**Fingerprint Identification with fusion of Gabor and** **Minutiae features using BPNN classifier**

**Abstract:**

This study presents an innovative approach to fingerprint identification by leveraging the fusion of Gabor and Minutiae features, employing a Backpropagation Neural Network (BPNN) classifier for accurate categorization. The process involves initial handling of a fingerprint image dataset, including crucial pre-processing steps such as resizing images and implementing morphological operations like dilation, erosion, and opening. Subsequently, Gabor features and minutiae extraction are performed, followed by the fusion of these features to create a comprehensive representation. To address dimensionality concerns, Principal Component Analysis (PCA) is applied. The dataset, comprising the fused features and corresponding labels, is then loaded for the final step - classification using a BPNN. The network is configured for feed-forward backpropagation, distinguishing fingerprint patterns into categories such as arch, left loop, right loop, tented, and whorl. The evaluation metric used to measure the success of the classification process is accuracy. This approach aims to enhance fingerprint recognition by combining distinctive Gabor and minutiae features, ultimately achieving a more robust and precise identification system through the utilization of neural network-based classification.

**Keywords**: Finger print images dataset, BPNN, Deep learning techniques, PCA, classification and pre-processing, Minutiae features.

**Existing System:**

**Block Diagrams:**

Input Image

Pre - Processing

PCA

Convolution Neural Network

Layers

Training Options

Classification

Image Resize

Morphological Operations

* Dilate Image
* Erode Image
* Opening of Image

Accuracy

Gabor Features

Classification

* Arch
* Left Loop
* Right Loop
* Tented
* Whorl

**Figure 1. Existing Method Block Diagram**

The Existing Method involves leveraging Gabor features and a Convolutional Neural Network (CNN) classifier to enhance fingerprint identification. Initially, the fingerprint images undergo preprocessing steps, including resizing, morphological operations, and extraction of Gabor phase and texture features. These preprocessing techniques aim to standardize image sizes, enhance feature extraction, and improve the quality of fingerprint representations. Principal Component Analysis (PCA) is then utilized for dimensionality reduction, optimizing feature selection and improving computational efficiency. Subsequently, the CNN classifier, powered by deep learning techniques, is employed for classification. The CNN model is trained using labelled data to recognize various fingerprint patterns, such as Arch, Left Loop, Right Loop, Tented, and Whorl. Through the training process, the CNN learns to differentiate between different fingerprint patterns based on the extracted Gabor features. The classification accuracy of the system is evaluated to gauge its effectiveness in accurately categorizing fingerprints into their respective patterns. By integrating Gabor features with CNN classification, this methodology aims to achieve heightened accuracy in fingerprint identification, thereby advancing the capabilities of biometric security systems.

**Disadvantages:**

* Using a CNN for fingerprint ID needs lots of computer time.
* Neural networks need lots of data for good training, making it tough for fingerprint datasets with various patterns.
* CNNs are like black boxes, hard to understand how they work.

**Proposed System:**

The proposed methodology for fingerprint identification involves several sequential steps to enhance accuracy through the fusion of Gabor and Minutiae features using a Backpropagation Neural Network (BPNN) classifier. Initially, a dataset of fingerprint images is collected, followed by a preprocessing stage. This includes resizing images and applying morphological operations, such as dilation, erosion, and opening, to improve the quality and clarity of the features. Gabor features, capturing texture information, and minutiae extraction, identifying specific ridge characteristics, are then extracted. The fusion of Gabor and minutiae features aims to create a comprehensive representation of fingerprint patterns. To manage the high-dimensional feature space, Principal Component Analysis (PCA) is applied for dimensionality reduction. Subsequently, the reduced feature set along with their corresponding labels are loaded for the final classification step. A feed-forward BPNN is created to train the model to classify fingerprints into distinct categories, such as arches, left loops, right loops, tented arches, and whorls. The accuracy of the classification results is evaluated, demonstrating the effectiveness of the proposed methodology in accurately identifying and categorizing various fingerprint patterns.

Input Image

Pre-Processing

Minutiae features

Gabor Features

Fusion of Minutiae Features and Gabor features

Principal Component Analysis (PCA)

Create a feed-forward backpropagation network (BPNN)

Resize Image

Features

 Labels

Classification

* Arch
* Left Loop
* Right Loop
* Tented
* Whorl

Accuracy

Morphological Operations

* Dilate Image
* Erode Image
* Opening of Image

**Fig: Proposed Method Block Diagram**

**Advantages:**

* Combining Gabor and Minutiae features boosts fingerprint system accuracy, securing access.
* BPPN learns well, helps classify, makes fingerprint ID smoother, more effective.
* System uses BPPN and Minutiae, works well for all fingerprint types.
* Minutiae features enable unique and precise fingerprint identification.

**Applications:**

* Biometric Security.
* Fingerprint help police catch criminals and track suspects in investigations.
* Fingerprint systems help border control verify travellers and spot fake documents.
* Fingerprint security safeguards banking, blocks unauthorized access to accounts and data.

**Software & Hardware Requirements:**

**Software:** MATLAB 2020a or above

**Hardware:**

**Operating Systems:**

* Windows 10
* Windows 7 Service Pack 1
* Windows Server 2019
* Windows Server 2016

**Processors:**

Minimum: Any Intel or AMD x86-64 processor

Recommended: Any Intel or AMD x86-64 processor with four logical cores and AVX2 instruction set support

**Disk:**

Minimum: 2.9 GB of HDD space for MATLAB only, 5-8 GB for a typical installation

Recommended: An SSD is recommended A full installation of all MathWorks products may take up to 29 GB of disk space

**RAM:**

Minimum: 4 GB

Recommended: 8 GB

**Learning outcomes:**

* Introduction to MATLAB
* What is EISPACK & LINPACK
* How to start with MATLAB
* About MATLAB language
* MATLAB coding skills
* About tools & libraries
* Application Program Interface in MATLAB
* About MATLAB desktop
* How to use MATLAB editor to create M-Files
* Features of MATLAB
* Basics on MATLAB
* What is an Image/pixel?
* About image formats
* Introduction to Image Processing
* How digital image is formed
* Importing the image via image acquisition tools
* Analyzing and manipulation of image.
* Phases of image processing:
* Acquisition
* Image enhancement
* Image preprocessing
* Image restoration
* Color image processing
* Image compression
* Morphological processing
* Segmentation etc.,
* CNN architecture
* How to extend our work to another real time applications
* Project development Skills
  + Problem analyzing skills
  + Problem solving skills
  + Creativity and imaginary skills
  + Programming skills
  + Deployment
  + Testing skills
  + Debugging skills
  + Project presentation skills
  + Thesis writing skills