

Ensemble CNN-Based Palm Vein Recognition for Secure and Contactless Mobile Authentication

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Abstract: The increasing demand for secure and contactless biometric authentication has accelerated the development of lightweight mobile recognition systems for healthcare and institutional applications. This study presents a smartphone-based palm vein recognition framework utilizing near-infrared imaging, ensemble Convolutional Neural Networks (CNNs), and TensorFlow Lite deployment for mobile edge environments. The proposed system was designed to address engineering challenges associated with cost, portability, scalability, and real-time biometric authentication, particularly within the context of Serbia's digital healthcare transformation initiatives. Palm vein images were acquired using a compact near-infrared imaging device and processed using image enhancement techniques, including contrast-limited adaptive histogram equalization and adaptive thresholding. An EfficientNet-inspired CNN architecture enhanced with ensemble convolution learning was implemented to improve feature extraction and classification robustness. To support smartphone deployment, model compression and quantization techniques were applied using TensorFlow Lite. Experimental evaluation demonstrated that the baseline CNN architecture achieved an identification accuracy of 98.6%, while the proposed ensemble CNN framework improved accuracy to 99.5% with an inference time of 100–200ms. The findings confirm that lightweight palm vein recognition systems can provide highly secure, contactless, and real-time authentication suitable for hospitals, laboratories, and public service infrastructures. The proposed framework offers a cost-efficient engineering solution for emerging smart healthcare and digital identity systems in Serbia.

Keywords: Palm Vein Recognition, Biometric Authentication, Convolutional Neural Network, Mobile Edge Computing, Near-Infrared Imaging, TensorFlow Lite, Healthcare Engineering, Smartphone Authentication

1. Introduction

Biometric authentication technologies have become increasingly important in modern engineering systems due to the growing demand for secure, contactless, and reliable identification methods across healthcare, transportation, banking, and critical infrastructure.

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Among these technologies, palm vein recognition has emerged as a highly secure biometric modality because vein structures are located beneath the skin surface and are difficult to duplicate or forge [1][2]. Unlike fingerprint recognition, palm vein authentication remains effective even for individuals with damaged fingerprints, aging skin, or occupational wear, making it particularly suitable for medical and industrial environments [3].

Recent advances in artificial intelligence, deep learning, and mobile edge computing have accelerated the development of lightweight biometric systems capable of operating on smartphones and portable devices [4][5]. Convolutional Neural Networks (CNNs), especially EfficientNet and ensemble-based architectures, have demonstrated strong performance in image classification and biometric pattern recognition tasks while maintaining computational efficiency for embedded applications [6][7]. These developments are highly relevant to emerging engineering initiatives in Serbia, where digital transformation strategies increasingly prioritize smart healthcare systems, cybersecurity, and intelligent public services [8].

In Serbia, the modernization of healthcare infrastructure and digital identity systems presents both opportunities and engineering challenges. Serbian hospitals and public institutions continue to rely heavily on barcode wristbands, manual verification, and RFID-based identification systems, which remain vulnerable to labeling errors, patient misidentification, and operational inefficiencies [9]. Engineering researchers have emphasized that inaccurate patient identification can lead to incorrect treatments, medication errors, and increased healthcare costs, particularly in high-density clinical environments [10]. Furthermore, Serbia's growing investment in Industry 4.0, smart city technologies, and secure e-government platforms has created a need for robust, privacy-preserving biometric authentication mechanisms that can operate in resource-constrained environments [11].

Palm vein recognition technology offers several advantages for Serbian healthcare and industrial applications, as it supports contactless authentication, reduces fraud risks, and enhances operational security [12]. However, existing commercial palm vein systems require expensive near-infrared cameras and dedicated hardware infrastructures, limiting their adoption in developing and transitional economies [13]. This challenge is particularly relevant in Serbia, where engineering solutions must balance performance, scalability, and implementation cost to support broader deployment across hospitals, laboratories, and public service facilities [14].

Several recent studies have explored lightweight biometric architectures, mobile deep learning systems, and compressed neural networks for embedded authentication applications [5][6][15]. Nevertheless, there remains a significant research gap in the development of low-cost smartphone-compatible palm vein recognition systems optimized for practical deployment in emerging European healthcare environments such as Serbia. Existing systems frequently prioritize accuracy while overlooking hardware affordability, mobile compatibility, and real-time inference performance under practical operating conditions [16].

To address these limitations, this study proposes a lightweight, robust palm vein recognition framework that leverages a compact near-infrared imaging device integrated with smartphone-based authentication. The study employs EfficientNet-inspired CNN architecture, enhanced with ensemble convolutional learning and model compression techniques, for TensorFlow Lite deployment. The objective is to develop a cost-efficient biometric identification solution capable of achieving high recognition accuracy while supporting mobile implementation for healthcare, laboratory, and institutional applications in Serbia.

2. Literature Review

Recent studies in biometric engineering have emphasized the growing importance of contactless authentication systems for healthcare, banking, and smart infrastructure applications. Palm vein recognition has emerged as a promising biometric modality because vascular structures are internal to the human body and highly resistant to duplication or spoofing attacks [17]. Compared with fingerprint and facial recognition systems, palm vein authentication demonstrates improved stability under variations in skin condition, aging, and environmental exposure [18].

Advances in near-infrared imaging technologies have significantly improved vein extraction and visualization capabilities. Yang et al. developed an enhanced multispectral imaging framework that improves vein contrast under low-light conditions, achieving higher feature visibility and greater recognition reliability [19]. Similarly, Kumar and Zhou proposed adaptive palm vein preprocessing techniques that reduced noise and enhanced vascular segmentation accuracy in real-world acquisition environments [20].

Deep learning techniques have also become central to modern biometric recognition systems. Khan et al. demonstrated that hybrid CNN architectures outperform conventional handcrafted feature extraction methods in palm vein classification tasks [21]. Their findings showed that automated feature learning improves recognition robustness under rotational variation, motion blur, and inconsistent illumination. In addition, transformer-assisted deep learning models have recently been introduced to improve the analysis of long-range feature dependencies in biometric image processing [22].

Mobile and embedded biometric systems have received increased research attention because of the rapid expansion of smartphone-based authentication services. Li et al. developed a lightweight biometric framework optimized for edge computing environments, reducing computational overhead while maintaining high inference accuracy [23]. Their study highlighted the importance of model compression and quantization techniques for real-time mobile deployment.

Several researchers have investigated the integration of biometric systems within healthcare engineering applications. Stojanović et al. examined digital healthcare modernization initiatives in Serbia and identified secure patient identification as a critical requirement for improving clinical workflow efficiency and reducing medical errors [24]. Their findings emphasized the need for affordable, scalable biometric systems that can be integrated with existing hospital information infrastructures.

In industrial and cybersecurity applications, biometric authentication has become increasingly important for protecting sensitive infrastructure and digital assets. Petrović and Nikolić analyzed the role of AI-driven biometric systems in Southeast European smart city initiatives. They concluded that contactless biometric technologies can significantly improve data security and public service reliability [25]. However, they also identified challenges related to hardware costs, interoperability, and deployment scalability in transitional economies.

Recent studies have additionally explored ensemble learning strategies to improve biometric classification accuracy. Ahmed et al. proposed a multi-branch ensemble CNN model for vein recognition that improved feature diversity and minimized false acceptance rates [26]. Their approach demonstrated improved robustness against image distortion and acquisition variability compared with single-stream CNN architectures.

Despite these advances, existing palm vein recognition systems still face several engineering limitations. Many current solutions depend on expensive proprietary imaging

hardware and cloud-based computational resources, limiting their feasibility for widespread implementation in resource-constrained healthcare systems [27]. Furthermore, relatively few studies have focused on smartphone-compatible biometric architectures specifically designed for practical deployment in Southeast European environments such as Serbia.

Accordingly, this study addresses the existing research gap by developing a lightweight smartphone-integrated palm vein authentication framework that leverages compact near-infrared imaging, ensemble CNN learning, and TensorFlow Lite optimization to support cost-efficient biometric deployment in Serbian healthcare and institutional systems.

3. Methodology

3.1. Research design

This study employed a developmental, experimental research design to develop a lightweight, smartphone-compatible palm vein recognition system for secure biometric authentication. The framework integrates near-infrared vein imaging, deep learning-based feature extraction, ensemble convolution learning, and mobile edge deployment techniques. The proposed system was designed to address engineering requirements for portability, computational efficiency, scalability, and real-time biometric authentication in healthcare and institutional environments in Serbia.

The methodological framework consisted of four major phases: (1) vein image acquisition, (2) preprocessing and data augmentation, (3) deep learning model development, and (4) mobile deployment and performance evaluation.

3.2. Vein image acquisition

Palm vein images were collected using a compact near-infrared imaging device mounted on a smartphone. The acquisition system utilized near-infrared illumination within the 720–850 nm wavelength range to enhance vascular visibility beneath the skin surface. The captured images were processed through an infrared-sensitive camera equipped with optical filters to isolate vein patterns from surrounding tissues.

The primary dataset was obtained from the CASIA Multi-Spectral Palmprint Database, which contains approximately 7,200 grayscale palm images collected from 100 individuals under multiple spectral conditions. Additional datasets were collected under simulated hospital lighting conditions to reflect practical healthcare environments in Serbia. The acquired images were standardized to 640×480 pixels to balance recognition performance and mobile storage efficiency. Approximately 3,000 supplementary images were collected to improve environmental robustness and dataset diversity.

3.3. Image preprocessing and data augmentation

To improve vein visibility and enhance feature extraction accuracy, several preprocessing techniques were applied to the acquired images. Contrast Limited Adaptive Histogram Equalization (CLAHE) was utilized to improve local contrast and highlight vascular structures. Median filtering was additionally applied to reduce image noise while preserving edge information. Adaptive thresholding techniques were employed to isolate vein regions from background components.

Data augmentation techniques were implemented to improve model generalization and robustness against environmental variation. The augmentation process included rotational adjustment, brightness variation, Gaussian blur simulation, and angle transformation. These modifications enabled the training model to recognize vein patterns under diverse imaging conditions commonly encountered in real-world healthcare and institutional applications.

3.4. Deep learning architecture

The proposed recognition framework employed a convolutional neural network (CNN) architecture inspired by EfficientNet, given its high computational efficiency and suitability for mobile applications. The architecture consisted of convolutional, pooling, and fully connected layers for hierarchical feature extraction and classification. EfficientNet scaling techniques were adopted to optimize network depth, width, and image resolution while minimizing computational overhead.

To improve classification performance, an ensemble convolution strategy was incorporated into the model architecture. Multiple convolution branches were trained in parallel using both positive and negative vein image samples. The ensemble learning mechanism dynamically adjusted the weight parameters to improve feature discrimination and reduce false recognition rates. This approach enabled enhanced feature diversity and improved recognition robustness under image distortion and illumination variation.

3.5. Model compression and mobile deployment

To support smartphone implementation, the trained deep learning model was compressed using quantization techniques and converted into TensorFlow Lite (TFLite) format. Quantization reduced memory consumption and computational complexity by converting floating-point operations into lower-precision numerical representations suitable for mobile edge devices.

The mobile application was developed using Flutter 3.0.3 and Dart 2.17.5 on Android. The system architecture followed a Model–View–Controller (MVC) framework consisting of image acquisition, vein detection, and database management modules. The compressed TFLite model was integrated into the mobile application to enable real-time palm vein recognition directly on the smartphone without dependence on cloud processing.

3.6. Performance evaluation

The developed system was evaluated using training, validation, and test datasets split at an 8:1:1 ratio. Performance evaluation metrics included recognition accuracy, inference time, false acceptance rate, and false rejection rate. Laboratory experiments were conducted using smartphone-connected vein imaging devices to assess practical usability and authentication reliability.

Experimental results demonstrated that the baseline CNN architecture achieved an identification accuracy of 98.6%. After integrating ensemble convolution learning and augmented training datasets, the system achieved an average recognition accuracy of 99.5% with inference times ranging from 100 to 200 ms. These results indicate that the proposed lightweight framework is suitable for real-time biometric authentication applications within healthcare, laboratory, and institutional environments in Serbia.

4. Results and Discussion

4.1. Vein image acquisition and preprocessing results

The near-infrared imaging system successfully captured palm vein patterns under different environmental and lighting conditions. The preprocessing pipeline, which combined CLAHE enhancement, median filtering, and adaptive thresholding, significantly improved vascular visibility and reduced background noise. Enhanced images produced clearer vein segmentation, allowing the CNN architecture to extract more discriminative biometric features.

Table 1 summarizes the preprocessing techniques applied during image enhancement.

Table 1: Image preprocessing techniques and functions

Preprocessing Technique	Function	Expected Outcome
CLAHE	Enhances local image contrast	Improved vein visibility
Median Filtering	Removes salt-and-pepper noise	Reduced image distortion
Adaptive Thresholding	Separates the vein region from the background	Improved segmentation accuracy
Brightness Adjustment	Simulates varying illumination conditions	Increased model robustness
Gaussian Blur Augmentation	Simulates motion and acquisition noise	Improved generalization

The preprocessing stage improved image clarity and contributed to more stable training convergence during CNN learning.

4.2. Training dataset and augmentation performance

The training dataset consisted of approximately 7,200 palm vein images from the CASIA Multi-Spectral Palmprint Database combined with 3,000 additional images collected under healthcare-oriented environmental conditions. Data augmentation techniques increased dataset diversity by generating multiple variations of each image through rotation, brightness transformation, and blur simulation.

Table 2 presents the dataset configuration used for model training and evaluation.

Table 2: Dataset Distribution

Dataset Category	Number of Images	Percentage
Training Dataset	8,160	80%
Validation Dataset	1,020	10%
Testing Dataset	1,020	10%
Total Images	10,200	100%

The augmented dataset improved the model's ability to recognize palm vein patterns under non-ideal acquisition conditions frequently encountered in practical healthcare and institutional settings.

4.3. CNN and ensemble learning performance

The baseline EfficientNet-inspired CNN architecture demonstrated strong feature extraction capability for palm vein classification. Initial experiments using the standard CNN framework achieved a recognition accuracy of 98.6%. However, performance degradation was observed under rotational variation and inconsistent illumination conditions.

To address these limitations, the proposed ensemble convolution learning architecture was implemented. Parallel convolution branches processed positive and negative image samples simultaneously while dynamically adjusting feature weights. The ensemble framework improved feature diversity and minimized classification errors.

Table 3 compares the performance of the baseline CNN and the proposed ensemble CNN architecture.

Table 3: Performance Comparison of CNN Architectures

Model Architecture	Recognition Accuracy	Average Inference Time
Baseline CNN	98.6%	220 ms
Ensemble CNN	99.5%	100–200 ms

The ensemble CNN model achieved higher recognition accuracy while simultaneously reducing inference latency. These findings demonstrate that ensemble feature learning significantly improves robustness for mobile biometric authentication systems.

4.4. Mobile Deployment Results

The compressed TensorFlow Lite (TFLite) model was successfully integrated into the smartphone application environment. Quantization techniques reduced model size and computational overhead without causing significant accuracy degradation. The mobile application operated effectively on Android-based smartphones using the Flutter development framework.

The developed application supported real-time palm vein registration and authentication via a compact near-infrared imaging module connected to the smartphone. Authentication results were displayed immediately after image acquisition, enabling practical deployment for healthcare and institutional access control applications.

Table 4 summarizes the mobile deployment performance.

Table 4: Mobile application performance evaluation

Evaluation Metric	Result
Recognition Accuracy	99.5%
Average Inference Time	100–200 ms
Mobile Platform	Android 7.1.1
Development Framework	Flutter 3.0.3
ML Deployment Framework	TensorFlow Lite 1.1.2
Real-Time Authentication	Supported

The lightweight deployment framework demonstrated the feasibility of implementing secure biometric authentication directly on mobile edge devices without reliance on cloud infrastructure.

4.5. Discussion

The experimental findings indicate that the proposed smartphone-based palm vein recognition framework provides high authentication accuracy while maintaining low computational complexity. The combination of near-infrared imaging, ensemble CNN

learning, and lightweight model compression enabled stable real-time biometric recognition suitable for mobile healthcare and institutional environments.

From an engineering perspective, the proposed framework addresses several challenges relevant to Serbia's digital transformation initiatives. First, the use of low-cost compact imaging hardware reduces infrastructure expenses compared with conventional dedicated biometric systems. Second, mobile deployment capability supports scalability across hospitals, laboratories, and public service facilities where portable authentication systems are increasingly required. Third, the contactless authentication mechanism improves operational safety and hygiene in healthcare environments.

The results further demonstrate that lightweight AI-based biometric systems can achieve enterprise-level authentication performance while remaining suitable for resource-constrained deployment environments. These characteristics make the proposed framework a viable engineering solution for emerging smart healthcare and secure digital identity systems in Serbia.

5. Conclusion and Future Work

This study developed a lightweight and robust smartphone-based palm vein recognition framework using near-infrared imaging, ensemble convolutional neural networks, and TensorFlow Lite for mobile deployment. The proposed system achieved high biometric authentication performance while maintaining computational efficiency suitable for mobile edge environments. Experimental evaluation demonstrated that the enhanced ensemble CNN architecture improved recognition accuracy from 98.6% to 99.5% while reducing inference latency to approximately 100–200 ms.

The findings confirm that palm vein recognition technology can provide highly secure and reliable contactless authentication for healthcare, laboratory, and institutional applications. Unlike traditional biometric modalities, palm vein patterns are internal to the human body and difficult to replicate, making the proposed framework highly resistant to spoofing and identity fraud. The integration of lightweight deep learning and smartphone deployment further demonstrates the feasibility of implementing advanced biometric systems without requiring expensive dedicated infrastructure.

From an engineering perspective, the proposed framework addresses several critical challenges relevant to Serbia's ongoing digital transformation initiatives. The use of compact low-cost near-infrared imaging hardware supports scalable deployment in hospitals, smart public facilities, and secure institutional environments. In addition, mobile edge implementation minimizes dependence on centralized cloud processing, improving real-time responsiveness, operational flexibility, and data privacy.

The study also advances healthcare engineering by presenting a portable biometric authentication solution that reduces patient identification errors and improves clinical workflow efficiency. The system's contactless operation is particularly beneficial in healthcare environments, where hygiene, safety, and rapid authentication are essential operational requirements.

Despite the promising results, several limitations remain. The current system was evaluated primarily under laboratory-controlled conditions, and additional large-scale validation in real healthcare and institutional environments is still required. Environmental factors such as severe illumination variation, sensor displacement, and motion artifacts may affect recognition stability during practical deployment. Furthermore, power consumption and

miniaturization of the detachable near-infrared imaging module remain important engineering considerations for long-term mobile usage.

Future research should therefore focus on optimizing energy-efficient imaging hardware, improving multimodal biometric fusion techniques, and expanding real-world testing within Serbian healthcare and public service infrastructures. Additional studies may also explore federated learning, privacy-preserving AI frameworks, and cloud-edge collaborative architectures to improve further scalability, cybersecurity, and deployment flexibility for next-generation biometric authentication systems.

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