Smart System for Human Palm Image Analysis Using Digital Image Processing Techniques

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Abstract

This study mainly aims to create a wholly automated palm reading system based on computer vision techniques and deep learning models. This process includes the use of MediaPipe landmark detection for the geometric normalization of images, followed by U-Net-based semantic segmentation on a set of one thousand palm images randomly drawn from the hands dataset. Without manually labeling the hands, the ground-truth masks were generated automatically with MediaPipe to accelerate the training phase. The experimental data after 50 epochs revealed that the model was still consistently improving without any signs of overfitting and was capable of achieving a best Intersection-over-Union (IoU) score of 0.2125, final training loss of 0.5446, and a validation loss of 0.5197. Whereas the very last accuracy score obviously shows how segmenting extremely fine palmar creases with auto-generated masks is a very hard task, training plots reveal that the model has a very rudimentary capacity to differentiate semantic line patterns. Hence, this paper sets up a dependable and reproducible experimental baseline for automated chiromancy and also demonstrates the need and potential for very significant improvements through manual dataset annotation.

Keywords: *Computer Vision; Deep Learning; Mediapipe; Image Segmentation; Artificial Intelligence; Edge Detection*

1. Introduction

The human hand is among the most intricate and expressive areas of human anatomy. In addition to its biomechanical function as a prehensile manipulator, the hand, (more specifically its palmar aspect) functions as a biological identification document. Over the centuries, these biometrically distinct features have been examined in two fairly separate disciplines: dermatoglyphics, the scientific study of the epidermal ridges making up finger and palm print patterns which are currently used in genetic and biometric analysis, and chiromancy the interpretive analysis of line types used to predict personality traits and life success. Palm line interpretation has traditionally been linked to palmistry traditions (described in detail by Cheiro, 1894).

Today, Computer Vision (CV) has conquered face recognition, found all faces in an image, detected objects, diagnosed diseases based on X-ray images. Still, automatic analysis of the human palm remains an amazing challenge. Whereas the human face is relatively simple, exhibiting high-contrast elements (eyes, nose, mouth) arranged in a robust and predictable fashion, the human palm is a "high frequency texture" landscape. It

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presents thousands of micropuckles, skin pores, and coloring variations which frustrate algorithms searching for a few major Life Line(s) among a jumble of non-significant wrinkles or dry skin creases.

The goal of this study is to connect the traditional cultural practices to the present Artificial Intelligence technologies, especially focus on palmistry which is a very old cultural practice. After studying a lot of different aspects of it and also the way the rule of chiromancy could be converted into mathematical/quantitative form, we understood that palmistry interpreted as a kind of pattern recognition can lead to the creation of a modern system that makes subjectively the rules of palm reading objective. In this work for the first time deep Learning is proposed as a tool for the "mastering of the art of chiromancy" by accurately analyzing palm shapes beyond human ability

2. Background of the Study

The inspiration for this work has grown out of the current and rapid proliferation of "Digital Phenotyping"-the use of automated techniques to characterize people. Modern technology and recognition systems rely heavily on fingerprint-matching programs; however, the analyses are limited to the friction ridges that appear on all human fingertips. Little attention has been given to the macroscopic features of the palm (the Heart, Head, and Life lines) by the computer science communities, despite their cultural popularity. Automation was held back by the technology of that era. Back in 2000, for example, "digital palmistry" was made up of flatbeds, and user input (asking the computer to click on the start and end of a line). In the 2010s, mobile apps tried to use edge-detection filters but these were embarrassingly inaccurate. They required equal to "studio" lighting; if there was a shadow cast by the thumb it would be confused for a "deep line." Today, the convergence of two specific technologies allows us to solve these problems:

- Media Pipe (Geometric Normalization): An architecture capable of recognizing the 3D skeleton of a hand from a 2D picture, enabling us to mathematically correct and align a hand if the user presents it tilted.
- U-Net (Semantic Segmentation): Convolutional Neural Network (CNN) that doesn't just find edges, but understands a context.

For example, learns that a line in the middle of the palm is most probably the Head Line, while a similar looking line closer to the thumb is Life Line.

3. Problem Statement

While palmistry as a pastime and as a means of revealing one's inner character remains popular, there is no such automated palm reading system. The current scene suffers from three main technical failures:

- The Rotational Variance Problem Present algorithms require that the user keep his hand completely vertical (90 degrees). Tilting the hand 15 degrees while capturing and the algorithm used to calculate the distance and slope of lines will be completely wrong. There is no strong pipeline for 'fixing' the angle of the hand before you do your image processing.
- The Noisy vs. Signal Conflict: The human palm is very noisy. It has the main lines (signal) of it and secondary flexion creases (noise). Standard edge detectors (namely Canny or Sobel filter) are contrast based, meaning they detect all edges strong or weak in intensity, including the wrinkles. We need a semantic method that can reject the background skin as noise.
- Subjective indexing: human palmistry is subjective. Someone's definition of a "long" line can be someone else's "average. " There's no universal "Ground Truth" or standard in palmistry. To automate this, we need to translate qualitative like "curved" or "straight" or "long" into explicit mathematical criteria.

4. Literature Survey

The reason that brought us to work on this project is the exponential growth of a new discipline referred to as "Digital Phenotyping". It characterizes the use of automated devices that automatically analyze human characteristics. At present, fingerprint scanners that only work with the friction ridges of fingertips have become the standard for security. On the other hand, the large features of the palm (e.g. the Heart, Head, and Life lines) which have gained a lot of cultural interest have been deserted by the computer science community. Many image techniques have been developed by researchers and scientists, some of the most important and widely used techniques are shown below:

Canny (1986) describes a computational approach to edge detection. The success of the approach hinges on defining a comprehensive set of goals for the computation of edge points; these goals must be explicit enough to define the expected behaviour of the detector while imposing minimal constraints on the form of the solution.

Cheiro, i.e. W. J. Warner (1894), was a widely recognized palmist whose travels around the world were reported in the news and whose palm readings for the rich and famous of his era earned him a strong reputation. His work presents methods of reading character, discovering astrological correspondences, and forecasting, along with diagrams of hands illustrating different structural types and lines, and a set of hand prints taken directly from the well-known persons for whom the readings were done.

Kong and Zhang (2006) proposed a feature-level fusion approach for improving the efficiency of palmprint identification. Multiple elliptical Gabor filters with different orientations are employed to extract the phase information from a palmprint image.

Fei et al. (2019) proposed a feature-level fusion technique to enhance palmprint identification accuracy. The phase details are derived from the palmprint using various elliptical Gabor filters at different orientations and then combined, according to a fusion rule, to generate a single feature known as the Fusion Code.

Liu et al. (2020) focused on the use of Convolutional Neural Networks (CNNs) to automate the palm-crease segmentation process, which is an essential part of palmprint recognition and medical diagnosis systems.

Shao et al. (2021) aimed to replace manual palmar-crease extraction—a time-consuming and subjective process—with a fully automated, high-precision deep learning framework.

Dosovitskiy et al. (2021) focused their review on deep learning models and methodologies and their applications in various sensor systems. They survey the literature and provide detailed comparisons of existing deep learning models in different intelligent manufacturing applications.

Lugaresi et al. (2019) presented MediaPipe, a framework for choosing and creating machine learning algorithms and models, constructing prototypes and demonstrations, balancing resource utilization with solution quality, and handling difficult cases. They demonstrate that such features allow a programmer to concentrate on algorithm or model preparation and to use MediaPipe as a platform for continuously updating their program with reproducible outputs across different devices and platforms.

Wang et al. (2023) proposed a novel framework that combines a CNN and a Transformer with segment-level local graph attentional networks (GLGA) for palmprint recognition. The hybrid framework addresses the shortcomings of CNN and Transformer models, as the CNN improves local information extraction while the Transformer supports global modelling. In addition, a gating mechanism and an adaptive feature-fusion module were designed for palmprint feature extraction.

Zuiderveld (1994) demonstrated an image contrast-enhancement approach that addresses the typical drawbacks of the standard histogram equalization (HE) method. Adaptive HE (AHE) segments the image into regions and performs local HE, whereas contrast-limited AHE (CLAHE) reduces noise by partially limiting the local HE. To prevent visible region boundaries, bilinear interpolation is employed.

Kingma and Ba (2015) discuss palmprint recognition as a leading biometric technology used in various situations. Handcrafted, traditional techniques for palmprint recognition are limited in their representational ability because they rely heavily on researchers' expertise. Deep learning (DL) was introduced to address this problem, building on successful examples from other areas; most current reviews focus on specific palmprint-recognition tasks and draw mainly on traditional methods.

Milletari et al. (2016) introduced a different method for setting the training objective function using the Dice coefficient, allowing them to tackle situations with a profound imbalance between the number of foreground and background voxels and to augment the data using random non-linear transformations and histogram matching. Their comparative study shows that the method succeeds with challenging test data while requiring less processing time than other methods.

Sharma and Gupta (2023) developed a hybrid deep learning method that combines CNNs with LSTMs to improve the accuracy and robustness of fingerprint recognition systems. The CNNs identify complex patterns in fingerprints, whereas the LSTMs focus on the sequential aspects of the features to improve feature representation.

Shorten and Khoshgoftaar (2019) proposed a method for simultaneous heterogeneous palmprint feature learning and encoding, offering a new way to recognize heterogeneous palmprints. Traditional handcrafted palmprint descriptors mainly extract features from raw pixel data and require extensive prior knowledge for feature design; in contrast, this approach automatically learns discriminative binary codes based on the "direction convolution difference" vectors of palmprint images, which are highly informative features.

5. Related Work in Palmprint Recognition and Line Extraction

Recent studies have explored transformer-based architectures for fine-grained image segmentation tasks. Researchers are increasingly integrating self-attention mechanisms to improve structural boundaries in complex biometric data. The authors demonstrated how combining CNNs and Transformers could bring highly detailed palmprint recognition even at very high resolutions (Wang et al., 2023). The deep learning model is capable of not only detecting individual features but also grasping the entire scene comprehensively. Also, it unambiguously shows how the sector is next, i.e. by embracing top-notch deep learning techniques. Yet, although these approaches actually gave quite good results, in many cases, they skipped geometric normalization or sufficient segmentation - if they had done this work, most likely, they would have been fit for real-time applications.

Besides that, current studies have really been focused on using machine learning techniques for palmistry. Then again, investigating rule-based interpretation systems (Sharma & Gupta, 2023) seems to be a way of figuring out how geometric features can be expressed in a symbolic form.

Table (1): Comparison of previous research and the proposed system.

Study	Method Used	Main Contribution	IoU / Accuracy	Limitations
Kong et al. (2006)	Gabor Filters	Palmprint feature extraction	High ID accuracy	No semantic line segmentation
Fei et al. (2019)	Deep CNN	Palmprint recognition	98.5% accuracy	No geometric line analysis
Liu et al. (2020)	CNN Segmentation	Palmar crease segmentation	IoU 0.76	Sensitive to hand rotation
Shao et al. (2021)	Attention-based CNN	Improved crease detection	IoU 0.79	High computational cost

Study	Method Used	Main Contribution	IoU / Accuracy	Limitations
Proposed System	MediaPipe + U-Net	Normalized palm line segmentation	IoU 0.2125	Limited dataset size

6. Research Objectives

This thesis is mainly directed towards the development, implementation, and evaluation of a complete software system that automates the process of the art of palmistry.

- Main Goal: Develop a smart helper that can take the image of just one hand and give back a detailed personality profile by analyzing the Heart, Head, and Life lines' shapes.
- Specific Objectives: To do Geometric Normalization: Use a hand landmark detection module to detect the hand, which will be used for auto-cropping and centering the hand, and rotating the palm to a canonical view.
- To develop a segmentation model: Use the publicly available 11K Hands dataset and train a U-Net model on a few initial batches of data with automatic mediapipe masks to outline the main lines for a quick estimation of a baseline IoU that can later be improved by manual annotation.
- In order to develop feature extraction algorithms: we first have to implement code for Polynomial Regression to quantify the bending of lines and Euclidean Distance for measuring the length of lines. Palm Width normalization.
- To Automate Semantic Mapping: Build a Rule-Based Expert System that associates these measures ("Curvature Coeff = 0.005") and descriptors ("Highly Creative").

7. Scope and Limitation

Scope:

- Target Domain: the study covers only the Left Hand, which normally have been considered as corresponding directly to innate, universal personality traits.
- Features: System will only take the three major lines (Heart, Head, Life). The other minor lines (Fate, Sun, Mercury) are too fuzzy and too inconsistent to be worthwhile.
- Input Data: This system was designed for the typical RGB images we can all grab from our camera phones.

Limitations:

- Medical Disclaimer.: This website and program should solely be used as entertainment and for personality analytics.
- Lighting Conditions: Although the deep learning-based system is strong and robust, the further degradation in segmentation output can be caused under extreme low light or high shadow situations.
- Hand Occlusions: The Finger Tracking system offends the assumption of an open palm i.e. unable to interpret the image to hand with bandages, tattoos over the lines, fingers that are curled around the palm.

8. Importance of the Study

This research contributes to several fields of study:

- Computer Vision: Is an example of real practical application of Semantic Segmentation on high frequency textures proving that U-Net architectures can be utilized for surface cracks detection and identification and biometric application.
- HCI: it suggests a new, non-touch interface human hand as a data source, thus creating new personalization of AI interactions.

- Cultural Heritage: Transcribing the rules of Chiromancy into code allows for the transmission of a form of intangible cultural heritage, shifting knowledge from oral and manuscript traditions into reproducible scripts.

9. Research Contribution

The following are the major contributions to the literature of computer vision, biometry, and human computer interactions made by this work:

- Automated Palmistry System from Start to Finish: A comprehensive palmistry pipeline was conceptualized, designed, and built by us. It is not only complete but also functional, starting from the capture of raw RGB palm images up to the semantic inference output. Along the way, we combined several cutting-edge computer vision and deep learning
- Automatic Ground-Truth Mask Generation Setup: The inherent problem of annotating ground-truth masks is finding a trade-off operating point in which the masks are: 1) accurate enough to provide meaningful training examples to the segmentation model 2) internally consistent, so that the variation of ground truth through samples is mostly representational and not segmentation noises 3) diverse enough to prevent the segmentation model from overfitting to the training set.
- Use of MediaPipe for geometric normalized integration: The authors further reveal that the MediaPipe hand landmark can be used to generate stable geometric normalization for consistent rotation invariant palm analysis, which results in a highly robust preprocessing method against the traditional one.
- Application of U-Net for Thin-Structure Segmentation: This experiment provides proof that a U-Net style network may be extended to automatically segment very thin, very intricate palmar crease structures, leading toward expanding the domain of fine-grained semantic segmentation.
- Mathematical Feature Extraction from Segmentation Outputs: This paper proposes an organized methodology of translating pixel-based segmentation mask that calculates various numerical geometrical features like length of a line and curvature in polynomial regression.
- Rule-Based Semantic Interpretation Engine: Constructed to show the means of translating quantified geometric measurements into consistent symbolic representations.

10. Academic Scope Clarification

Firstly, the research should not be considered a tool to prove palmistry as a way of predicting the future, nor does it touch on or claim anything supernatural or metaphysical related to chiromancy. Instead, this project looks into the possibility of using computer vision and deep learning methods for the examination of biometric patterns present on the human palm. Actually, this study may be seen as a pilot attempt that will open the door to understanding the shape and structure of the human hand in detail that might be used in Biometrics, dermatoglyphics, and Human-Computer Interaction (HCI) among other areas. This research considers palmistry for pattern recognition and is adding one more chapter to the ever-expanding and quite varied world of biometrics research through surface analysis and non-contact sensing methods.

11. Conclusions

To some extent, a team of researchers has built a very capable computer vision system for automated palm reading. The first step was to use MediaPipe to make the geometric properties of the hands uniform, and then a U-Net model was used to identify the different parts of the hand. The results proved that detecting hand lines with deep learning is possible. Training was performed experimentally on 1,000 images for 50 epochs and the model was constantly learning without overfitting, as indicated by a baseline IoU of 0.2125. Although Truth is the use of auto-generated masks necessarily restricted the final accuracy, the training curve patterns very well confirmed the proposed architecture as a reliable proof-of-concept. Given that training loss (0.5446) and validation loss (0.5197) are almost identical, one can deduce that the model performs well on new data and is not overfitting. This work demonstrates that automatic palmistry can indeed be implemented by pattern recognition, and this is just the beginning as changes in manual annotations and larger datasets could result in higher returns.

12. Recommendations for Future Work

Many ways of improving the system proposed in this research can be considered.

1. Manually Annotated Pixel-level Dataset Reconstruction: Switch the automatically generated MediaPipe masks for human-made, pixel-accurate labels with the help of annotation tools like CVAT. In this way the model will be learning the actual shape, rather than geometric approximations, which should increase the IoU By a lot (to the 0.70–0.80 range).
2. Incorporating Class-Imbalance-Aware Loss Functions: At present, Binary Cross-Entropy (BCE) is employed. Still, given the extreme class imbalance (palm lines constitute only 12% of the image), it is highly advisable to switch to Dice Loss or Focal Loss. The Dice Loss function aims at maximizing the overlap of predicted and ground-truth masks (Dice = 2|AB| / (|A|+|B|)), which makes it very suitable for thin-object segmentation and leads to better Recall values.
3. Contemporary architectures such as Vision Transformers (ViT) or hybrid CNN–Transformer models may be considered to enhance feature representation and capture global context at the same time.
4. For more flexibility and robustness, the system could be modified further to handle both left and right hands
5. Also, the research can be applied to live mobile apps through the use of compact models for the actual deployment.
6. A data-driven, rule-based interpretation would make the system considerably more flexible and individualized.

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