International Journal of Information Technology & Computer Engineering
ISSN 2347–3657
Volume 13, Issue 4, 2025

Improving Fingerprint Recognition With CNN

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Abstract
A deep learning-based fingerprint recognition system is developed to match contactless fingerprint inputs with stored contact-based fingerprint records. Using a lightweight yet powerful MobileNetV2 architecture, the system efficiently extracts deep features from fingerprint images while maintaining high accuracy and fast performance. The model is trained with a distance-aware loss function and incorporates ridge-based features to improve matching reliability between the two modalities. When a user uploads a contactless fingerprint image, the system preprocesses it, generates a feature embedding, and compares it with a database of contact-based fingerprints to identify the best match.
The matched person ID is then displayed through an attractive and interactive user interface designed for ease of use. This solution avoids physical contact with sensors, making it suitable for touch-free, hygienic authentication in public or mobile environments. The integration of MobileNetV2 makes the system highly scalable and lightweight, suitable for deployment on both desktops and embedded platforms. Overall, this project demonstrates the practical application of deep learning in bridging modality gaps in fingerprint biometrics, offering a robust and future-ready identity verification system.

Keywords: Fingerprint Recognition, Deep learning, MobileNetV2, Contactless authentication, Feature Extraction, Biometric matching, Lightweight Model.

1. Introduction

Fingerprint recognition is a fundamental component of biometric security, extensively used in law enforcement, border control, and mobile identification. Nevertheless, conventional minutiae-based techniques encounter difficulties with low-quality or incomplete fingerprints, resulting in elevated mistake rates. The growing use of contactless fingerprint technology requires precise matching with conventional contact-based fingerprints for smooth integration and improved security. Nonetheless, considerable disparities in picture quality, distortion, and feature representation across various fingerprint forms constitute a serious difficulty.

Current fingerprint matching techniques often inadequately resolve these inconsistencies, leading to diminished accuracy and heightened error rates, especially in cross-sensor contexts. Consequently, there is an urgent need for a resilient and flexible solution that utilizes sophisticated deep learning methodologies to extract distinctive characteristics that remain consistent despite sensor variances, facilitating dependable and precise matching across contactless and contact-based fingerprints.

This study presents a deep learning solution using a lightweight MobileNetV2 architecture tailored for fast extraction of fingerprint features to address these problems.

The model employs a distance-aware loss function, augmenting its capacity to differentiate between analogous and disparate fingerprint pairs.

Ridge-based feature integration enhances the resilience of feature representation across many sensing modalities. Comprehensive preprocessing methods are used to standardize and improve fingerprint photos, guaranteeing uniform input quality.

Existing System:

Conventional systems often use optical or capacitive sensors to acquire fingerprints, using minutiae-based matching that compares distinctive features such as ridges and valleys. These techniques are often used in fingerprint scanners on smartphones and computers. Cloud-based biometric systems store and analyze fingerprint data in cloud settings, using sophisticated algorithms for matching and managing extensive datasets.

Proposed System:

We offer a Multi-Siamese-CNN architecture to provide resilient representations for both contactless and contact-based fingerprints. The network employs minutiae and ridge map characteristics, trained using a distance-sensitive loss function. Deep feature concatenation facilitates precise cross-comparison across fingerprint categories. This method improves matching efficacy, addressing sensor-specific picture discrepancies. The objective is to enhance precision and dependability in cross-sensor fingerprint identification.

2. Literature Survey:

An orderly evaluation of current biometric identification approaches was undertaken to develop an effective model for fingerprint recognition with Convolutional Neural Networks (CNN). The main objective was to ascertain the prevailing approaches for fingerprint comparison, evaluate existing deficiencies, and investigate critical research domains in biometric authentication systems.

This study presents a sophisticated fingerprint identification system designed to precisely match contactless fingerprint photos with those obtained from conventional contact-based scanners, using deep learning and contemporary web technologies. The fundamental methodology is derived from the CNN-based framework established by Srilatha et al., which illustrated the viability and efficacy of employing convolutional neural networks for cross-modality fingerprint matching, tackling both technical and practical obstacles in biometric identification [1]. To augment identification accuracy, the system employs sophisticated deep learning methodologies and effective feature extraction strategies, as examined by Sudhakar et al., who emphasized the advantages of applying deep convolutional neural networks for enhanced fingerprint recognition efficacy [3]. The study utilizes research by Lin and Fan, who examined the use of deep neural networks for contactless fingerprint identification, offering critical insights into the preprocessing and feature extraction processes essential for dependable cross-modality matching [4]. The extensive context of biometric research, encompassing its historical achievements, current obstacles, and prospective avenues, is elucidated by the thorough review by Jain, Nandakumar, and Ross, which emphasizes the necessity for resilient and scalable solutions in fingerprint recognition. The project employs advanced approaches for image preprocessing and segmentation, as reviewed by Minaee et al., to guarantee that input fingerprint photos are of superior quality before feature extraction and matching [5]. The project prioritizes user experience and security alongside technical advancements in fingerprint recognition, featuring a professional web interface designed according to best practices in HTML and CSS as detailed by Duckett, facilitating secure user authentication and smooth system interaction [6]. By incorporating these research-based methodologies, the project enhances the precision and dependability of fingerprint identification while providing a scalable, secure, and user-friendly solution for contemporary biometric applications, thereby facilitating future advancements in remote and contactless identification technologies.

3. Design

Architecture:

System Architecture:

System architecture delineates the configuration and functionality of a system or solution, demonstrating the interaction of different components to achieve designated goals. It offers an abstract depiction of the application's progression, sometimes shown via diagrams. The main objective of system architecture is to design a thorough and logically coherent solution grounded on recognized ideas and concepts. It guarantees that all system components operate synergistically to fulfill both functional and non-functional criteria. Architectural efforts concentrate on aligning the system with business objectives and stakeholder expectations, while also considering scalability, dependability, and performance. By recognizing possible hazards early, the architecture facilitates improved planning and execution. It functions as a blueprint, directing developers and engineers throughout the implementation phase. Ultimately, system design guarantees that the solution is efficient, adaptable, and prepared for future developments in response to increasing requirements.

Technical Architecture:

The technological design of the fingerprint recognition system emphasizes the development of a modular, scalable, and user-friendly application using deep learning. The client interface, constructed using HTML, CSS, and JavaScript, facilitates the submission of contactless fingerprint photos to a Python-based HTTP server. The Flask-based server orchestrates routing and assigns duties to backend services for data processing and fingerprint matching. A machine learning module manages preprocessing, deep feature extraction using CNNs, and comparison with contact-based fingerprint information stored in a SQL database. The technology provides precise, instantaneous results, guaranteeing smooth, sanitary authentication appropriate for both public and integrated applications.

Data Flow Diagram:

The DFD is sometimes referred to as a bubble chart. This is a straightforward graphical formalism used to depict a system in relation to its input data, the different processing conducted on this data, and the output data produced by the system. The data flow diagram (DFD) is a crucial modeling tool. It is used to represent the system components. The components include the system process, the data used by the process, an external entity that interacts with the system, and the information flows inside the system.

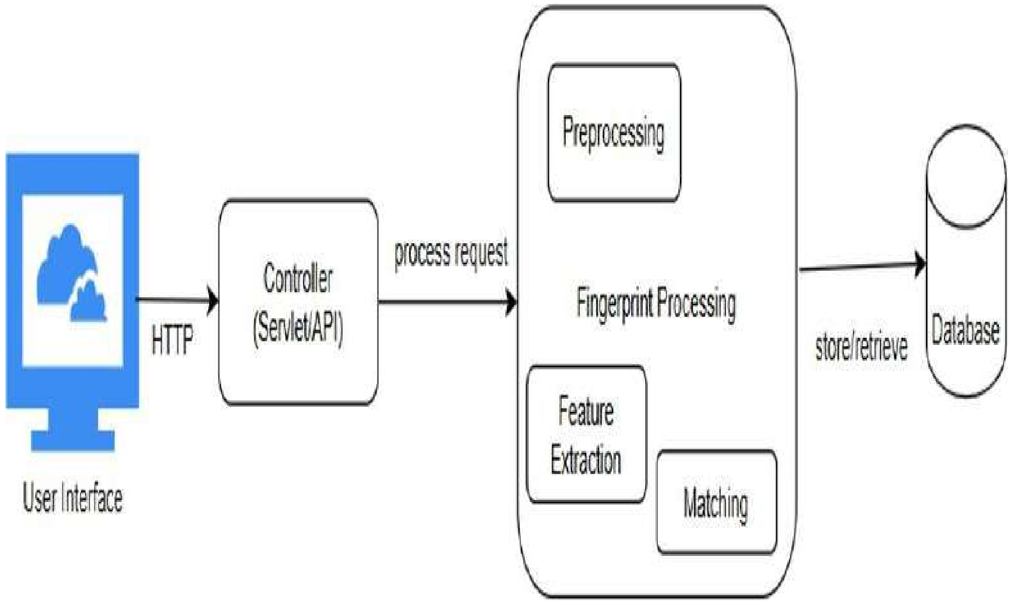


Fig. 1 System Architecture

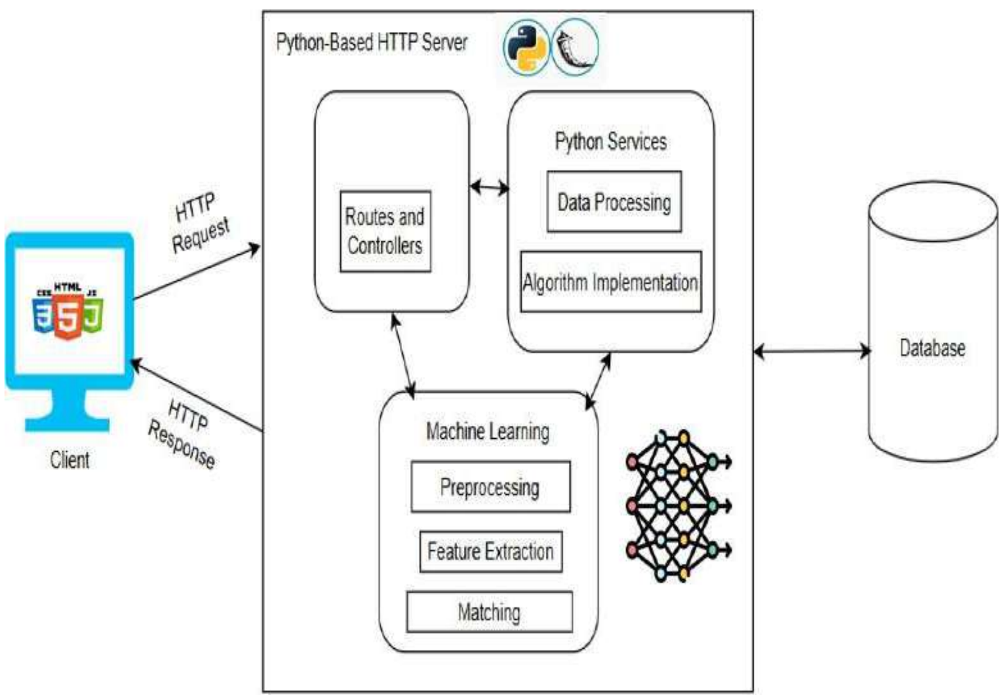


Fig. 2 Technical Architecture

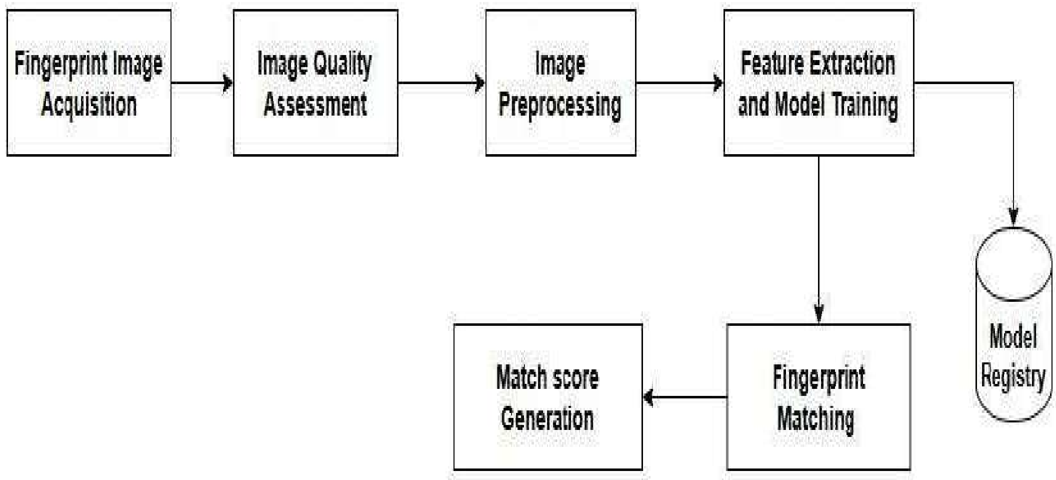


Fig. 3 Data Flow diagram

Methodology:

Developing a fingerprint recognition system that is based on deep learning and that connects contactless fingerprint inputs with contact-based information is the method that we are using for our research. In the beginning, we collect and organize fingerprint data from the PolyU dataset, making sure that there are pairs of contactless and contact-based photographs available. In order to enhance the overall image quality, preprocessing techniques are used. These operations include scaling, grayscale conversion, contrast improvement, and the production of ridge maps where they are desired. For the purpose of extracting deep features from both modalities, a Siamese CNN that is based on MobileNetV2 is used. A distance-aware loss function, such as contrastive or triplet loss, is applied to the features throughout the processing phase in order to provide embeddings that are resilient and invariant. All contact-based fingerprints are stored in a database, and the trained model is responsible for generating embeddings for each unique fingerprint. A contactless photo is uploaded to the backend server using an easy-to-use web interface that was designed with HTML, CSS, and JavaScript. The backend server then preprocesses the image, extracts its embedding, and does a nearest-neighbor search against the database. Following the discovery of a match, the user ID that is pertinent is returned. The system was developed with scalability, real-time efficiency, and cross-sensor resiliency in mind from the beginning. Performance evaluation is accomplished by the use of metrics such as Rank-1 accuracy and Equal Error Rate (EER).

4. Implementation

Numpy

For numerical calculations and matrix operations, NumPy is an indispensable package for the Python programming language. For the purpose of our fingerprint comparison project, it is necessary to analyze the pixel data of fingerprint photographs and convert them into arrays that are appropriate for deep learning models. Using NumPy arrays, pre-processed photographs (such as those that have been scaled, normalized, and reshaped) may be properly represented in memory. Rapid element-wise operations, the reshaping of multi-dimensional image tensors, and seamless interaction with TensorFlow for training and inference are all made possible by this feature.

Pandas

The Pandas programming language is a high-performance tool for data analysis and manipulation that makes it easier to work with structured data. For the purpose of maintaining tabular data related with the fingerprint dataset, the fingerprint comparison system makes use of Pandas. This includes the storage of information such as user IDs, photo URLs, timestamps, and similarity scores. The usage of Pandas DataFrames allows for the generation of logs for the purposes of analysis and documentation whenever users submit fingerprints or execute matching requests. Additionally, it is advantageous for the purpose of purifying and transforming the data before it is visualized or fed into the machine learning model.

TensorFlow

The strong deep learning framework known as TensorFlow was developed by Google and is extensively used for the purpose of training and deploying machine learning models. In the course of our research, we used TensorFlow to create and train a Convolutional Neural Network (CNN) that was capable of recognizing detailed fingerprint patterns from contactless and contact-based photographs. The GPU acceleration that TensorFlow provides makes it possible to speed up the process of training models on huge datasets. In addition to facilitating the loading and processing of image datasets, the system is responsible for monitoring the training loop and evaluating performance based on metrics such as accuracy and loss respectively. Utilizing a Flask backend, the model is used for the purpose of real-time forecasting.

Matplotlib

The Matplotlib toolkit is a popular Python toolkit that is used for the generation of graphs and visualizations. In the research that we conducted on fingerprint comparison, Matplotlib was an essential component in shedding light on the training behavior of the CNN. Consequently, it allows the viewing of accuracy and loss graphs throughout epochs, which helps to validate the effectiveness of the model's learning capabilities. It is also possible to use it to display fingerprint images prior to and during the preprocessing stage, which may be of assistance in the identification of any issues that may arise with regard to the loading or resizing of images. When it comes to developing presentation materials or reports, as well as analyzing the performance of the model, these visual representations are quite helpful.

OpenCV

OpenCV, which stands for Open Source Computer Vision Library, is a comprehensive library that may be used for applications related to image processing and computer vision. via the use of OpenCV, our project is able to scan fingerprint photographs, transform them into grayscale, resize them to the input dimensions required by the CNN, and enhance features via the use of methods such as filtering and thresholding approaches. These preprocessing procedures are very necessary in order to provide accurate and dependable predictions using the model. The durability of the comparison system is improved as a result of OpenCV's ability to assist the handling of real-world photographs that may vary in terms of lighting, perspective, or resolution. Not only may OpenCV be used for preprocessing, but it can also be used to display matching results on photographs or to identify disparities for further study.

Flask

A Python web framework that is used for the construction and deployment of online applications, Flask provides a basic development environment. In the fingerprint comparison system that we have developed, Flask acts as a bridge between the machine learning backend and the frontend user interface. Authentication, registration, the uploading of pictures, and the display of results are some of the tasks that may be accomplished using its provisions. Flask is used to deploy the trained fingerprint comparison model, which provides real-time answers to user uploads. This is accomplished by evaluating the contactless fingerprint and giving the contact-based photo or user ID that corresponds to the fingerprint. In addition to assisting in the dynamic generation of result pages, Flask's templating engine, Jinja2, makes it possible for authorized users to participate in safe browsing sessions.

Scikit-learn

Scikit-learn is a Python program that is well regarded for its user-friendliness and comprehensive capabilities. It is a machine learning software that has several facets. This project includes actions such as dividing the dataset into training and testing subsets, computing similarity scores across feature vectors, and evaluating the model using metrics like as the confusion matrix or accuracy score. These are only few of the activities that are included inside this project. The evaluation of similarities between fingerprint embeddings (feature vectors) is made easier by the distance functions provided by Scikit-learn. These distance functions include cosine and Euclidean distance, among others.

Imbalanced Learn

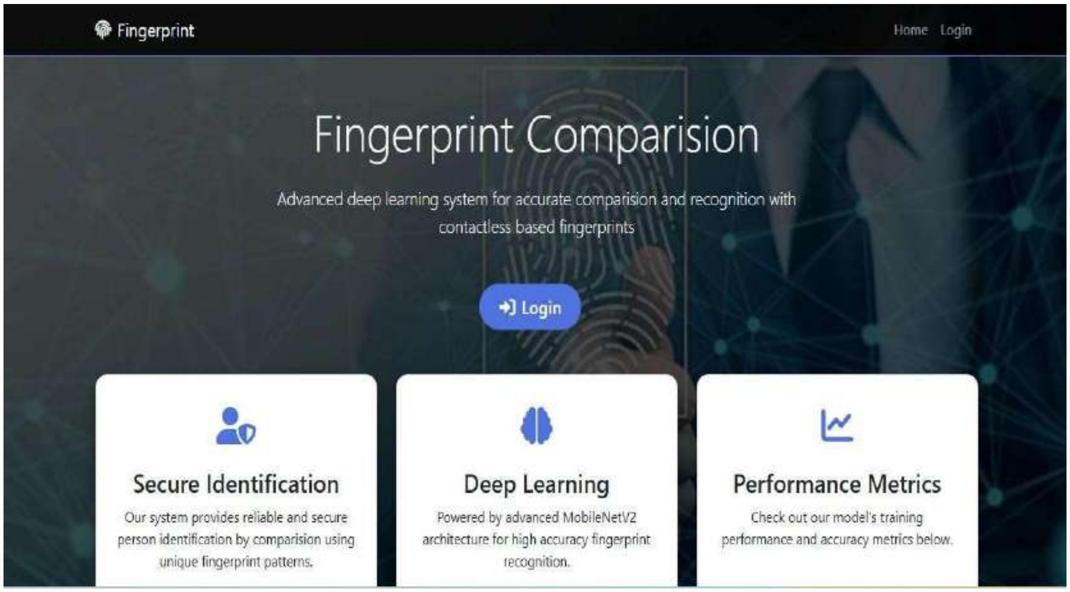
Imbalanced-learn is a dedicated package designed to address datasets with skewed class distributions, a prevalent challenge in real-world biometric datasets. Our fingerprint project guarantees equitable representation of each user (or fingerprint class) during model training by using approaches such as SMOTE (Synthetic Minority Oversampling Technique). This mitigates the risk of the model developing bias towards majority classes (users possessing a greater number of fingerprint samples).

International Journal of Information Technology & Computer Engineering

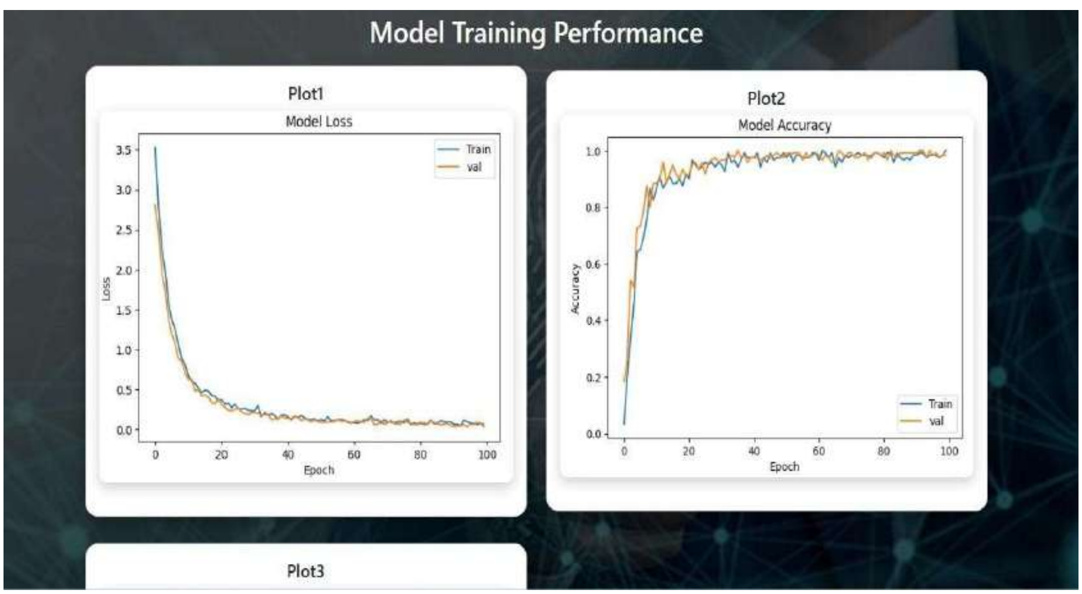
ISSN 2347–3657

Volume 13, Issue 4, 2025

5. Screenshots



Screenshot 1 Home Page



Screenshot 2 About Page

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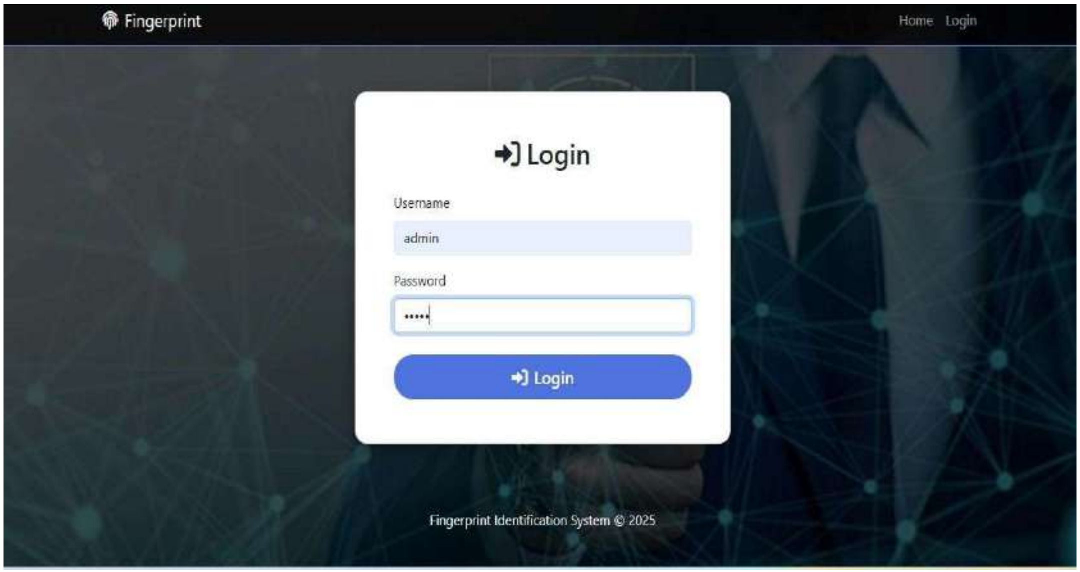
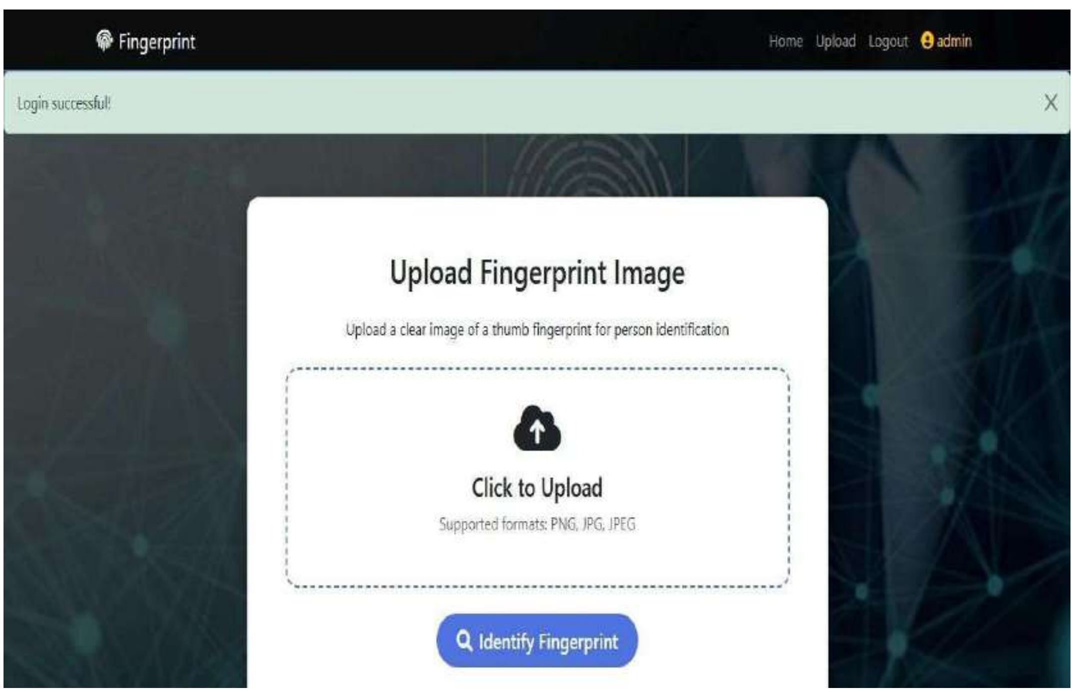


Screenshot 3 Login Page



Screenshot 4 Upload Page

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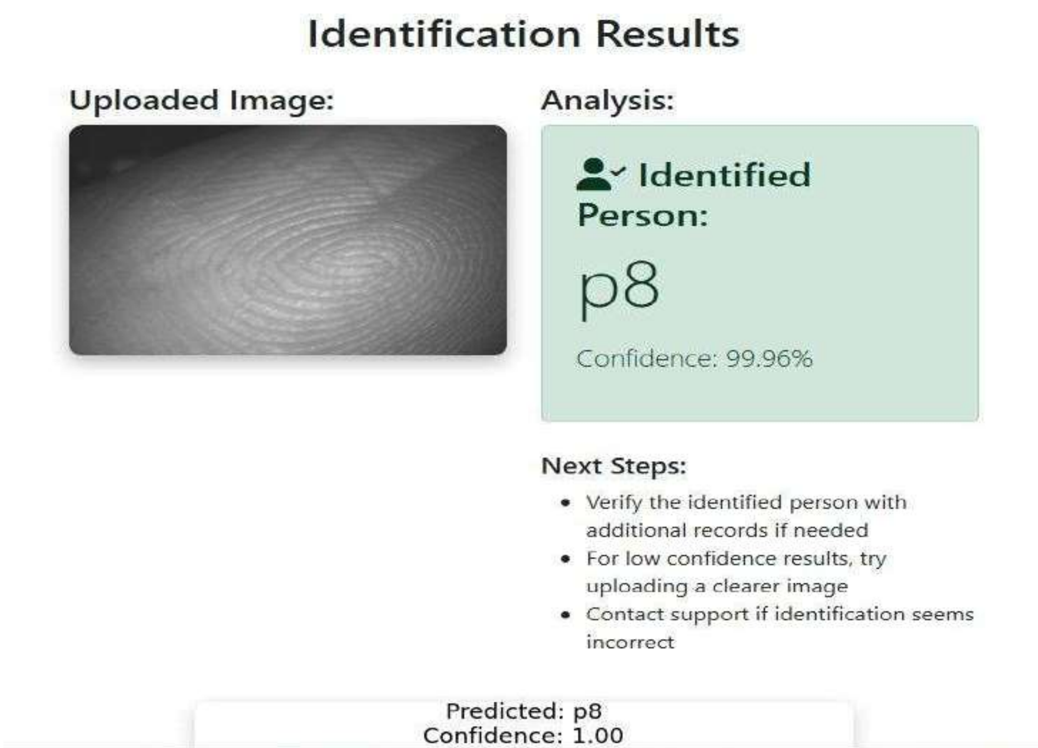
Volume 13, Issue 4, 2025



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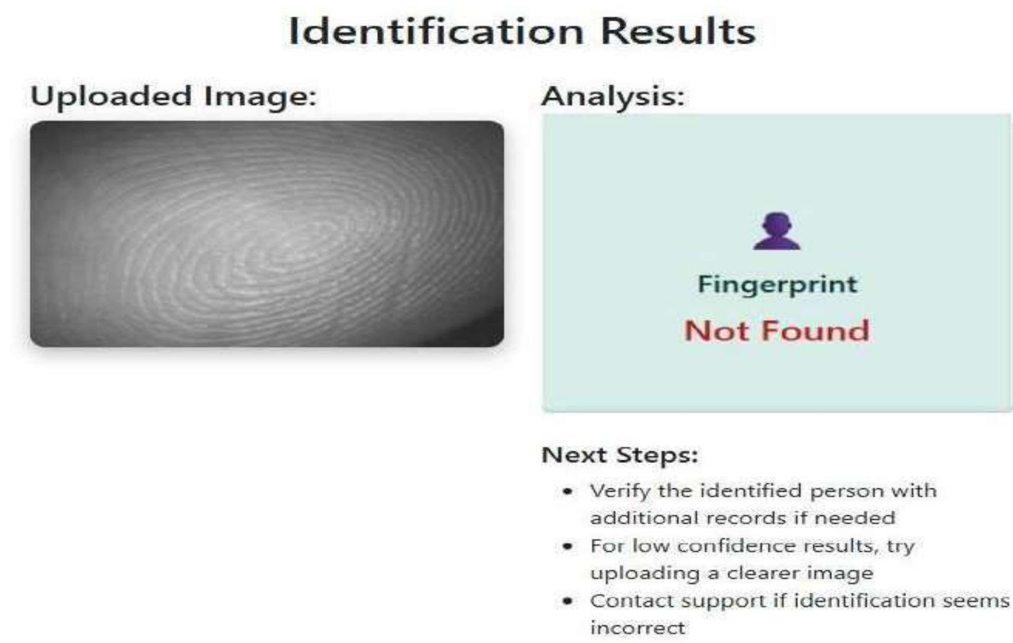

Screenshot 5 Result Page

6. Conclusion

This research included the creation of a powerful fingerprint identification system that correctly matches contactless fingerprint photos, such as those obtained from smartphones, with a vast database of traditional contact-based fingerprints. Our methodology utilizes the efficient and robust MobileNetV2 architecture as the foundational deep learning model, chosen for its shown efficacy in image processing tasks and its capacity to function effectively on devices with constrained computing resources. The system was trained on an extensive dataset of paired contactless and contact-based fingerprints, using meticulous preprocessing such as contrast enhancement and texture filtering to guarantee uniform picture quality across both modalities. Upon the upload of a contactless fingerprint picture by a user, the system utilizes MobileNetV2 to extract unique features, which are then compared to feature vectors derived from stored contact-based fingerprints using cosine similarity. Upon finding a match, the system retrieves the associated unique ID from the database. To improve security and usability, we created a professional online interface that includes user identification via login and registration, role-based access limits, and real-time result displays. This project illustrates the easy transfer of contemporary biometric identification to contactless technologies without compromising accuracy, while the use of MobileNetV2 guarantees efficiency and scalability for deployment across diverse devices and locations. Furthermore, the system's adaptable design facilitates future integration with supplementary biometric technologies, establishing it as a progressive solution for safe, sanitary, and efficient user identification.

Future Scope

This initiative has considerable potential for future growth and practical use. Enhancing the system's training with a wider and more varied dataset, which includes persons of different ages, races, and skin kinds, may significantly augment its accuracy and dependability, enabling it to operate well across various settings. The refining of algorithms and the incorporation of sophisticated deep learning approaches, including self-supervised learning and ensemble modeling, will improve efficiency and flexibility. The technology may be integrated into mobile devices or drones, facilitating remote and portable identification that is essential for security personnel, law enforcement, and emergency responders. Furthermore, expanding the concept to wearable devices will provide effortless, hands-free authentication in critical settings. This project establishes a robust foundation for future progress in remote biometric identification, facilitating the creation of multimodal authentication systems that integrate fingerprint, facial, and other recognition techniques for enhanced security and adaptability in applications such as border control, smart cities, healthcare, and digital identity management.

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