The Journal of Computational Science and Engineering.
ISSN: 2583-9055

Detection of Palmer Creases From Hand Images Using Deep Learning

MilindKumar B Vaidya, Urmila Barkade, Rajashri Dond, Kirti Dighe

Department of Computer Engineering Amrutvahini College of Engineering
Sangamner - 422605, India
milind.vaidya@avcoe.org,rutujaathare05@gmail.com, barkadeurmila@gmail.com,
rajashridond@gmail.com,kirtidighe15112002@gmail.com

***Abstract*—Hand images are crucial for identifying individuals in serious crimes such as sexual abuse, ATM robbery, vehicle crime, and drug offenses. Traditional biometric methods like fingerprint, iris, and face recognition may fail due to injuries or burns. Alternative methods like hand vein recognition and palm print analysis offer resilience to damage and can integrate with other modalities.This project introduces a novel approach using palmar patterns found on the palm's surface for personal iden- tification. By collecting palm images and applying preprocessing techniques, we enhance visibility and use data augmentation to diversify the dataset. Training a ResNet50 transfer learning model enables pattern recognition. The system includes frontend and backend components with a user-friendly interface developed using HTML, CSS, and Flask. Real-time testing is facilitated by local deployment. Relative positional encodings improve attention focus in the model. Extensive evaluations on multi-ethnic hand datasets demonstrate state-of-the-art performance, surpassing existing methods. This project offers a robust solution for personal identification, promising applications in security and authentication.**

***Index Terms*—CNN(Convolutional Neural Network), ResNet50, Person Identification, Classification**

I. INTRODUCTION

Biometric identification systems have gained importance due to their ability to provide secure and convenient authenti- cation. It provides solution in various fields like security, medi- cal forensic, human-computer interface etc. Biometric features like palm prints, fingerprints, hand shapes, knuckles, and hand veins can be used for identifying a person. Among various biometric modalities, palm prints offer a unique advantage as they are both distinctive and non-intrusive. In serious crime like vehicle robbery, drug offence, ATM robbery, sexual abuse the hand image is the only available information. Hand-based identification plays a significant role in criminal investigations, where hand images often provide crucial information about the perpetrator's identity, particularly in cases of serious crimes. The biometric traits of hands offer less variability than facial features, which are highly variable due to expressions and angles. This makes them all the more suitable for identifi- cation. Palmar patterns encompass a variety of features such as creases, ridges, and other distinctive characteristics present on the surface of the palm These patterns are highly individu- alistic and remain largely unchanged over time, making them ideal for biometric authentication.

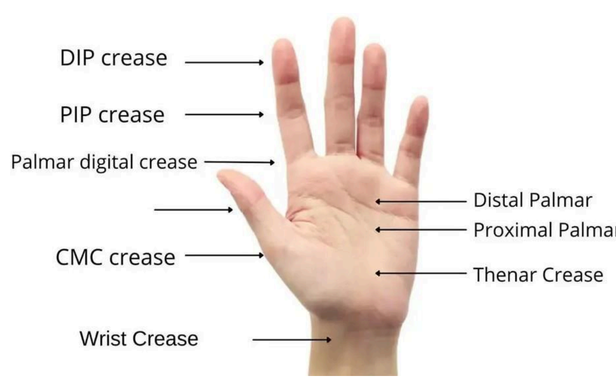

Fig. 1. Hand Image with Different Types of creases,from OTFocus.com

A branch of artificial intelligence (AI) called "deep learn- ing" uses multi-layered neural networks which gradually ex- tract more complex features from data. These models are trained on large amounts of data to learn patterns and re- lationships. In deep learning, Convolutional Neural Network or CNN is a type of neural network, which is widely used for image/object recognition and classification. Thus, Deep Learning uses a CNN to identify objects in an image [11]. An input layer, hidden layers, and an output layer are the three main components of a neural network. The structure of the brain served as the model for CNNs. Artificial neurons, also known as nodes in CNNs, receive inputs, process them, and send the outcome as an output, just like a neuron in the brain does the same throughout the body. A wide known architecture of CNN known as Resnet50 is used for training the model. Microsoft Research created ResNet50 in 2015. It is a 50-layer version of the well-known ResNet architecture that allows it to learn far deeper architectures than was previously feasible without running into the issue of vanishing gradients [10].

This project presents a novel approach to personal identification by leveraging the distinctive features present in palmar patterns. By utilizing deep learning techniques like Resnet50 and transfer learning models, the aim is to develop a robust system capable of accurately identifying individuals based on their palm prints. The approach involves pre-processing palm images to highlight these distinctive features, followed by training a deep learning model to recognize and classify these patterns. Through this project, we seek to offer a reliable and user-friendly solution for personal identification.

II. Litrature Survey

In palm creases identification, researchers have found that creases on the hand are particularly useful for distinguishing between individuals. These creases are unique and stay relatively the same throughout a person's life, making them a reliable tool for identification.

Identifying people from hand images is valuable for investigations where other evidence is unavailable. While traditional methods that analyze the entire image can be limited, this research introduces a new approach that considers both general and specific details within the hand.This method, called GPA-Net, uses a clever way to learn distinctive features from both the whole hand and individual parts. Unlike other techniques that require dividing the image beforehand, GPA-Net achieves this by creating separate processing paths within its internal structure.The researchers tested GPA-Net on large datasets containing hands from many ethnicities, and it outperformed existing methods. The core of GPA-Net is based on a well-established network (ResNet50), which is then adapted to create the separate processing functions. Because GPA-Net learns from the entire image throughout training and uses a versatile starting structure, it shows promise as a powerful tool for identifying people based on hand images [1].

Recent research suggests that the unique patterns on the back of the fingers (finger dorsal patterns) can be used to identify people. This study proposes a new identification system that combines information from three sources: the entire back of the finger, the wrinkles around the larger knuck- les (major knuckle patterns), and the bumps near the finger base (minor knuckle patterns).The system extracts identifying features from each of these regions using a technique called BSIF. It then combines this information at a fundamental level to create a more robust identifier. To improve efficiency, the system reduces the complexity of the data using two techniques (PCA and LDA) while maximizing its ability to distinguish between individuals. Finally, it employs a specific method (cosine Mahalanobis distance) to compare an unknown fingerprint to the database and determine a match.Tests on a publicly available dataset show that this multimodal approach performs better than systems that rely on a single source of information or older methods. The system offers several advantages,including using finger knuckle prints, incorporating different fingerprint regions, and creating compact data profiles for storage. The effectiveness of the system is measured by metrics like Rank-1 recognition rate and cumulative match curves (CMC) [2].

Hand biometrics, like fingerprints, palm prints, and vein patterns, are proven techniques for verifying and identifying people. Researchers have explored these methods extensively, including palm print recognition, vein pattern recognition, and even fingerprint wrinkles. This study proposes a new approach that combines image cleaning techniques, deep learning, and special classification tools (SVM classifiers) to identify in- dividuals from hand images. The method first cleans the images using two techniques (guided filter and CLAHE) and then uses a powerful artificial intelligence structure called a convolutional neural network to extract unique features from the hand. Finally, it combines the results from multiple SVM classifiers to improve accuracy. Tests on various datasets show that combining these features leads to very accurate identification, highlighting the continued potential of hand biometrics for security purposes [3].

Hand X-rays are emerging as a valuable tool for identifying people when traditional methods like fingerprints or facial recognition are unusable. This is particularly beneficial in situations where injuries or damage compromise other forms of identification.Unlike fingerprint scanners or iris recognition, hand X-rays reveal unique underlying bone structures that can be used to distinguish between individuals. This research explores using a specific type of artificial intelligence called a convolutional neural network to extract these identifying features from hand X-ray images.The system then employs two classification techniques (KNN and SVM) to recognize individuals based on the extracted features. Tests show that this approach is significantly more effective than traditional methods for person identification using hand X-rays [4].

Hand biometrics, encompassing fingerprints, palm prints, and dorsal vein patterns, have established themselves as reliable tools for verifying and identifying individuals.This research introduces a novel approach that leverages a com- bination of image preprocessing techniques, deep learning methods, and Support Vector Machine (SVM) classifiers for hand-based identification. The effectiveness of this approach stems from the use of guided filters and the Contrast Lim- ited Adaptive Histogram Equalization (CLAHE) method for image preprocessing, followed by feature extraction using a Convolutional Neural Network (CNN) architecture. Additionally, the study incorporates a fusion strategy that combines multiple SVM classifiers to enhance classification accu- racy.Experiments conducted on various datasets demonstrate that fusing these features leads to highly accurate hand image identification, further solidifying the potential of hand biomet- rics for verification and identification purposes [5].

The research describes a new method for extracting crease features from specific areas of the palm print: the fleshy area below the little finger (hypothenar region) and the spaces between the fingers (interdigital region). To speed things up, the method first reduces the image size by a factor of 10. Then, it extracts the creases using a series of steps including thresholding (converting the image to black and white based on brightness), applying shapes to identify crease patterns, and using a mathematical technique to find lines (Hough line transform). Tests on over 100 hand images showed that this method successfully extracts these crease regions with a high degree of accuracy [6].

The research explores whether the bumpy patterns on the back of the hand, near the base of the fingers (minor fin- ger knuckle patterns), can be used to automatically identify people. The authors achieve this by isolating these knuckle regions from images of the back of the hand. To account for differences in lighting, hand position, and size, they then adjust and improve the image quality. Next, they test different techniques (both spatial and spectral) to see how well these knuckle patterns match between individuals. The study also investigates whether combining this information with other features from the back of the hand improves identification accuracy. The results are promising and suggest that minor finger knuckle patterns have potential as a new biometric tool for identification. In essence, the paper explores a novel approach to personal identification using hand biometrics and finds encouraging initial results [8].

Hands hold unique characteristics that can be used to determine a person's gender. This makes them valuable biometric identifiers.This research introduces a large dataset of human hand images, including both the back (dorsal) and palm (palmar) sides. This dataset is labeled with accurate gender information, making it ideal for training computer programs to recognize gender and identify individuals based on hand images.The study utilizes a type of artificial intelligence called a Convolutional Neural Network (CNN) trained on this dataset for gender recognition. Interestingly, a two-part CNN architecture is proposed, where the initial network is used to extract key features from the hand images. These features are then fed into a separate network for the biometric identification task.The research also reveals that the back of the hand, captured with a standard camera, provides equally useful, or even more informative, features for these tasks compared to the palmAfifi, M. 11K Hands: Gender recog- nition and biometric identification using a large dataset of hand images. Multimed Tools Appl 78, 20835–20854 (2019). https://doi.org/10.1007/s11042-019-7424-8 [12].

Person re-identification (Re-ID) systems are a hot topic in computer vision research, with major applications in smart surveillance and security. These systems aim to identify individuals across different cameras or video footage.Deep learn- ing has become a game-changer for person Re-ID, leading to significant advancements in accuracy. Researchers often evaluate these models using benchmark datasets like PRID2011, iLIDS-VID, MARS, and RPIfield.A crucial factor in building robust Re-ID systems is access to large datasets for train- ing deep learning models. These datasets should encompass real-world challenges like variations between people (inter-class) and variations of the same person's appearance (intra- class). These variations can include pose differences, occlu- sions (being partially hidden), and changes in lighting condi- tions.Current research in person Re-ID focuses on overcoming these challenges and further improving the effectiveness of deep learning models [7].

III. Proposed System

This section describes the process of building a system to detect palm creases from images. It involves collecting and preparing data, choosing a deep learning model (specifically a Convolutional Neural Network) to analyze the images, training the model on labeled data, evaluating its performance.

A. Dataset

A dataset of hand images created manually by capturing images of staff members' from Computer Department, Am- rutvahini College of Engineering,Sangamner. Offers a valuable resource for the system. This dataset comprises high-resolution images of hands from different angles, capturing variations in hand posture and lighting conditions.Every image in the dataset is carefully labeled to identify important details like palm creases, fingerprints, and nail patterns.

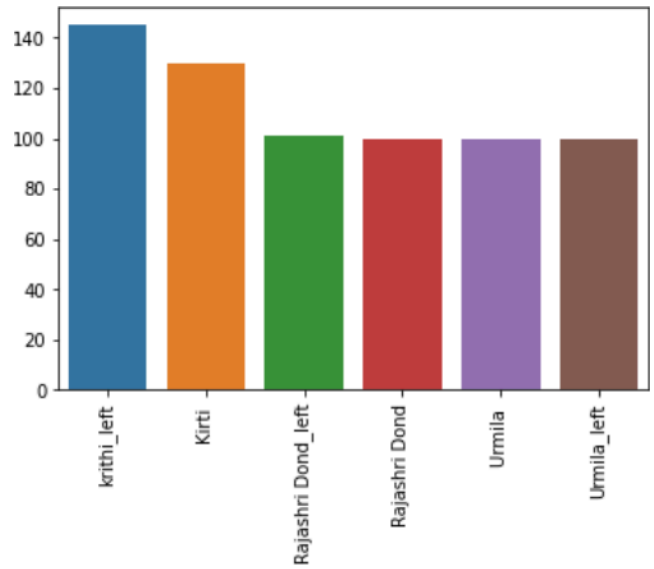

Fig. 2. Dataset Graphical Representation

B. System Architecture

The process begins with collecting a diverse dataset of high- quality palm images, particularly focusing on palm creases. Preprocessing steps follow, including intensity normalization, noise removal, and crease feature enhancement. Deep learning model, particularly Convolutional Neural Networks (CNNs) and ResNet50, ar then employed for palm crease detection, leveraging their ability to extract features from images ef- fectively. Model training involves adjusting parameters for accurate crease prediction using labeled data. Evaluation on a separate validation dataset, utilizing metrics like F1-score, ensures model performance.

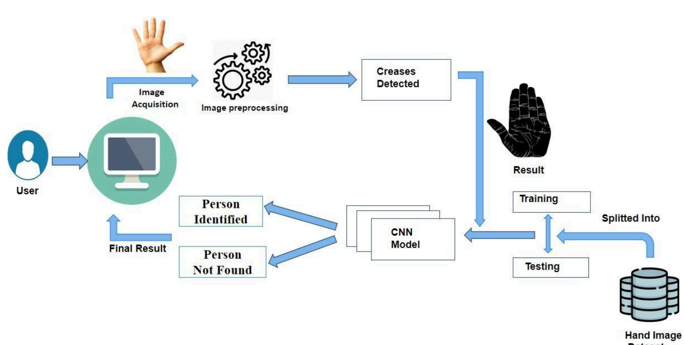

Fig. 3. System Architecture

C. Data Pre-processing And Agumentation

The collected images undergo several preprocessing steps to enhance the visibility of palmar patterns:

- Grayscale Conversion: Convert the RGB images to grayscale to simplify processing and reduce computa- tional complexity.
- Histogram Equalization: Enhance image contrast by equalizing the histogram, improving the visibility of creases and ridges.
- Gaussian Blur: Apply Gaussian blur to reduce noise and smooth out irregularities in the images, aiding in feature extraction.
- Canny Edge Detection: Detect edges in the images using the Canny edge detection algorithm to highlight the boundaries of palmar features.
- Organizing Dataset: The preprocessed images are orga- nized into a structured dataset, with each image labeled according to the corresponding individual.

Data Augmentation: To increase dataset diversity and im- prove model generalization, data augmentation techniques are applied. This includes random rotations, flips, translations, and scaling to simulate variations in palm orientation and positioning.

D. Training and Optimization

- Dataset Splitting: The prepared dataset is split into train- ing and testing sets, typically using an 80-20 or 70-30 ratio.
- Transfer Learning: A pre-trained deep learning model, such as ResNet50, is employed as the base architecture for feature extraction. The weights of the pre-trained model are frozen to prevent overfitting and allow the model to focus on learning palm-specific features.
- Compilation: The model is compiled with appropriate hy- perparameters, including the Adam optimizer, categorical cross-entropy loss function, and evaluation metrics such as accuracy.
- Training:The model is trained using the training dataset over multiple epochs, with batch size typically set to 32
- During training, the model learns to recognize and classify palmar patterns based on the extracted features.

IV. Results Analysis

The model achieved a high overall accuracy of 97.06% on unseen test data, indicating successful identification of individuals based on hand crease patterns in most cases. This is further supported by the classification report, where metrics like precision (0.97), recall (0.97), and F1-score (0.97) demonstrate strong performance across individuals.

The accuracy and validation accuracy graph visually con- firms the learning process. Both training and validation accu- racy increase over epochs, suggesting the model effectively learns from the training data. Notably, the validation accuracy remains consistently close to the training accuracy, indicating good generalizability and avoiding overfitting to the training set.

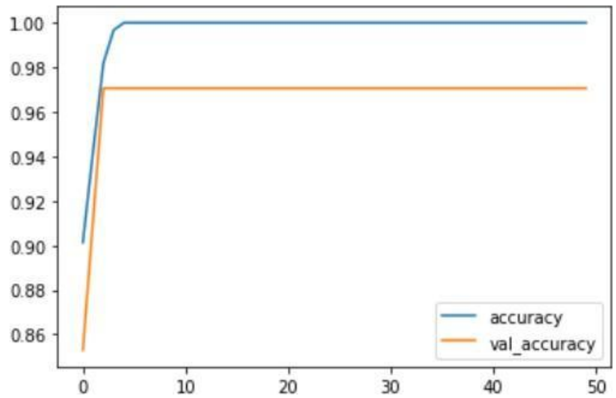

Fig. 4. Accuracy

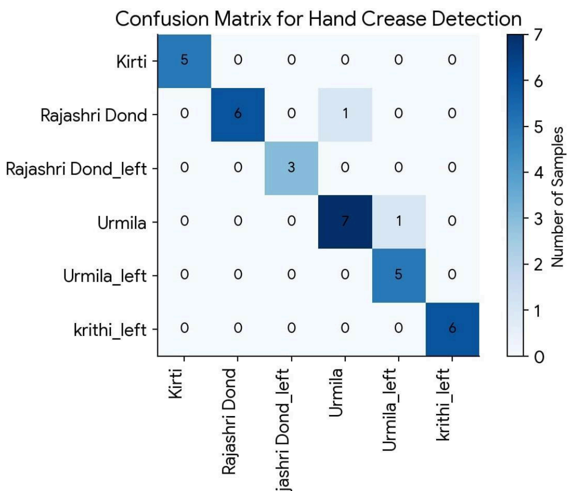

Fig. 5. Result of System

A. Performance Metrics

While the overall results are promising, a deeper dive into individual performance revealed some variations (refer to clas- sification report). Individuals like Kirti, Rajashri Dond left, Urmila left, and krithi left achieved perfect scores (1.00) for all metrics, demonstrating consistent and accurate identifi- cation. However, Rajashri Dond had a lower recall (0.86) with a precision of 1.00. This suggests the system might have missed identifying Rajashri Dond in one instance (False Negative) while not misclassifying others as Rajashri Dond. Further investigation into this specific case can be conducted to understand potential causes.

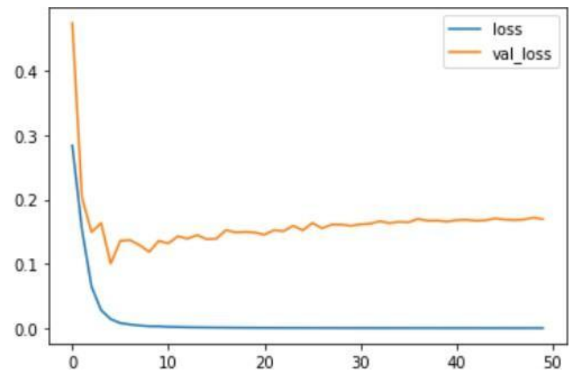

Fig. 6. Loss

B. Test Loss

The final test loss of 0.16951 signifies a relatively low error rate during testing on unseen data. This aligns with the high test accuracy and reinforces the model's ability to perform well on new hand crease detection tasks.

V. Conclusion

The project presents an innovative solution for personal identification through the analysis of palm patterns. By lever- aging advanced deep learning techniques and a dataset of hand images, the system achieves a remarkable accuracy rate of 97% in identifying individuals based on their unique palm features. The approach offers significant potential in enhancing security measures and aiding in criminal investigations where traditional biometric methods may fall short. With its user- friendly interface and robust performance, the system demon- strates promising applications in various fields requiring secure authentication. Overall, the system showcases the power of deep learning in harnessing distinctive biometric traits for reliable personal identification, paving the way for future advancements in security technology.

References

[1] N. L. Baisa, B. Williams, H. Rahmani, P. Angelov and S. Black, "Hand-Based Person Identification using Global and Part-Aware Deep Feature Representation Learning," 2022 Eleventh International Conference on Image Processing Theory, Tools and Applications (IPTA), Salzburg, Austria, 2022, pp. 1-6, doi: 10.1109/IPTA54936.2022.9784133.

[2] Attia, A., Akhtar, Z., & Chahir, Y. Feature-level fusion of major and minor dorsal finger knuckle patterns for person authentication. *SIViP*, 15, 851–859 (2021). https://doi.org/10.1007/s11760-020-01806-0

[3] Yuan, Yimin et al. "HandNet: Identification Based on Hand Images Us- ing Deep Learning Methods." Proceedings of the 2020 4th International Conference on Vision, Image and Signal Processing (2020): n. pag.

[4] S. V. Joshi and R. D. Kanphade, "Deep Learning Based Person Authenti- cation Using Hand Radiographs: A Forensic Approach,"

in IEEE Access, vol. 8, pp. 95424-95434, 2020, doi: 10.1109/ACCESS.2020.2995788.

[5] Utari, Rahayu Sri et al. “Palm Print Recognition Using CANNY Edge Detection, Gray Level Co-Occurrence Matrix and Classified Using K- Nearest Neighbor.” (2020).

[6] Roszaharah Yaacob, Chok Dong Ooi, Haidi Ibrahim, Nik Fakhuruddin Nik Hassan, Puwira Jaya Othman, Helmi Hadi, ”Automatic Extraction of Two Regions of Creases from Palmprint Images for Biometric Identification”, Journal of Sensors, vol. 2019, Article ID 5128062, 12 pages, 2019.

[7] M. O. Almasawa, L. A. Elrefaei and K. Moria, ”A Survey on Deep Learning-Based Person Re-Identification Systems,” in IEEE Access, vol. 7, pp. 175228-175247, 2019, doi: 10.1109/ACCESS.2019.2957336.

[8] A. Kumar and Z. Xu, ”Personal Identification Using Minor Knuckle Pat- terns From Palm Dorsal Surface,” in IEEE Transactions on Information Forensics and Security, vol. 11, no. 10, pp. 2338-2348, Oct. 2016, doi: 10.1109/TIFS.2016.2574309.

[9] https://www.google.com/imgres?imgurl=https://otfocus.com/wp-content/uploads/2022/03/5-creases-every-hand-therapist-should-know-1024x569.jpgtbnid=ZGXk n9SRaq6YMvet=1imgrefurl=https://otfocus.com/5-hand-creases-every-hand-therapist-should know/&docid=FVEbmkIX0QCd3Mw=1024h=569hl=en-GBgl=GBsource=sh/x/im/m1/2kgs=ba359233cabc5c34shem=abme,trie.

[10] https://medium.com/@nitishkundu1993/exploring-resnet50-a n-in-depth-look-at-the-model-architecture-and-code-implementati on- d8d8fa67e46f#: ˜:text=ResNet50

[11] https://www.happiestminds.com/insights/convolutional-neural-netw orks- cnns/#:˜:text=Within

[12] Afifi, M. 11K Hands: Gender recognition and biometric identifica-tion using a large dataset of hand images. Multimed Tools Appl 78, 20835–20854 (2019). https://doi.org/10.1007/s11042-019-7424-8.