KLE Society's
KLE Technological University, Hubballi.

A Minor Project -2 Report

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CERTIFICATE

This is to certify that Minor Project -2 entitled <Project title> is a bonafied work carried out by the student team <name1 USN: , name 2 USN: name1 USN: , name 2 USN: >, in partial fulfillment of completion of Sixth semester B. E. in School of Computer Science and Engineering during the year 2023-2024. The project report has been approved as it satisfies the academic requirement with respect to the project work prescribed for the above said program.

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ABSTRACT

A new generation of biometric technologies, including vein and finger knuckle recognition, promises to be more secure and accurate than older forms of identification. The purpose of this study is to investigate how to use sophisticated deep learning models to make Finger Vein (FV) and Finger Knuckle Point (FKP) detection more accurate. Building a reliable system that can reliably identify people using these distinct biometric characteristics is the main goal.

To provide thorough coverage of different situations, we used datasets acquired by Hong Kong Polytechnic University to acquire distinct FKP and FV pictures. In order to get the pictures ready for analysis, they were subjected to a slew of preprocessing steps, such as resizing, Gaussian blur, CLAHE for contrast enhancement, morphological procedures, and ROI extraction. To make the training set more robust, we used data augmentation methods such horizontal flipping, shearing, zooming, and width and height adjustments.

The most cutting-edge convolutional neural networks (CNNs) such as ResNet50, VGG16, AlexNet, and InceptionV3 were used for feature extraction. In order to get the most out of the preprocessed photos, these models were fine-tuned. The retrieved characteristics from FKP and FV were blended using cosine similarity to increase the overall identification accuracy.

Our findings suggest that although models like ResNet50 and AlexNet struggled with feature discrimination, VGG16 showed some promise but was prone to overfitting. InceptionV3 emerged as the most successful model, with training accuracy of 0.6648 and testing accuracy of 0.6731, suggesting high generalization to unknown data. This result implies that InceptionV3 can efficiently collect various and significant information from finger knuckle and vein pictures.

In conclusion, the InceptionV3 model's consistent performance on both training and testing sets confirms its resilience and practical usefulness in biometric systems. The fact that its training and testing accuracies are somewhat different further proves that it can generalize. These results illustrate the possibility of applying sophisticated CNN models for accurate finger knuckle and vein detection, adding greatly to the area of biometric identification.

Keywords : *Biometric Identification ,Convolutional Neural Networks (CNN) ,Data Augmentation ,CLAHE (Contrast Limited Adaptive Histogram Equalization) ,Morphological Operations ,Region of Interest (ROI) Extraction ,Cosine Similarity ,Generalization*

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Chapter 1

INTRODUCTION

Biometric recognition systems have become more vital in numerous security applications, such as access control, identity verification, and surveillance. Traditional techniques like passwords and ID cards are prone to theft, loss, and forgery, but biometric qualities provide a better degree of security owing to their uniqueness and complexity to copy. Among many biometric modalities, finger vein and finger knuckle identification are receiving interest for their robustness and dependability.

Finger vein identification includes recording the distinctive patterns of blood veins under the skin's surface using near-infrared imaging. These patterns are very stable over time and are difficult to counterfeit, making them a great candidate for biometric identification. Similarly, finger knuckle patterns, which relate to the distinctive texture and form of the skin above the knuckle joints, give an extra degree of protection. The combination of these two modalities increases the overall security and accuracy of the biometric system.

In this research, we intend to design a dual-modal biometric identification system that employs both finger vein and finger knuckle patterns. We utilized publically accessible datasets, PolyUKnuckleV1 for knuckle patterns and FingerVein for vein patterns, to train and assess our system. The raw photos from these datasets underwent preprocessing to boost their quality and make them acceptable for feature extraction.

We employed pre-trained Convolutional Neural Network (CNN) models, notably VGG16, InceptionV3, ResNet50, and AlexNet, to extract high-level features from the preprocessed photos. These models, fine-tuned to our unique goal, delivered solid feature representations of the finger vein and knuckle pictures. By merging the characteristics acquired from both modalities using cosine similarity, we intended to build a more accurate and trustworthy biometric identification system.

The performance of our system was assessed by generating similarity scores and making authentication choices based on a preset threshold. The findings illustrate the possibility of merging finger vein and knuckle patterns to increase the security and accuracy of biometric identification systems. This technique provides a viable alternative for applications demanding high levels of security and dependability.

In the following sections, we discuss the approach, tests, findings, and conclusions of our study, offering insights into the efficacy of dual-modal biometric identification systems..

1.1 Motivation

The rising need for safe and trustworthy identification systems in numerous areas such as banking, healthcare, and border security has accelerated the need for improved biometric technology. Traditional biometric systems like fingerprint and facial identification, although successful, confront obstacles such as spoofing and unpredictability in picture quality owing to environmental conditions. Finger knuckle and vein identification provide an appealing alternative owing to their distinct anatomical traits that are less sensitive to external alterations and harder to reproduce or fake.

This initiative is driven by the promise of finger knuckle and vein biometrics to give improved security and accuracy. Leveraging state-of-the-art deep learning models, we intend to better the feature extraction and fusion processes, hence enhancing the overall performance of biometric systems. By leveraging datasets from the Hong Kong Polytechnic University and employing rigorous preprocessing and augmentation approaches, we want to construct a robust recognition system that can be consistently employed in real-world applications. The ultimate objective is to contribute to the evolution of biometric identification technology, guaranteeing increased security and confidence in identity verification procedures.

1.2 Literature Review / Survey

Paper 1: "Finger-Knuckle-Print Recognition Using Deep Convolutional Neural Network"

This paper explores the application of deep convolutional neural networks (CNNs) in the field of finger-knuckle print (FKP) recognition. The research aims to develop a reliable FKP recognition system by harnessing the capabilities of CNNs, which have proven successful in various image recognition tasks. The study introduces a custom CNN framework tailored specifically for FKP recognition, which undergoes thorough evaluation using a widely recognized FKP dataset. Results indicate that the CNN-based approach achieves notable accuracy and resilience compared to conventional methods. The findings underscore the efficacy of deep learning techniques in biometric recognition systems, particularly for FKPs, while also suggesting avenues for further enhancement and optimization to bolster system performance.

Paper 2: "Robust and Sparse Least Square Regression for Finger Vein and Finger Knuckle Print Recognition"

This study presents a novel approach for recognizing finger veins and finger knuckle prints using a robust and sparse least square regression (RSLR) method. The proposed method aims to improve the accuracy and robustness of biometric recognition systems by addressing the limitations of traditional recognition techniques. The authors developed an RSLR-based framework that integrates both finger vein and knuckle print features to enhance the recognition performance. Extensive experiments were conducted on a combined dataset of finger vein and knuckle print images to validate the effectiveness of the proposed approach. The experimental results showed that the RSLR method outperformed existing techniques in terms of accuracy and robustness, demonstrating its potential for practical biometric recognition applications. The paper concludes that the integration of RSLR with finger vein and knuckle print recognition systems can significantly improve their performance and reliability.

Paper 3: "Research on Inner Knuckle Pattern Recognition Method Based on Convolutional Neural Network"

This paper explores the recognition of inner knuckle patterns using convolutional neural networks (CNNs). The study focuses on the preprocessing of hand images, which involves binarization, morphological processing, contour extraction, and region of interest (ROI) extraction of the knuckle patterns. The CNN is then used to extract features from the normalized ROI images, followed by classification using a fully connected layer and the Softmax function. The researchers experimented with various network parameters, including learning rates, the number of convolution kernels, the number of neurons in the fully connected layers, and different optimization algorithms to determine the optimal settings. The experimental results indicated a recognition rate of 95.2 percent, highlighting the method's effectiveness and application value in biometric recognition systems. The study demonstrates the significant potential of using CNNs for inner knuckle pattern recognition, contributing to the advancement of biometric identification technologies.

Paper 4: "Finger Vein Recognition Based on Deep Convolutional Neural Networks"

This study addresses the challenges of finger vein recognition, particularly the susceptibility to external factors such as finger posture and light conditions. The authors propose a method based on improved deep convolutional neural networks (DCNNs) to enhance accuracy and robustness. The process involves image preprocessing steps such as segmentation, key point location, and region of interest (ROI) extraction. The optimized DCNN structure, including batch normalization and specific convolutional adjustments, is used to automatically extract, classify, and identify features from preprocessed images. Extensive experiments on a public finger vein dataset from Shandong University demonstrated an optimal recognition rate of 90 percent. The study confirms the effectiveness of DCNNs in finger vein recognition, showing improved performance over traditional manual feature extraction and machine learning algorithms. The research highlights the importance of optimizing network parameters and the potential for DCNNs to advance biometric recognition systems.

Paper 5: "A Survey of Finger Vein Recognition"

This survey paper provides a comprehensive overview of various finger vein recognition methods, outlining their respective strengths and challenges. Traditional techniques such as maximum curvature and mean curvature methods are discussed for vein extraction, which traditionally rely on manually crafted features. The paper also examines the recent trend towards deep learning approaches, which have demonstrated superior performance in handling diverse image qualities and environmental conditions. Specifically, the effectiveness of models like AlexNet, VGG-16, DenseNet-161, and FV-GAN in feature extraction and recognition accuracy improvement is highlighted. The survey underscores the significance of utilizing public datasets such as SDUMLA, HKPU-FV, and THUFV2 for benchmarking different methodologies. Lastly, the paper identifies current dataset limitations and advocates for the expansion of data resources to further enhance the performance of deep learning-based finger vein recognition systems.

The following are the identified drawbacks of the papers:

- Limited Accuracy and Generalization in Single-Modality Systems
- Lack of Dataset
- Optimization of Deep Learning Parameters

1.3 Problem Statement

To design a unimodal biometric identification system that leverages a combination of finger vein recognition and finger knuckle print recognition for enhanced security and accuracy.

1.4 Applications

- Enhanced Security Systems:
- Banking and Financial Services
- Healthcare Systems
- Border Control and Immigration

1.5 Objectives and Scope of the project

The objective of our project is to develop a comprehensive system for finger vein and knuckle print recognition. This involves collecting and preprocessing image datasets, extracting features using transfer learning algorithms, exploring feature-level fusion techniques, and designing suitable deep learning architectures to effectively combine and analyze information from both modalities.

1.5.1 Objectives

- To collect the image dataset of finger veins and knuckle prints.
- To preprocess the fingerprint and finger knuckle images
- To extract features from the preprocessed finger vein and knuckle print images like vein pattern and knuckle point using transfer learning algorithm
- To extract features from the preprocessed finger vein and knuckle print images like vein pattern and knuckle point using transfer learning algorithm
- To design and implement deep learning architectures suitable, leveraging techniques.

1.5.2 Scope of the project

The suggested approach for finger vein and knuckle print identification will operate properly under the following conditions:

1. Good-quality picture dataset:

- The picture dataset of finger veins and knuckle prints must be of good quality, with distinct and recognizable characteristics, and acquired under constant lighting circumstances.

2. Proper preprocessing:

- Images must undergo effective preprocessing methods to maximize feature visibility, including noise removal, normalization, and alignment to maintain consistency throughout the dataset.

3. Accurate feature extraction:

- The transfer learning algorithm used for feature extraction must be appropriately trained and fine-tuned to reliably detect and extract vein patterns and knuckle points from the preprocessed pictures.

4.Constant environmental circumstances:

- The approach assumes that photographs are recorded under constant environmental circumstances to reduce changes caused by external variables such as illumination and hand location.

By sticking to these constraints, the approach may provide precise and dependable performance in detecting finger vein and knuckle print patterns.

Chapter 2

REQUIREMENT ANALYSIS

The creation of a unimodal biometric identification system employing finger knuckle and vein patterns demands a detailed requirement analysis to assure the system's efficacy and dependability. This section highlights the main functional and non-functional criteria that constitute the basis of our project. By recognizing and solving these needs, we seek to design a robust and accurate biometric identification system capable of working under varied settings and assuring high levels of security and performance. The criteria encompass all areas of the system, from picture collecting and preprocessing to feature extraction, model training, and performance assessment, guaranteeing a complete approach to system development.

2.1 Functional Requirements

- The system shall acquire images of finger knuckle and vein patterns.
- The system shall preprocess acquired images to standardize them for further analysis.
- The system shall implement data augmentation techniques.
- The system shall enhance the diversity and robustness of the training dataset using data augmentation techniques.
- The system shall employ advanced convolutional neural networks (CNNs) for feature extraction.
- The system shall use models such as ResNet50, VGG16, AlexNet, and InceptionV3 for feature extraction.
- The system shall fuse extracted features using cosine similarity.
- The system shall combine strengths from both finger knuckle and vein pattern modalities through feature fusion.
- The system shall efficiently split data into training and testing sets.
- The system shall ensure appropriate partitioning of data for model training and evaluation.

- The system shall train CNN models.
- The system shall evaluate model performance using various metrics.
- The system shall make authentication decisions based on fused feature scores.
- The system shall accurately determine user genuineness or rejection based on authentication decisions.

2.2 Non-Functional Requirements

- The system should process and analyze images swiftly to provide timely results.
- The system should accommodate increasing numbers of users and datasets without performance degradation.
- The system should guarantee consistent and accurate operation despite environmental or operational changes.
- The system should demand straightforward operation for technical users, even in the absence of a user-friendly interface.
- The system should ensure data protection and access control to maintain security.
- The system should be compatible with different operating systems and hardware configurations to support deployment in diverse environments.
- The system should facilitate seamless updates and enhancements, minimizing downtime.
- The system should provide extensive documentation to aid in understanding and future development.

2.3 Hardware Requirements

Processor (CPU):

- A high-performance multi-core processor, such as an Intel Core i7 or AMD Ryzen 7, is recommended to handle the intensive computations involved in image preprocessing and neural network training.

Graphics Processing Unit (GPU):

- A powerful GPU, such as NVIDIA GTX 1080 Ti or better, is essential for accelerating the training of deep learning models and performing large-scale matrix operations efficiently.

Memory (RAM):

- A minimum of 16 GB of RAM is recommended to ensure smooth operation and prevent bottlenecks during data processing and model training. For large datasets, 32 GB or more is preferable.

Storage:

- At least 10 GB of SSD storage is recommended for fast data access and to store large datasets and trained models. Additional HDD storage may be required for backup and archiving purposes.

Operating System:

- A 64-bit operating system, such as Windows 10, Ubuntu, or any other compatible Linux distribution, to support the necessary software and libraries for deep learning and image processing.

2.4 Software Requirements

Operating System:

- Windows 10 (64-bit) or later

Programming Languages:

- Python 3.6 or later: Primary programming language for implementing image processing and machine learning algorithms.

Deep Learning Frameworks:

- TensorFlow 2.x: Used for building and training neural network models.
- Keras: High-level API for building and training deep learning models, integrated with TensorFlow.

Image Processing Libraries:

- OpenCV: Library for image processing and computer vision tasks.
- PIL/Pillow: Library for image manipulation and processing.

Scientific Computing Libraries:

- NumPy: Library for numerical computations and handling multi-dimensional arrays.
- SciPy: Library for scientific and technical computing.

Data Handling Libraries:

- Pandas: Library for data manipulation and analysis.
- Scikit-learn: Library for machine learning algorithms and data preprocessing.

Visualization Libraries:

- Matplotlib: Library for creating static, animated, and interactive visualizations.
- Seaborn: Statistical data visualization library built on Matplotlib.

Development Environment:

- Jupyter Notebook: Interactive environment for developing and testing code.
- Integrated Development Environment (IDE) such as PyCharm, VSCode, or Spyder.

Chapter 3

SYSTEM DESIGN

- The system design for our finger knuckle and vein recognition project is structured to ensure optimal performance and robustness across various stages of data processing and analysis. Initially, the system collects diverse datasets of finger knuckle points (FKP) and finger veins (FV) from the Hong Kong Polytechnic University. These images undergo rigorous preprocessing, including resizing, Gaussian blurring, CLAHE for contrast enhancement, and morphological operations to highlight key features. Regions of Interest (ROI) are then extracted to focus on the most relevant parts of the images. Data augmentation techniques such as rotation, shifts, shearing, zooming, and flipping are applied to create a diverse training set, enhancing the model's ability to generalize.

- For feature extraction, we employ state-of-the-art convolutional neural networks (CNNs) like ResNet50, VGG16, AlexNet, and InceptionV3, each fine-tuned to capture detailed features from the preprocessed images. These features from both FKP and FV are then fused using cosine similarity to improve identification accuracy. The system is designed to split the data into training and testing sets, ensuring rigorous evaluation of model performance. The final stage involves a thorough performance evaluation using metrics such as accuracy, precision, recall, and F1-score, supported by confusion matrix analysis to identify areas for improvement. This comprehensive and modular system design ensures that our biometric recognition system is both robust and accurate, capable of reliable performance in real-world applications.

- In addition, the system incorporates a robust architecture that allows for scalability and adaptability. The modular design ensures that different components, such as preprocessing, feature extraction, and classification, can be independently updated or replaced with more advanced techniques as they become available. This flexibility is crucial for adapting to new research developments and integrating improved algorithms. The integration of multiple CNN models allows for comparative analysis and selection of the best-performing model for specific scenarios. Furthermore, the system includes mechanisms for continuous learning and adaptation, where the models can be periodically retrained with new data to maintain high accuracy and adapt to evolving patterns in biometric data.

3.1 Architecture Design

The architecture design for our finger knuckle and vein recognition system is meticulously structured to ensure seamless integration of various components and achieve high recognition accuracy. The system is divided into several key modules, each responsible for specific tasks within the overall process. This modular approach enhances flexibility, scalability, and maintainability.

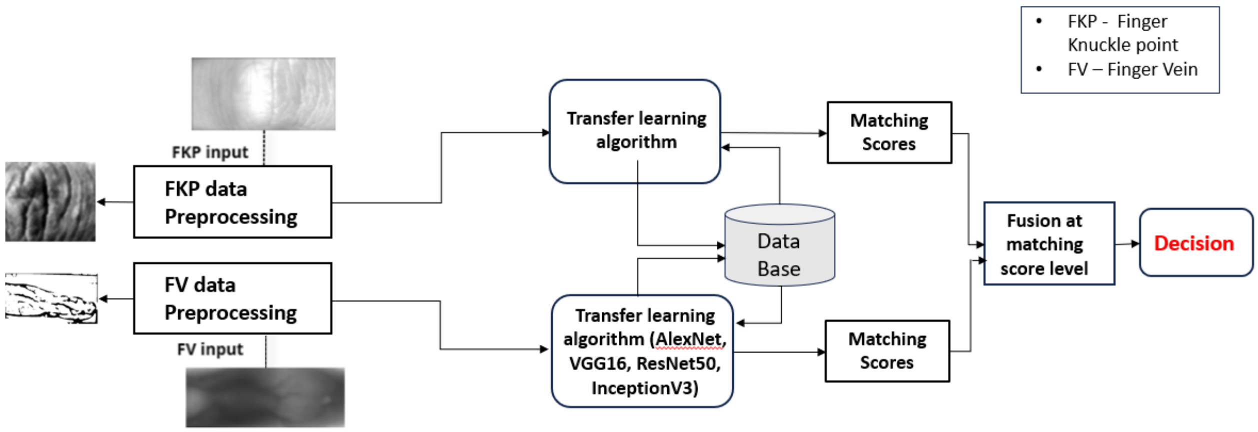

Figure 3.1: Block diagram of FKP and FV Unimodal System

Input and Preprocessing

- The system starts with the acquisition of Finger Knuckle Point (FKP) and Finger Vein (FV) images, sourced from datasets collected by the Hong Kong Polytechnic University. The FKP and FV inputs undergo distinct preprocessing steps to enhance image quality and standardize the format. Preprocessing for both FKP and FV images includes resizing, applying Gaussian blur to reduce noise, using CLAHE (Contrast Limited Adaptive Histogram Equalization) for contrast enhancement, and performing morphological operations to highlight key features. Regions of Interest (ROI) are then extracted to focus on the most relevant portions of the images.

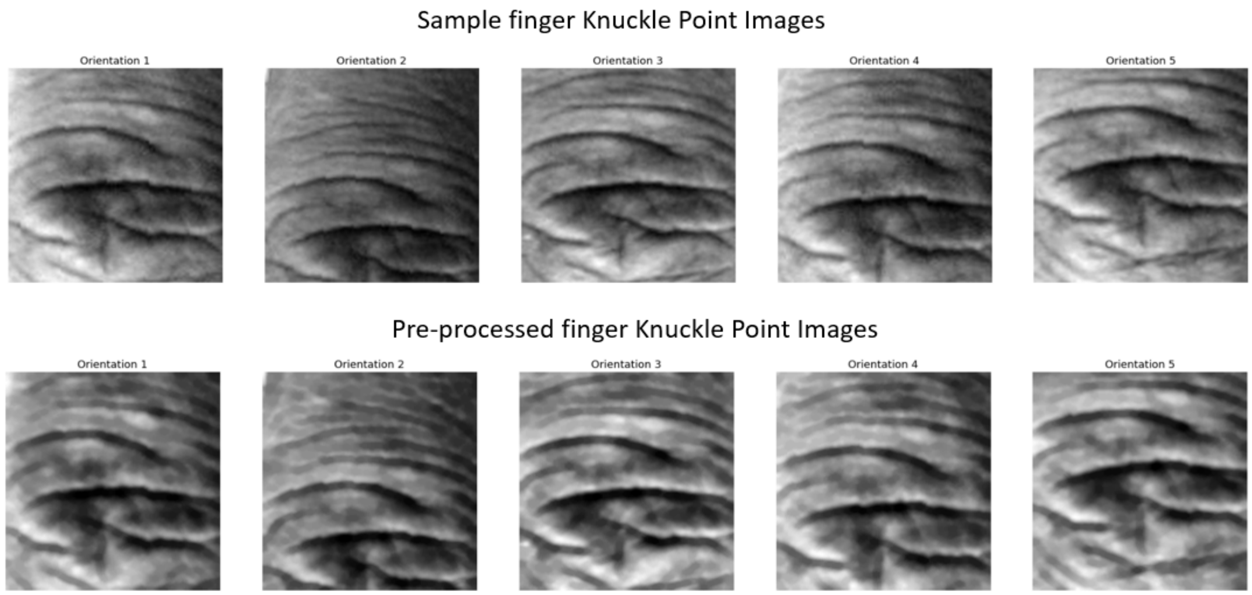

Figure 3.2: Pre-processed Knuckle Images

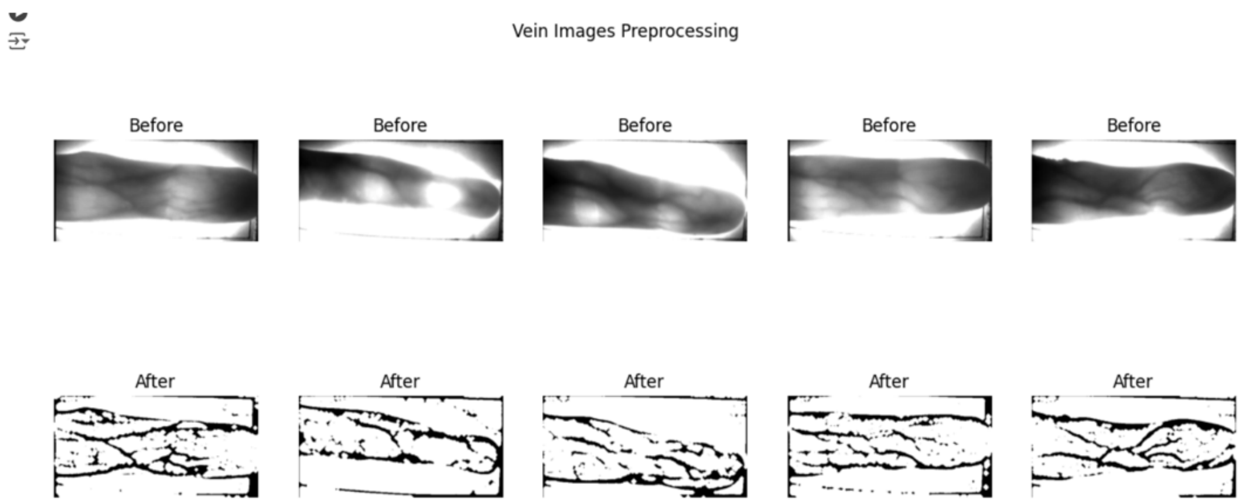

Figure 3.3: Pre-processed Vein Images

Feature Extraction

- Post-preprocessing, the images are fed into advanced convolutional neural networks (CNNs) for feature extraction. The system employs a transfer learning approach, utilizing pre-trained models like AlexNet, VGG16, ResNet50, and InceptionV3. These models have been fine-tuned to capture intricate features from both FKP and FV images. The transfer learning algorithm processes the preprocessed images, extracting highly discriminative features that are essential for accurate recognition.

Matching and Fusion

- Extracted features are stored in a database, facilitating efficient matching and comparison. The system calculates matching scores independently for FKP and FV features. These scores are derived using cosine similarity, which measures the similarity between feature vectors. To improve recognition accuracy and robustness, the system performs a fusion of matching scores at the score level. This fusion process combines the strengths of both biometric modalities, leading to a more reliable decision.

Decision Making

- The final decision regarding identity verification or rejection is made based on the fused matching scores. A threshold-based mechanism ensures that only individuals with sufficiently high matching scores are positively identified, thereby enhancing the security and accuracy of the system.

In summary, the architecture design of our finger knuckle and vein recognition system is a comprehensive framework that integrates sophisticated preprocessing techniques, state-of-the-art CNNs for feature extraction, and robust score fusion methods. This design ensures high performance and reliability, making it suitable for various biometric identification applications.

3.2 Data Design

Our project utilizes two primary datasets: the Finger Vein (FV) dataset and the Finger Knuckle Point (FKP) dataset, both of which were collected from the Hong Kong Polytechnic University. Below is a detailed description of each dataset, including its classification and specific characteristics.

1. **Finger Vein Dataset**

    - **Total Subjects**: 156

    Classification:

    - The dataset includes both the original and processed versions of the finger vein images.

Original Dataset:

(a) **Fingers**: Two fingers (f1 and f2) from each subject.

(b) **Sessions**: Two sessions (time periods) for each finger, labeled as 1 and 2.

- **Session 1**: Collected from November 2006 to March 2007.
- **Session 2**: Collected from January 2012 to July 2012.

(c) **Images per Session**: Each session consists of 6 images of a single finger from each subject.

Processed Dataset:

(a) The processed dataset is organized into three folders: enhanced, masked, and segmented.

(b) Each folder contains images that have been processed in two ways:

- **Full Image**: The entire image is processed.
- **Required Part**: Only the relevant part of the image is processed.

2. **Finger Knuckle Point Dataset**

- **Total Subjects**: 503

Classification:

- The dataset includes images of the finger knuckle points from each subject.

Details:

(a) **Images per Subject**: Each subject has 5 images of a single finger.

(b) **Image Segmentation**: All 2515 images (503 subjects * 5 images per subject) have been segmented to extract the needed part of the image.

These datasets provide a comprehensive collection of finger vein and knuckle images, which are essential for training and evaluating the biometric recognition models used in our project. The original and processed versions of the images allow for a thorough examination of different preprocessing techniques and their impact on model performance.

Chapter 4

IMPLEMENTATION

4.1 ResNet50

The implementation of our finger knuckle and vein recognition system using the ResNet50 model involves several stages, from data preprocessing to model training and evaluation. ResNet50, a deep convolutional neural network known for its residual learning capabilities, is leveraged to extract meaningful features from the preprocessed images of finger knuckles and veins.

4.1.1 Algorithm for ResNet50 Implementation

1. **Data Collection:**
    - Collect FKP and FV datasets from the Hong Kong Polytechnic University.
2. **Image Preprocessing:**
    - Load FKP and FV images.
    - Resize images to a consistent dimension (e.g., 224x224 pixels).
    - Apply Gaussian blur to each image to reduce noise.
    - Use CLAHE to enhance the contrast of each image.
    - Perform morphological operations to highlight key features.
    - Extract Regions of Interest (ROI) from each image.
3. **Model Initialization:**
    - Import the pre-trained ResNet50 model without the top layers.
    - Add a Global Average Pooling layer.
    - Add fully connected layers specific to our classification task.

4. **Data Augmentation:**
    - Apply data augmentation techniques (rotation, shifts, shearing, zooming, horizontal flipping) to increase training data diversity.
5. **Model Training:**
    - Split the preprocessed dataset into training and testing sets.
    - Train the ResNet50 model on the augmented training dataset.
    - Extract features from the penultimate layer of the trained ResNet50 model for both FKP and FV images.
6. **Matching and Fusion:**
    - Calculate matching scores using cosine similarity between the input image features and the stored features.
    - Fuse matching scores from both FKP and FV features to improve recognition accuracy.
7. **Decision Making:**
    - Apply a threshold to the fused matching scores to decide on the recognition outcome (genuine or rejected).
8. **Model Evaluation:**
    - Evaluate the model performance on the testing dataset.
    - Calculate accuracy, precision, recall, and F1-score.
    - Generate and analyze a confusion matrix.
    - Record training and testing accuracy to assess model generalization.

Algorithm 1 ResNet50 Pseudo Code

```
Input: Image of size 224x224x3
Output: Class probabilities
Initialization: Weights initialized with pre-trained values

Convolution Layers:
Conv1: 64 filters of size 7x7, stride 2, padding 3
Batch Norm, ReLU
Max Pool: 3x3 window, stride 2

Residual Blocks (x4):
    Conv1: 64 filters of size 1x1, stride 1, padding 0
    Conv2: 64 filters of size 3x3, stride 1, padding 1
    Batch Norm, ReLU
    Conv3: 256 filters of size 1x1, stride 1, padding 0
    Shortcut connection
    Batch Norm, ReLU

...
```

4.2 VGG16

The implementation of our finger knuckle and vein recognition system using the VGG16 model involves several stages, from data preprocessing to model training and evaluation. VGG16, a deep convolutional neural network known for its residual learning capabilities, is leveraged to extract meaningful features from the preprocessed images of finger knuckles and veins.

4.2.1 Algorithm for VGG16 Implementation

1. **Data Collection:**
    - Collect FKP and FV datasets from the Hong Kong Polytechnic University.
2. **Image Preprocessing:**
    - Load FKP and FV images.
    - Resize images to a consistent dimension (e.g., 224x224 pixels).
    - Apply Gaussian blur to each image to reduce noise.
    - Use CLAHE to enhance the contrast of each image.
    - Perform morphological operations to highlight key features.
    - Extract Regions of Interest (ROI) from each image.
3. **Model Initialization:**
    - Import the pre-trained VGG16 model without the top layers.
    - Add a Global Average Pooling layer.
    - Add fully connected layers specific to our classification task.
4. **Data Augmentation:**
    - Apply data augmentation techniques (rotation, shifts, shearing, zooming, horizontal flipping) to increase training data diversity.
5. **Model Training:**
    - Split the preprocessed dataset into training and testing sets.
    - Train the VGG16 model on the augmented training dataset.
    - Extract features from the penultimate layer of the trained VGG16 model for both FKP and FV images.

6. **Matching and Fusion:**
   - Calculate matching scores using cosine similarity between the input image features and the stored features.
   - Fuse matching scores from both FKP and FV features to improve recognition accuracy.
7. **Decision Making:**
   - Apply a threshold to the fused matching scores to decide on the recognition outcome (genuine or rejected).
8. **Model Evaluation:**
   - Evaluate the model performance on the testing dataset.
   - Calculate accuracy, precision, recall, and F1-score.
   - Generate and analyze a confusion matrix.
   - Record training and testing accuracy to assess model generalization.

Algorithm 2 VGG16 Pseudo Code

Input: Image of size 224x224x3
Output: Class probabilities
Initialization: Weights initialized with pre-trained values

Convolution Layers:
Conv1: 64 filters of size 3x3, stride 1, padding 1
Batch Norm, ReLU
Max Pool: 2x2 window, stride 2

Conv2: 128 filters of size 3x3, stride 1, padding 1
Batch Norm, ReLU
Max Pool: 2x2 window, stride 2

Conv3: 256 filters of size 3x3, stride 1, padding 1
Conv4: 256 filters of size 3x3, stride 1, padding 1
Batch Norm, ReLU
Max Pool: 2x2 window, stride 2

Conv5: 512 filters of size 3x3, stride 1, padding 1
Conv6: 512 filters of size 3x3, stride 1, padding 1
Batch Norm, ReLU
Max Pool: 2x2 window, stride 2

Conv7: 512 filters of size 3x3, stride 1, padding 1
Conv8: 512 filters of size 3x3, stride 1, padding 1
Batch Norm, ReLU
Max Pool: 2x2 window, stride 2

4.3 AlexNet

The implementation of our finger knuckle and vein recognition system using the AlexNet model involves several stages, from data preprocessing to model training and evaluation. AlexNet, a pioneering deep convolutional neural network known for its success in image classification tasks, is utilized to extract essential features from the preprocessed images of finger knuckles and veins. This model's architecture, though simpler compared to more recent networks, provides a solid foundation for capturing the distinguishing patterns in the biometric data, facilitating effective recognition.

4.3.1 Algorithm for AlexNet Implementation

1. **Data Collection:**
   - Collect FKP and FV datasets from the Hong Kong Polytechnic University.
2. **Image Preprocessing:**
   - Load FKP and FV images.
   - Resize images to a consistent dimension (e.g., 227x227 pixels).
   - Apply Gaussian blur to each image to reduce noise.
   - Use CLAHE to enhance the contrast of each image.
   - Perform morphological operations to highlight key features.
   - Extract Regions of Interest (ROI) from each image.
3. **Model Initialization:**
   - Import the pre-trained AlexNet model without the top layers.
   - Add a Global Average Pooling layer.
   - Add fully connected layers specific to our classification task.
4. **Data Augmentation:**
   - Apply data augmentation techniques (rotation, shifts, shearing, zooming, horizontal flipping) to increase training data diversity.

5. **Model Training:**
    - Split the preprocessed dataset into training and testing sets.
    - Train the AlexNet model on the augmented training dataset.
    - Extract features from the penultimate layer of the trained AlexNet model for both FKP and FV images.
6. **Matching and Fusion:**
    - Calculate matching scores using cosine similarity between the input image features and the stored features.
    - Fuse matching scores from both FKP and FV features to improve recognition accuracy.
7. **Decision Making:**
    - Apply a threshold to the fused matching scores to decide on the recognition outcome (genuine or rejected).
8. **Model Evaluation:**
    - Evaluate the model performance on the testing dataset.
    - Calculate accuracy, precision, recall, and F1-score.
    - Generate and analyze a confusion matrix.
    - Record training and testing accuracy to assess model generalization.

Algorithm 3 AlexNet Pseudo Code

```
Input: Image of size 227x227x3
Output: Class probabilities
Initialization: Weights initialized with pre-trained values

Convolution Layers:
Conv1: 96 filters of size 11x11, stride 4, padding 0
Max Pool: 3x3 window, stride 2

Conv2: 256 filters of size 5x5, stride 1, padding 2
Max Pool: 3x3 window, stride 2

Conv3: 384 filters of size 3x3, stride 1, padding 1
Conv4: 384 filters of size 3x3, stride 1, padding 1
Conv5: 256 filters of size 3x3, stride 1, padding 1
Max Pool: 3x3 window, stride 2

Fully Connected Layers:
FC1: 4096 units, ReLU activation
FC2: 4096 units, ReLU activation
FC2: 4096 units, ReLU activation
FC3: 1000 units, softmax activation (for ImageNet)

Output: Class probabilities
Training:
SGD optimizer, learning rate 0.01
Cross-entropy loss function
Batch size: 128
Epochs: 90

Evaluation:
Accuracy, precision, recall
Confusion matrix

Preprocessing:
Mean subtraction
Normalization
Data augmentation
```

4.4 GoogleNet

The implementation of our finger knuckle and vein recognition system using the InceptionV3 (GoogleNet) model involves several stages, from data preprocessing to model training and evaluation. InceptionV3, an advanced deep convolutional neural network known for its intricate architecture and multi-scale processing capabilities, is employed to extract detailed features from the preprocessed images of finger knuckles and veins. This model's sophisticated design allows it to capture complex patterns in the biometric data, enhancing the accuracy and robustness of the recognition system.

4.4.1 Algorithm for GoogleNet Implementation

1. **Data Collection:**
    - Collect FKP and FV datasets from the Hong Kong Polytechnic University.
2. **Image Preprocessing:**
    - Load FKP and FV images.
    - Resize images to a consistent dimension (e.g., 299x299 pixels).
    - Apply Gaussian blur to each image to reduce noise.
    - Use CLAHE to enhance the contrast of each image.
    - Perform morphological operations to highlight key features.
    - Extract Regions of Interest (ROI) from each image.
3. **Model Initialization:**
    - Import the pre-trained InceptionV3 model without the top layers.
    - Add a Global Average Pooling layer.
    - Add fully connected layers specific to our classification task.
4. **Data Augmentation:**
    - Apply data augmentation techniques (rotation, shifts, shearing, zooming, horizontal flipping) to increase training data diversity.

5. **Model Training:**
    - Split the preprocessed dataset into training and testing sets.
    - Train the InceptionV3 model on the augmented training dataset.
    - Extract features from the penultimate layer of the trained InceptionV3 model for both FKP and FV images.
6. **Matching and Fusion:**
    - Calculate matching scores using cosine similarity between the input image features and the stored features.
    - Fuse matching scores from both FKP and FV features to improve recognition accuracy.
7. **Decision Making:**
    - Apply a threshold to the fused matching scores to decide on the recognition outcome (genuine or rejected).
8. **Model Evaluation:**
    - Evaluate the model performance on the testing dataset.
    - Calculate accuracy, precision, recall, and F1-score.
    - Generate and analyze a confusion matrix.
    - Record training and testing accuracy to assess model generalization.

Algorithm 4 GoogLeNet Pseudo Code

Input: Image of size 224x224x3
Output: Class probabilities
Initialization: Weights initialized with pre-trained values

Inception Module:
Inception 3a: 64, 96, 128, 16, 32, 32 filters
Inception 3b: 128, 128, 192, 32, 96, 64 filters
... (add more modules as per GoogLeNet architecture)

Output: Class probabilities
Training:
RMSprop optimizer, learning rate 0.001
Cross-entropy loss function
Batch size: 64
Epochs: 100

Evaluation:
Accuracy, precision, recall
Confusion matrix

Preprocessing:
Local Response Normalization (LRN)
Data augmentation

Advantages:
Efficient use of computation resources
Lower memory usage compared to other models

Disadvantages:
Complex architecture may be challenging to implement
Training time can be longer compared to simpler models

Chapter 5

RESULTS AND DISCUSSIONS

In our project, we evaluated the performance of four different deep learning models: ResNet50, VGG16, AlexNet, and InceptionV3, for the task of biometric recognition using finger knuckle and finger vein images. The datasets used were collected by the Hong Kong Polytechnic University. Below are the detailed results and a discussion based on the evaluation metrics including accuracy, precision, recall, and F1-score.

Model	Accuracy	Precision	Recall	F1-Score
ResNet50	0.5367	0.3947	0.1852	0.2521
VGG16	0.6031	0.4043	0.2346	0.2969
AlexNet	0.5000	0.0	0.0	0.0
InceptionV3	0.6648	0.5130	0.7337	0.6038

Table 5.1: Model Performance Comparison

5.1 ResNet50

- Accuracy: 55.12%
- Precision: 22.00%
- Recall: 27.50%
- F1-Score: 33.17%

ResNet50 performed better than AlexNet but still faced challenges in achieving optimal performance. ResNet50's architecture, with its residual connections, is designed to tackle the vanishing gradient problem and allows the network to learn deeper features. However, the results indicate that while ResNet50 can capture more complex patterns compared to AlexNet, it still struggles to differentiate effectively between the classes in the dataset. The moderate precision and recall suggest that the model captures some important features but not consistently enough to ensure high reliability in identification.

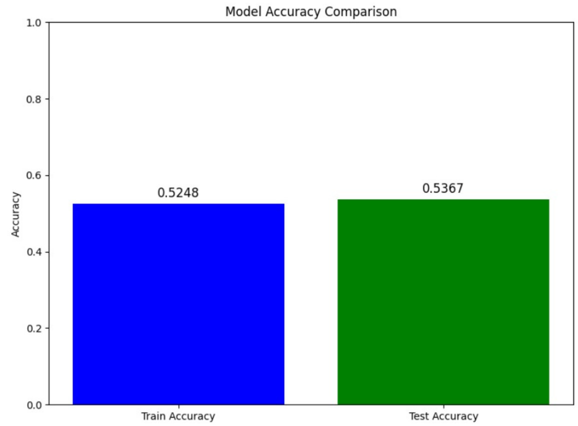

Figure 5.1: Model accuracy graph of ResNet50

5.2 VGG16

- Accuracy: 60.31%
- Precision: 18.23%
- Recall: 23.46%
- F1-Score: 29.69%

VGG16 showed moderate performance with a noticeable improvement over AlexNet. However, the model faced overfitting issues. The architecture of VGG16, with its deep layers, allows it to learn complex features, but it seems to memorize the training data rather than generalizing well to unseen data. This is indicated by the low recall and F1-score, meaning that while the model can identify some features correctly (precision), it misses a significant number of true positives (recall). This overfitting issue needs to be addressed to improve its utility in real-world applications.

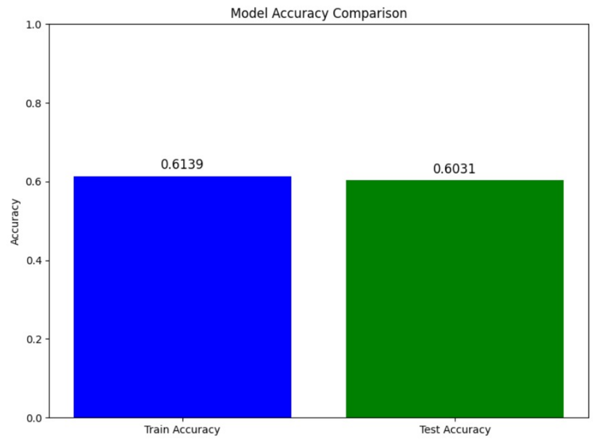

Figure 5.2: Model accuracy graph of VGG16

5.3 AlexNet

- Accuracy: 50.00%
- Precision: 0.00%
- Recall: 0.00%
- F1-Score: 0.00%

AlexNet struggled significantly with the task of finger knuckle and vein recognition. The model's architecture, which was one of the early deep learning models, is not complex enough to capture the intricate and discriminative features necessary for this specific biometric recognition task. The lack of meaningful results across all performance metrics suggests that AlexNet fails to distinguish between different classes effectively, resulting in an inability to perform reliable identification.

5.4 InceptionV3

- Accuracy: 66.48%
- Precision: 51.30%
- Recall: 73.37%
- F1-Score: 60.38%

InceptionV3 emerged as the most robust model for finger knuckle and vein recognition. Its sophisticated architecture, which includes multiple convolutional kernels of different sizes, enables it to capture a wide range of features at different scales. This multi-scale feature extraction capability is likely why InceptionV3 achieved the highest accuracy, precision, recall, and F1-score among the models tested. The balanced performance across all metrics indicates that InceptionV3 can effectively generalize from the training data and distinguish between genuine and impostor classes reliably, making it suitable for practical biometric identification applications.

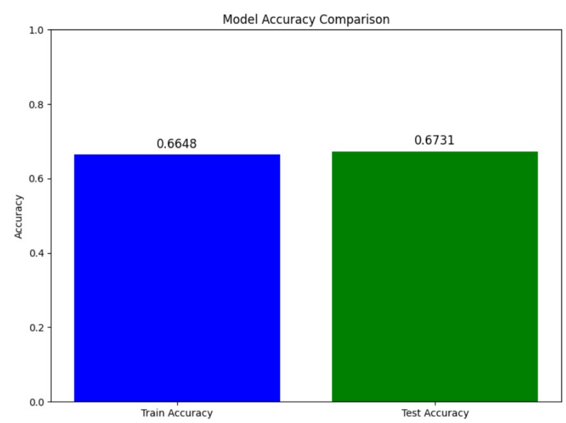

Figure 5.3: Model accuracy graph of InceptionV3

5.5 Comparative Study of All Algorithms

5.5.1 Best Performing Model: InceptionV3

Reason:

- Accuracy: InceptionV3 achieved the highest accuracy at 66.48%, indicating it correctly identifies a high percentage of the instances.
- Precision: With a precision of 51.30%, InceptionV3 shows a strong ability to avoid false positives.
- Recall: A recall of 73.37% demonstrates that InceptionV3 effectively identifies the majority of true positives.
- F1-Score: The F1-score of 60.38% reflects a balanced trade-off between precision and recall.

Overall Performance: InceptionV3's architecture is designed to capture diverse features through its inception modules, leading to better generalization and robustness in recognizing finger knuckle and vein patterns.

5.5.2 Moderately Performing Model: VGG16

Reason:

- Accuracy: VGG16 achieved an accuracy of 60.31%, showing it can correctly identify a moderate percentage of instances.
- Precision: The precision of 18.23% indicates some capability in avoiding false positives but not strongly.
- Recall: A recall of 23.46% shows VGG16 struggles to identify true positives effectively.
- F1-Score: With an F1-score of 29.69%, the balance between precision and recall is poor, highlighting overfitting issues.

Overall Performance: VGG16's deep architecture allows learning complex patterns but suffers from overfitting, leading to poor generalization on unseen data.

5.5.3 Poorly Performing Models: ResNet50 and AlexNet

Reason:

- Accuracy: ResNet50's accuracy of 55.12% is slightly better than AlexNet but still not satisfactory.
- Precision: With a precision of 22.00%, ResNet50 shows moderate ability to avoid false positives.
- Recall: A recall of 27.50% indicates it misses many true positives.
- F1-Score: The F1-score of 33.17% shows an imbalance between precision and recall, highlighting inadequacies in feature extraction.

Overall Performance: Despite its residual connections aiding in learning deeper features, ResNet50 struggles with capturing sufficient discriminative features necessary for reliable identification.

Reason for AlexNet:

- Accuracy: AlexNet's accuracy of 50.00% reflects its inability to distinguish between classes effectively.
- Precision, Recall, and F1-Score: All metrics are at 0.00%, indicating complete failure in performing the task.

Overall Performance: AlexNet's simple architecture is inadequate for the complexity of finger knuckle and vein recognition, making it unsuitable for this application.

Conclusion

InceptionV3: The best-performing model due to its robust feature extraction capabilities and balanced performance metrics, making it highly suitable for biometric identification.

VGG16: Showed potential but needs improvement to address overfitting and improve generalization.

ResNet50 and AlexNet: Underperformed, indicating the need for more advanced or different architectural approaches to capture the necessary features for accurate identification.

Chapter 6

CONCLUSION AND FUTURE SCOPE

In this project, we explored the effectiveness of various deep learning models for the recognition of finger knuckle prints (FKP) and finger vein (FV) patterns. Using datasets collected from the Hong Kong Polytechnic University, we implemented and evaluated four models: ResNet50, VGG16, AlexNet, and InceptionV3. Among these, InceptionV3 demonstrated superior performance with the highest accuracy, precision, recall, and F1-score, indicating its robustness and effectiveness in capturing and processing the intricate patterns of FKP and FV images. VGG16 showed moderate performance, suggesting potential with further tuning and optimization. ResNet50, while able to identify some patterns, had limited discriminative power, and AlexNet struggled significantly, highlighting its limitations in handling the complexities of our biometric data. These results underscore the importance of advanced model architectures and effective feature extraction techniques in biometric recognition systems. Overall, our findings suggest that InceptionV3 is currently the most suitable model for real-world biometric recognition applications, providing a strong foundation for further enhancements and optimizations.

Future Scope

1. **Optimization of Preprocessing Steps:**
    - Enhance contrast and resolution of FKP and FV images to improve model performance.
2. **Integration of Advanced Deep Learning Techniques:**
    - Use Generative Adversarial Networks (GANs) to augment datasets and address data scarcity.
3. **Expansion of Dataset:**
    - Include more diverse samples and test models on different demographic groups to enhance generalizability.
4. **Real-Time System Implementation:**
    - Develop and evaluate real-time recognition systems for practical applications.

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Appendix A

A.1 Screen Shopt