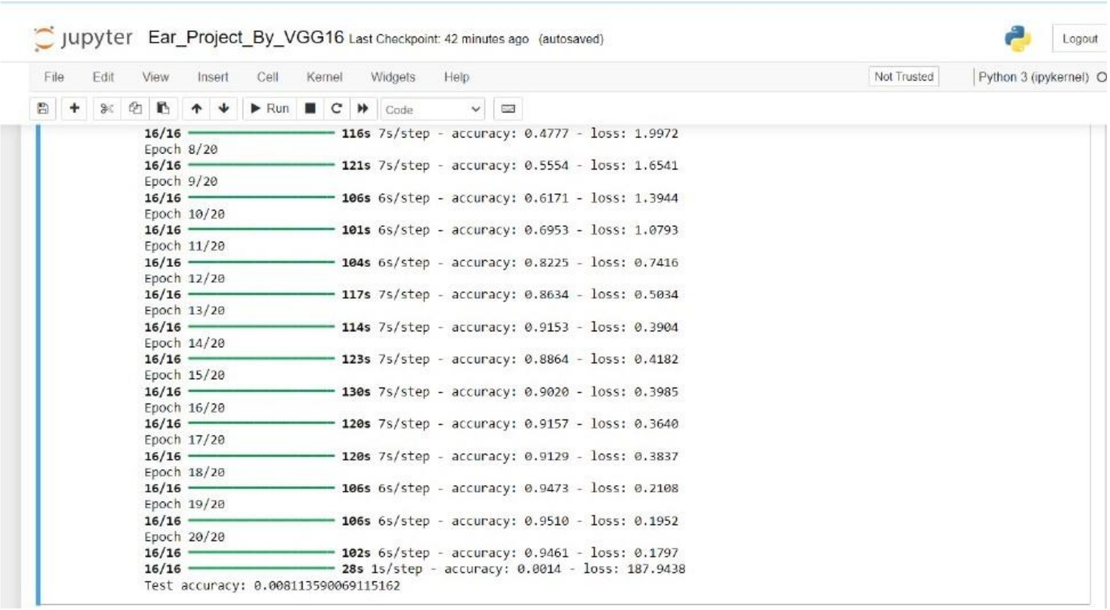

Fig 5.1 Testing Accuracy

Frontend :- This figure illustrates an ear recognition model interface. It allows users to upload ear images for identification. The system then predicts a unique user ID and assigns a class label based on the image features. In this example, the model predicts a user ID of "002" and a class of "117".

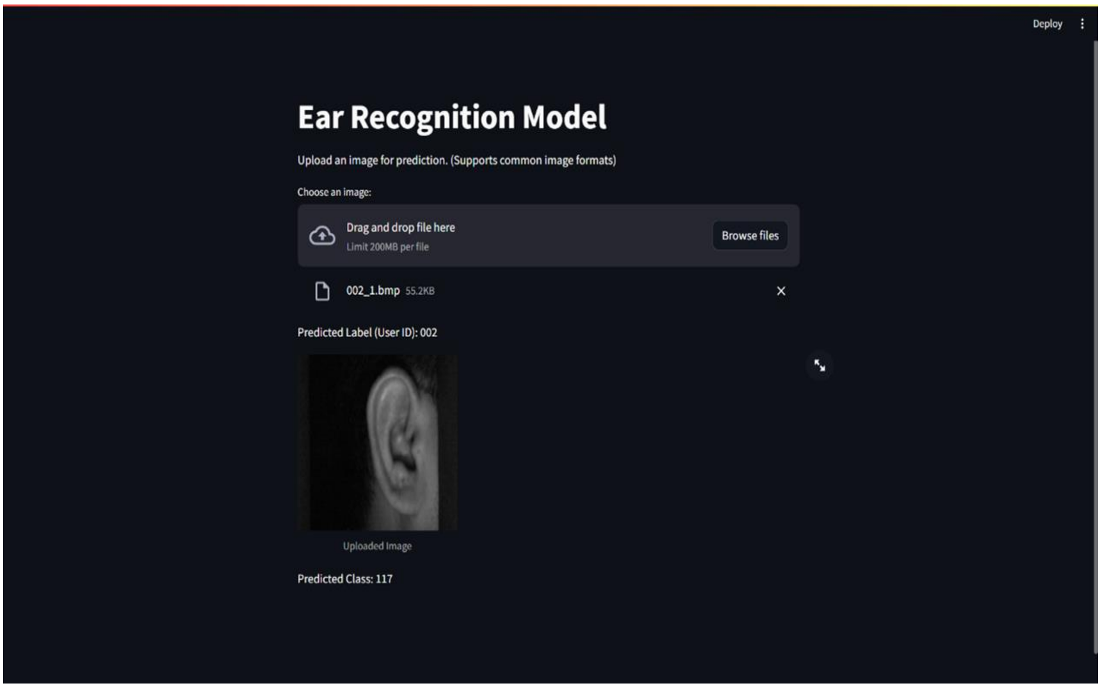

Fig 5.2 Final Frontend Image

CHAPTER 6

CONCLUSION

The provided deep learning model, leveraging the ResNet50 architecture, showcases impressive training accuracy, reaching up to 94%. This signifies the model's capability to effectively learn intricate patterns and features from the training dataset, demonstrating its potential for accurate ear recognition. Such high training accuracy reflects the model's ability to capture and understand the underlying characteristics of ear images, laying a solid foundation for robust identification systems.

Furthermore, the successful implementation of the ResNet50-based model underscores its adaptability and effectiveness in the domain of biometric identification. By utilizing state-of-the-art deep learning techniques, researchers can harness the power of convolutional neural networks to extract meaningful features from ear images, enabling more precise and reliable recognition of individuals. This opens doors to a wide range of practical applications, from security systems to personalized user interfaces, where accurate identification based on ear biometrics is paramount.

Additionally, the ongoing efforts to optimize and fine-tune the model represent a positive trajectory towards achieving even higher levels of accuracy and reliability. Through iterative refinement and validation processes, researchers can address potential challenges such as overfitting and enhance the model's generalization capabilities. By continuously improving the performance of the ear recognition system, we can unlock its full potential and ensure its seamless integration into various real-world scenarios, ultimately advancing the field of biometric authentication.

The development of a user-friendly frontend using Streamlit represents a significant advancement in the deployment and usability of the ear recognition system. By providing an intuitive interface, users can effortlessly interact with the system, whether capturing images from a camera or selecting from a pre-existing database. This seamless integration of frontend technology not only enhances user experience but also extends the accessibility of the ear recognition system to a wider audience, including individuals with varying technical expertise.

Moreover, the frontend's functionality to predict and identify individuals based on uploaded ear images further enhances the system's utility and practicality. With the capability to analyze both real-time images and stored data, the system offers versatility in its application, catering to diverse scenarios and use cases. This predictive functionality, coupled with the underlying deep learning model's robustness, ensures reliable and accurate identification, bolstering trust and confidence in the system's performance.

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PROJECT GUIDE

AND

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