PalmReader.ai: A Deep Network Driven Fortune-Teller

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Abstract

Palm-reading is the practice of fortune-telling by reading one's palm. While it dates back to centuries ago, it is regarded as a pseudoscience by many due to a lack of scientific evidence, and is generally performed subjectively by humans. However, with modern statistical and deep learning techniques, we propose an automatic palm reading system by learning characteristics and hidden features within datasets. We construct a pipeline with vision transformers, object detection, and large language models to produce palm reading results and predictions from simply an image of the user's palm. Our project also uncovers the statistical connection between palm features and personal life experiences, creating a path for further related work.

1. Introduction

Fortune-telling through palm reading, known as palmistry, has been practiced for centuries. However, such methods lack scientific support and are regarded by many as pseudoscience. There is also a lack of evidence for the connection between palm line features and the predictions stemming from this form of fortune-telling.

In the age of machine learning, large datasets can be leveraged along with machine learning techniques, such as deep neural networks, to uncover hidden characteristics and connections that were previously difficult to observe. Under this predicate, we propose that there may be statistical connections between palm features and palmistry fortune-telling results.

In this project, we propose PalmReader.ai, an application to perform palmistry fortune-telling using an image of a palm. We construct a full pipeline to predict scores for aspects of the user's life, such as character, emotional predispositions, health status, and life path. Our pipeline is composed of the following components.

- **Vision Transformer (ViT)**: A vision transformer serves to extract features to vector embeddings that encode geometric features of palm lines in the input image.
- **Scoring system**: We score different aspects of life by examining the geometric features of the detected palm lines, using a features extracted from the vision transformer.
- **LLM inference**: We produce, from the and scores, a report in natural language that outputs fortune-telling content.

We obtain satisfactory results from experiments with various architectures, with the final mean squared error (MSE) loss at around 0.028. Inference using an LLM provides accurate reports on fortune-telling results based on our framework's predicted scores.

2. Related Work

2.1. Palmistry with Machine Learning

[6] proposes palmistry inference using random forests and linear SVM models. While the problem formulation is similar, we note that this paper classifies a palm line to different fixed categories, that eventually output to predefined descriptions.

Building upon this idea, we perform score prediction for each palm line and aspect of life, and utilize an LLM for natural language inference. This gives more informative and personalized outputs with our method.

2.2. U-Net Context Fusion Module

[8] proposes a deep learning-based solution to efficiently detect and segment palm lines from an image of a palm. This paper proposes a novel component, the Context Fusion Module (CFM), which is integrated into the U-Net as a bottleneck. The CFM captures both global and local contextual features from an image of the palm, using an attention mechanism to capture global and local contextual features from the palm image. Experimental results showed that the proposed method showed large advantages over traditional palm line segmentation methods.

Inspired by this method, we include a feature fusion module, combining features from regional feature extractors and global feature extractors. This allows us to extract

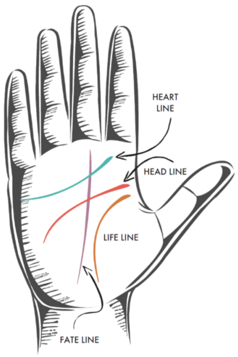


Figure 1. Different palm lines.

information from local to global levels of the image for further analysis and scoring.

3. Problem Formulation

3.1. Four Primary Lines for Palm Line Analysis

Palm line analysis is an ancient practice that interprets the lines on the palm of the hand to glean insights into an individual's personality traits, emotional tendencies, and life experiences. The four primary lines—Heart, Head, Life, and Fate—are central to this practice, each offering unique perspectives into various aspects of human life. All of our following tasks resolving these four lines [7]:

- **Heart Line**: Positioned at the top of the palm, the Heart Line is believed to reflect emotional stability, romantic perspectives, and cardiac health.
- **Head Line**: Running horizontally across the palm, the Head Line represents intellectualism, learning style, and communication abilities.
- **Life Line**: Encircling the thumb, the Life Line is traditionally associated with physical health, general wellbeing, and major life changes.
- **Fate Line**: Often running vertically from the base of the palm, the Fate Line indicates the degree to which external circumstances influence an individual's life path.

Therefore, one of our primary objectives is to successfully segment these primary palm lines. Achieving precise segmentation is essential before we can undertake further analytical tasks. This foundational step ensures that subsequent analysis will be based on accurate and distinct representations of each line.

3.2. Feature Extraction and Vision Transformer

Following the segmentation of the palm lines, a critical subsequent step involves the extraction of meaningful features from the segmented structures. This is achieved using a Vision Transformer (ViT) backbone. The ViT model meticulously processes the image, capturing detailed information about the shapes, intersections, lengths, and other significant spatial characteristics of the principal and minor lines. This stage transforms the visual data into a structured, high-level feature representation that encodes the essential attributes necessary for palmistry analysis, providing a robust foundation for subsequent interpretation.

3.3. Quantified Reasoning

To structure the analysis and mitigate uncertainties, the high-dimensional features extracted by the Vision Transformer are processed for direct numerical inference. The final representation is passed through a regression head, which flattens and maps the features to four distinct, continuous-valued scores. These scores correspond to core palmistry dimensions: strength, romantic, luck, and potential. This architecture transforms complex visual patterns into a concise, quantitative profile, enabling a structured and objective assessment. The regression-based approach provides a measurable and consistent basis for the subsequent interpretation, grounding the final analysis in a robust, data-driven foundation.

3.4. Final Analysis

After obtaining scores for various attributes and elaborating on the text descriptions of the palm lines, the final and critical step is to generate a comprehensive, user-friendly analysis. This task will be accomplished using a large language model (LLM), which will synthesize the scores and textual insights into a coherent narrative. The LLM will provide an accessible interpretation of the analysis, enabling users to easily understand the implications of the palm features concerning aspects such as luck, health, and personal insights. By leveraging the capabilities of the LLM, we aim to deliver a polished and informative report that enhances the user experience and facilitates deeper engagement with the results of the palm analysis.

4. Dataset Design

4.1. Data Origin and Characteristics

The data utilized in this study is purely based on images of hands, sourced from the Kaggle dataset titled "Human Palm Images.“ [1] To ensure a diverse and representative dataset, we selected images that capture an overhead view of hands, which aligns with our objective of scanning users' hands effectively. The dataset is well-balanced, encompassing both left and right hands, as well as involving both male and female images of 400 each. This careful selection aims to mitigate potential biases and ethical concerns associated with dataset representation. By prioritizing diversity in our dataset, we strive to prevent discriminatory practices and ensure that our findings are applicable across different demographics. This approach not only enhances the robustness of our analysis but also upholds ethical standards in research.

4.2. Data Preprocessing

The data preprocessing pipeline for our AI application involves several critical steps to enhance the quality of the input images and prepare them for effective analysis. We perform the following operations on the dataset.

4.2.1. Background Extraction

We isolate the palm from the surrounding background in an image. By effectively removing the background, we ensure that the model focuses exclusively on the palm, which leads to more accurate segmentation. We assume that the images are simple and there is no occlusion of our target objects.

4.2.2. Transformation to Grayscale

Grayscale conversion is the process of transforming a color image into a single-channel format that represents varying shades of gray. This technique simplifies the complexity of the image by reducing it from three color channels (RGB) to one, making it easier to process [5]. In the context of palm segmentation, grayscale images enhance the visibility of edges and contours while eliminating color distractions that may not be relevant to the task. By focusing solely on intensity values, we can better highlight the structural features of the palm, which is essential for accurately identifying and isolating it from the hand.

4.2.3. Black-Hat Morphological Transform

The Black-Hat morphological transform is a key preprocessing step for our palm image analysis, defined as

$$\text{BlackHat}(I) = \text{Closing}(I) - I$$

It isolates darker, smaller image structures—primarily palm lines—by subtracting the original image from its morphological closing [2]. This effectively enhances thin, dark creases while suppressing uniform skin texture.

This operation provides targeted feature amplification before Vision Transformer (ViT) processing. It increases the signal-to-noise ratio of palm lines, allowing the ViT to focus its attention mechanisms on high-level relationships between enhanced features rather than low-level feature extraction. The transform's illumination robustness also aids in input normalization across varying capture conditions.

For implementation, the structuring element size is tuned to match typical palm line widths (10-20 pixels). The output is a grayscale, line-enhanced image suitable for standard ViT preprocessing (resizing, patching, projection), foregrounding the geometric information essential for robust palm representation learning.

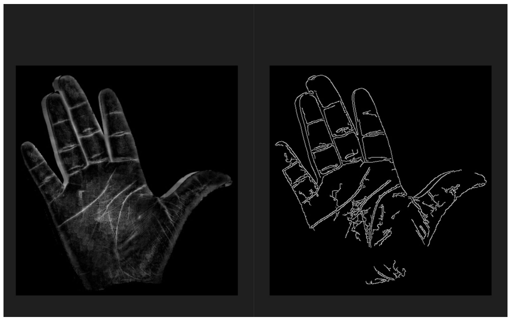


Figure 2. Example of preprocessing steps performed on an input palm image.

```
{
  "image": "FEMALE/IMG_0025.JPG",
  "scores": {
    "luck": 0.9,
    "health": 0.7,
    "romantic": 0.4.
  }
}
```

Figure 3. An example of labels produced by a VLM, in the format of a JSON dictionary.

4.3. Data Annotation

In our study, we utilize a Vision-Language Model (VLM) to perform the initial labeling of palm line images. The VLM leverages its ability to understand and process visual and textual information simultaneously, enabling it to generate accurate labels for the intricate patterns found in palm lines. This automated labeling process serves as a foundational step in our data annotation pipeline, significantly reducing the manual effort required and ensuring consistency across the dataset. By employing a VLM, we capitalize on advanced machine learning techniques to efficiently and effectively annotate our dataset, facilitating subsequent analysis and model training. This approach not only enhances the quality of the initial labels, but also accelerates the overall data preparation process.

5. Methods

Our system is designed as a novel, multi-modal pipeline that integrates computer vision and natural language processing to translate palm features into insightful descriptions. The architecture moves beyond a simple feature-to-text model by incorporating a rule-based scoring mechanism and a final Large Language Model (LLM) synthesis step for coherent and contextualized output.

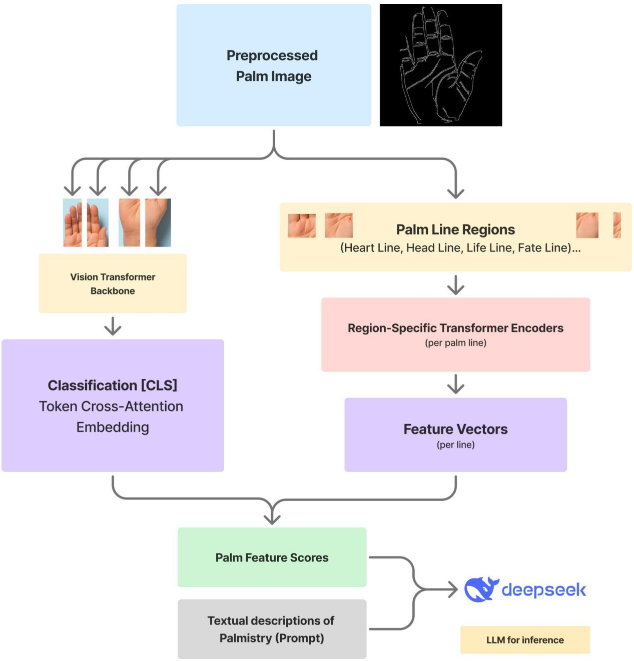


Figure 4. Our pipeline structure.

5.1. Feature Extraction

Input images are first converted to grayscale and denoised with Gaussian blur before edge extraction. The preprocessing module loads an image, converts it from BGR to grayscale, applies a configurable Gaussian blur, and then computes edges using Canny detection, producing an "edge-only" version that is saved per image.

5.1.1. Preprocessing

The pipeline begins by preprocessing the raw palm image to standardize input and highlight regions of interest. This involves:

- **Color Correction & Normalization**: Adjusting for lighting variations to ensure consistent color and contrast across images.
- **Pale Region Isolation**: A specialized segmentation model is employed to accurately identify and crop the four primary pale regions corresponding to the mounts of the palm (e.g., Mount of Venus, Mount of Jupiter, etc.), as well as the central palmar area containing the primary lines (Heart, Head, Life).
- **Image Patching**: The isolated full palm and/or specific regions are divided into a sequence of fixed-size patches, which are then linearly projected into a lower-dimensional space to create a patch embedding sequence.

5.1.2. Feature Extraction with Hybrid Transformer

Instead of a single transformer, we propose a Hybrid Transformer Encoder architecture with the following features, as shown in Figure 6.

- **Shared Backbone**: A Vision Transformer (ViT) backbone first processes the entire preprocessed palm image to generate a global context embedding, represented by the [CLS] token.
- **Region-Specific Encoders**: In parallel, the cropped image regions containing specific palm lines (Heart, Head, Life, Fate) are processed by smaller, independent transformer encoders. This allows for focused feature extraction tailored to the unique characteristics of each line.
- **Feature Fusion**: The global [CLS] token embedding and the features from the region-specific encoders are concatenated and passed through a fusion module (e.g., a cross-attention layer or a simple fully connected layer) to create a unified, comprehensive feature representation F_{score} that will be used for score regression.

5.2. Feature Processing and Multi-Modal Interpretation

This stage processes the unified feature representation F_{score} through a streamlined pipeline that directly maps visual patterns to quantitative assessments.

5.2.1. Direct Score Regression

The Vision Transformer backbone processes the segmented palm image and extracts high-level visual features. These features are then passed through a regression head that directly outputs four continuous-valued scores corresponding to refined palmistry dimensions: Strength, Romantic, Luck, and Potential. This end-to-end approach eliminates intermediate text generation steps, providing a more efficient and direct mapping from visual input to quantitative output.

5.2.2. LLM-as-Judge Evaluation Framework

To train and evaluate the regression model, we employ an LLM-as-Judge methodology. The Qwen3 VLM model is used to process and label the training dataset, generating ground truth scores for each palm image. These LLM-generated labels serve as the target values for training the Vision Transformer's regression head. The model is optimized using standard regression loss functions (e.g., Mean Squared Error) to minimize the discrepancy between its predicted scores and the LLM-generated ground truth. This approach leverages the powerful reasoning capabilities of large language models to provide consistent and structured supervision for the visual analysis task, ensuring that the model learns to capture the nuanced palmistry characteristics for the specified dimensions.

5.3. LLM Inference for Holistic Synthesis

The final stage leverages a Large Language Model (LLM) as a sophisticated information synthesizer.

- **Input Prompt Construction**: The outputs from previous stages are assembled into a detailed prompt for the LLM.

We include structured descriptions with output scores of vision transformer, the score vector S_{NN}, as well as a system prompt framing the task.

- **Natural Language Generation**: The LLM processes this rich, multi-modal input to produce the final output. It does not just paraphrase; it reasons about the interplay between different lines and scores, generating a novel, insightful, and human-readable report that includes character analysis and life suggestions. This step adds a layer of interpretation and narrative fluency that is absent in simpler sequence-to-sequence models.

6. Experiments

6.1. Preprocessing

6.1.1. Experimental Setup

Three datasets were constructed from the same 800 labeled palm images (train/validation split 640/160):

1. original images without preprocessing,
2. grayscale+blur preprocessed images, and
3. preprocessed images with edge extraction applied using the Canny-based edge extractor described above.

For all three datasets, the network architecture, optimization settings, and training schedule were kept identical to isolate the effect of the input representation on optimization behavior.

6.1.2. Convergence Comparison

Training and validation losses over 5 epochs were recorded for each dataset and plotted on a single curve for comparison. The original-image setting consistently produced the highest training and validation losses; applying basic preprocessing reduced both losses, while adding edge extraction on top of the preprocessing yielded the lowest losses and the steepest early decrease, indicating faster and more stable convergence. Therefore, subsequent experiments in the paper are conducted using this representation as the default input to the model.

6.2. Vision Transformer for Palm Image Regression

6.2.1. Architecture Overview

The Vision Transformer (ViT) processes palm images for regression of four scores: strength, romantic, luck, and potential. Key components:

- **Backbone**: Pre-trained ViT-Base (12 layers, 768-dim, patch size 16)
- **Input**: 224 × 224 RGB → 196 patches
- **Regression head**: 3-layer MLP with GELU, dropout, and sigmoid output
- **Output**: Four scores in $[0, 1]$ range

```
You are a palmistry expert.
You will assist the user in inferring
fortune-telling results based on their
palm line features.

## Supplementary Information on Palmistry
Palm lines of interest include the *Life
Line*, the *Heart Line*, the *Fate Line*,
and the *Head Line*. These lines
represent respectively, *enthusiasm
and strength*, *romantic life*, *fortune
and luck*, and *smartness and potential*.
You will receive scores predicted based
on palm line features by a Deep Learning
model. You are then to provide fortune-
telling results in natural language,
further instructions will be given in
the next section.

### About Each Palm Line
<supporting information>

## Inference Instructions
You will be provided with scores for
`strength`, `romantic`, `luck`, and
`potential`. These scores were previously
predicted using a deep learning model
based on geometric features of the user's
palm lines, and they correspond to the
above points provided to you as
supplementary information on palmistry.

Provide the user with fortune-telling
results based on these scores, and give
explanations to assist the user in
inferring their results. Explain what
those scores mean and how their luck
or fortune looks like. Give advice to
the user on how to face probable events
in their future life.
```

Figure 5. Contextual instructions provided through the system prompt to the LLM.

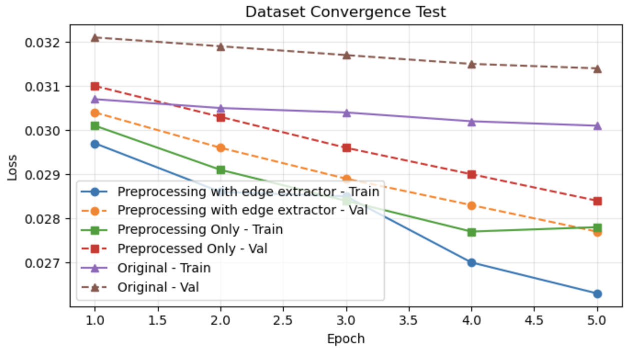


Figure 6. Comparison of convegence speeds when using datasets with different preprocessing steps for training.

6.2.2. Training Configuration

Parameter	Value
Batch size	8
Learning rate	2×10^{-4}
Epochs	80
Warmup	5% (fast)
Optimizer	AdamW (wd=0.01)
Loss	MSE
Scheduler	OneCycleLR

6.2.3. Data Processing

- **Augmentation**: Random crop, flip, rotation (±15°), color jitter
- **Normalization**: Mean = 0.5, std = 0.5
- **Labels**: JSON parsing with error handling

6.2.4. Training Results

The model achieved strong performance in palm score regression:

- **Best model at epoch 45** (early convergence)
- **Validation loss**: 0.0186 MSE
- **Validation MAE**: 0.1002 (average absolute error)
- **Practical implication**: Predictions within ±0.1 of true values

6.2.5. Training Curves

Training performance is visualized through loss curves showing model convergence:

6.2.6. Key Advantages

- **Global context**: Self-attention captures relationships across entire palm
- **Transfer learning**: ImageNet-21k pre-training provided strong initialization
- **Fast convergence**: Best performance reached at epoch 45 of 80
- **High accuracy**: MAE of 0.1002 indicates precise score prediction

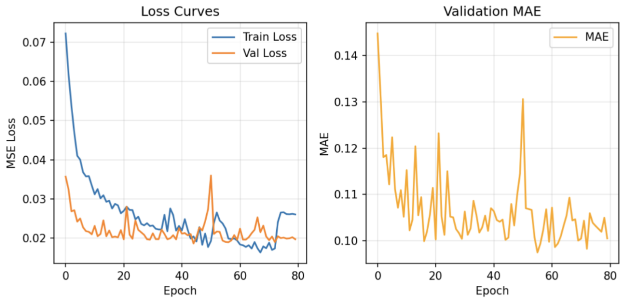


Figure 7. Training curves showing convergence at epoch 45. The model achieved validation loss 0.0186 and MAE 0.1002, indicating effective learning of palm features.

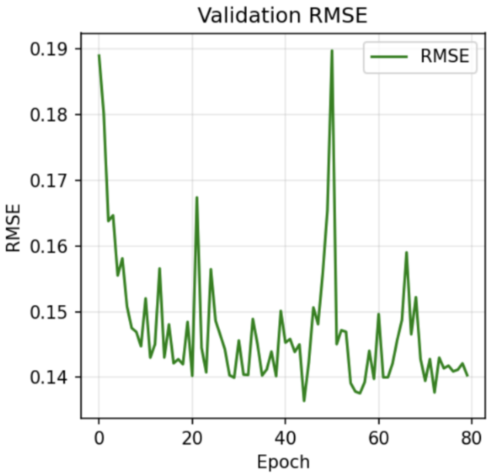


Figure 8. Root Mean Square Error (RMSE) curves during training. The model's RMSE decreased steadily till epoch 45.

6.3. Alternative Framework Using CNNs

We also explore an alternative implementation of our framework using different CNN architectures in place of our vision transformer. The architectures used and results are listed as follows.

6.3.1. Training Configuration

For all CNN architectures trained and tested, the parameters are the same and are listed in the following table.

Parameter	Value
Batch size	8
Learning rate	1×10^{-4}
Dropout rate	0.2 or 0.3
Epochs	20
Optimizer	AdamW (wd=0.01)
Loss	MSE
Scheduler	ReduceLROnPlateau

6.3.2. Multi-scale Feature Extraction CNN

This architecture performs multiple convolutions to extract features at different levels, then passes the features through an attention mechanism to focus on important palm line regions, and finally fuses the feature outputs to regress to 4 scores. The detailed flow is as follows.

- Initial convolution: 1 channel to 32 channels, kernel size 3, padding 1
- Mid-level features: 32 channels to 64 channels, kernel size 3, padding 1
- High-level features: 64 channels to 128 channels, kernel size 3, padding 1
- Attention (from high-level features): 2D Conv from 256 channels to 1 channel, kernel size 1, padding 0
- Global features (from attended features): 128 channels to 256 channls, kernel size 3, padding 1
- Further upscaling (from high-level features): 128 channels to 256 channls, kernel size 3, padding 1
- Feature fusion: combines further upscaling features and global features
- Regression to 4 scores: linear layers
- ReLU layer to clip values between 0 and 1

This architecture gave an average MSE loss of 0.0168 on evaluation using 800 images. The final training loss was 0.0096, and the best validation loss was 0.0231.

6.3.3. Transfer Learning CNN

This architecture utilizes a pretrained backbone, either EfficientNet [4] or ResNet [3], to extract features. The extracted features are subsequently flattened and passed through linear layers, culminating in a regression layer that outputs 4 scores. A sigmoid activation function is applied prior to the final output to constrain the scores within the range of 0 to 1.

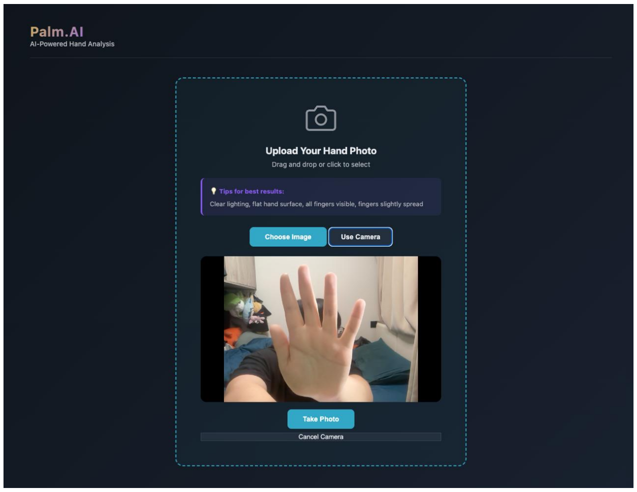
During evaluation on 800 images, this architecture achieved the best performance among all tested CNN models, attaining an average MSE loss of 0.0075. The final training loss was 0.0063, while the best validation loss reached 0.0251.

Given the limited scale of our dataset, comprising only 1,600 images, transfer learning proved to be the most effective approach, yielding optimal results. Specifically, the model was implemented using the ImageNet1K_V1 pretrained weights, with torchvision.models.resnet18 serving as the backbone for the transfer learning procedure.

6.3.4. Region-specialized CNN

This architecture uses a shared backbone to first extract features, then passes the features through 4 parallel branches, each attending to a different palm region, and finally concatenates the features from the branches to regress to 4 scores. The detailed flow is as follows.

- Shared backbone: 2D convolutionse to 32 then 64 and 128 channels, kernel size 3, padding 1



Clear lighting, flat hand surface, all fingers visible, fingers slightly spread

Figure 9. User interface prompting for palm scanning.

- Parallel branches:
  - Attention in each branch: 2D convolution from 128 to 64 then 32 channels, kernel size 1, padding 0
  - Region extractor in each branch: 2D convolution from 128 to 64 channels, kernel size 3, padding 1
- Feature concatenation: linear layer from 64 × 4 dimensions to 256 dimensions
- Regression to scores: linear layers from 256 dimensions to 128 then 4 dimensions
- ReLU layer to clip values between 0 and 1

This architecture gave an average MSE loss of 0.0304 on evaluation using 800 images. The final training loss was 0.0191, and the best validation loss was 0.0237.

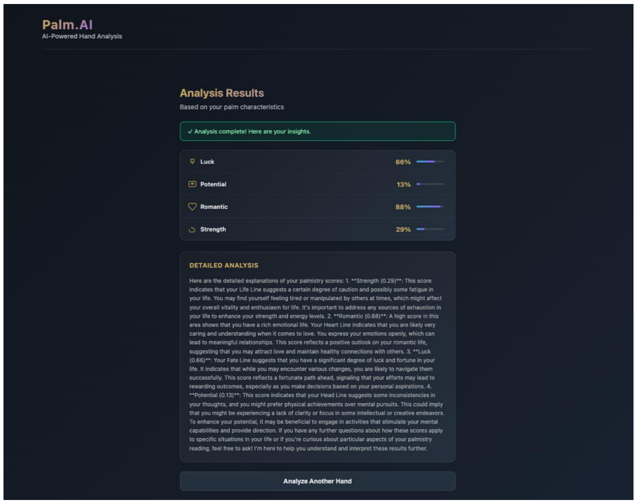
We hypothesize that each palm region has different semantic meanings, hence each gives one score per aspect of life. Thus in this architecture, we use parallel convolution operations on each region to extract features and translate those features to scores.

6.3.5. Summary of CNN Training

Architecture	Avg. Loss	Train Loss	Val. Loss
Multi-scale	0.0168	0.0096	0.0231
Transfer Learning	0.0075	0.0063	0.0251
Region-specialized	0.0304	0.0191	0.0237

6.4. User Interface

We provide a graphical user interface for seamless use of our pipeline, through a web app. The user first scans their palm using an on-device camera, and will receive predictions in natural language with an LLM. In our experiments, we use GPT-4o for the LLM.



Analysis Results

Based on your palm characteristics

✓ Analysis complete! Here are your insights.

Luck	66%
Potential	13%
Romantic	88%
Strength	29%

DETAILED ANALYSIS

Here are the detailed explanations of your palmistry scores: 1. **Strength (0.29)**: This score indicates that your Life Line suggests a certain degree of caution and possibly some fatigue in your life. You may find yourself feeling tired or manipulated by others at times, which might affect your overall vitality and enthusiasm for life. It's important to address any sources of exhaustion in your life to enhance your strength and energy levels. 2. **Romantic (0.88)**: A high score in this area shows that you have a rich emotional life. Your Heart Line indicates that you are likely very caring and understanding when it comes to love. You express your emotions openly, which can lead to meaningful relationships. This score reflects a positive outlook on your romantic life, suggesting that you may attract love and maintain healthy connections with others. 3. **Luck (0.66)**: Your Fate Line suggests that you have a significant degree of luck and fortune in your life. It indicates that while you may encounter various changes, you are likely to navigate them successfully. This score reflects a fortunate path ahead, signaling that your efforts may lead to rewarding outcomes, especially as you make decisions based on your personal aspirations. 4. **Potential (0.13)**: This score indicates that your Head Line suggests some inconsistencies in your thoughts, and you might prefer physical achievements over mental pursuits. This could imply that you might be experiencing a lack of clarity or focus in some intellectual or creative endeavors. To enhance your potential, it may be beneficial to engage in activities that stimulate your mental capabilities and provide direction. If you have any further questions about how these scores apply to specific situations in your life or if you're curious about particular aspects of your palmistry reading, feel free to ask! I'm here to help you understand and interpret these results further.

Figure 10. Prediction by LLM.

7. Conclusion

Palmreader.ai establishes a multi-modal pipeline that performs fortune-telling through palm reading, incorporating Vision Transformers (ViT), a Neural Network for scoring, as well as a Large Language Model (LLM) for final inference. We have provided a first step in using a data-driven approach to draw superstitious practices towards science. We expect to produce a robust model that can effectively generate accurate palm-reading results.

Further work may optimize the pipeline by employing powerful pretrained text decoders in describing extracted palm line features, which may be used as additional information in the final inference step. Additionally, external knowledge related to palmistry may be used in Retrieval-Augmented Generation (RAG) with the LLM in the final inference step, to provide context whenever required as additional support.

8. Appendix

Our implemention is linked at this Github repository. Additionally, this is a demo of the final app usage.

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