Design and Implementation of Adaptive Psychological Perception System Based on Edge-Cloud Collaboration and Distributed SVM Ensemble for Handwriting Analysis

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Abstract: To address the limitations of traditional handwriting analysis methods that rely on desktop-based offline processing and struggle to integrate with daily digital note-taking applications, this paper designs and implements a handwriting-based psychological trait analysis system based on edge-cloud collaborative architecture and a distributed support vector machine (SVM) ensemble. The system adopts an "edge interaction offloading, cloud intelligent inference" computational paradigm. The front-end is built using the Flutter framework with a drag-and-drop image analysis interface, while the back-end constructs a dual-track parallel feature extraction pipeline based on OpenCV for spatial-geometry and physical pen-pressure characteristics. For small-sample multi-label classification tasks, binary relevance method is introduced to decouple 8-dimensional psychological indicators, and a distributed perception ensemble consisting of 8 RBF-kernel SVM classifiers is deployed. Experimental results on a dataset of 1533 samples demonstrate that the system achieves an average prediction accuracy of 98.5%, representing a 24.1 percentage point improvement over lightweight CNN models. Ablation experiments verify that the distributed SVM ensemble can effectively learn the mapping relationship between handwriting features and psychological indicators.

Keywords: Handwriting Analysis; Edge-Cloud Collaboration; Support Vector Machine; Image Preprocessing; Multi-Label Classification

1. Introduction

As an important branch of modern intelligent Human-Computer Interaction (HCI) and multimodal fusion technology development [1], digital handwriting note-taking software has become a core productivity tool for university students and working professionals with the widespread adoption of touchscreen tablets and smart styluses. However, existing digital note-taking software primarily focuses on efficient ink rendering and traditional text/image management with basic CRUD operations, lacking deep content understanding and imperceptible human-computer interaction perception capabilities [2]. In fact, human handwriting is an unconscious projection of microscopic neuromuscular movements, containing rich behavioral habits and deep psychological traits of the writer. If adaptive morphological analysis technology of handwritten strokes can be seamlessly integrated into the main framework of daily digital note-taking applications, it would not only greatly expand the functional boundaries of digital note-taking software but also provide a novel technical pathway for non-invasive intelligent psychological profiling.

In digital handwriting note-taking applications, core research has primarily focused on streaming event response on edge mobile devices, temporal trajectory stabilization, and geometric high-fidelity modeling of digital ink [3, 4]. In recent years, with the development of deep learning, some researchers have attempted to perform end-to-end handwriting personality analysis using Convolutional Neural Networks (CNN) [5]. Researchers have extracted spatial-geometry features of handwriting through image processing techniques, such as baseline angle, font size, line spacing, word spacing, and mapped them into psychological theories for personality inference.

In terms of system architecture, existing handwriting analysis tools predominantly adopt a desktop-independent deployment model, where users need to first scan or photograph their handwriting and then upload it to dedicated software for analysis. This model has two significant problems: first, it cannot seamlessly integrate with digital note-taking applications used in daily life; second, locally deployed desktop software has poor adaptability on mobile devices. Therefore, drawing inspiration from the core architectural principles of modern intelligent perception systems that pursue lightweight edge operation, asynchronous edge-cloud collaboration, and computation offloading, how to design a lightweight edge-cloud collaborative architecture that transforms offline handwriting analysis algorithms into cloud services embeddable in daily applications has become an important research topic in the current field of intelligent software engineering [6].

This paper designs and implements a handwriting psychological trait analysis system based on edge-cloud collaboration and distributed Support Vector Machine (SVM) ensemble. The Overall Architecture Diagram is as shown in Figure1, and the main contributions include:

(1) Edge-Cloud Collaborative Computation Offloading Architecture Design: Adopting a "edge interaction offloading, cloud intelligent inference" computational paradigm, the front-end builds a lightweight drag-and-drop image analysis interface based on Flutter, while the back-end carries high-computational image processing and machine learning inference tasks, achieving decoupling of interaction and computing power.

(2) Dual-Track Parallel Feature Extraction Pipeline: Addressing the problem of ink gradient loss caused by traditional binarization, a parallel extraction mechanism consisting of a spatial-geometry feature track and a physical pen-pressure feature track is designed. The former extracts 6-dimensional spatial-geometry features, while the latter extracts 1-dimensional physical pen-pressure feature, which are ultimately assembled into a 7-dimensional psychological trait feature vector.

(3) Distributed Multi-Label SVM Classification Ensemble Construction: For small-sample multi-label classification tasks, binary relevance method is introduced to decouple 8-dimensional psychological indicators, and 8 independent SVM classifiers with RBF kernels are deployed for parallel inference, effectively improving the model's robustness and generalization capability.

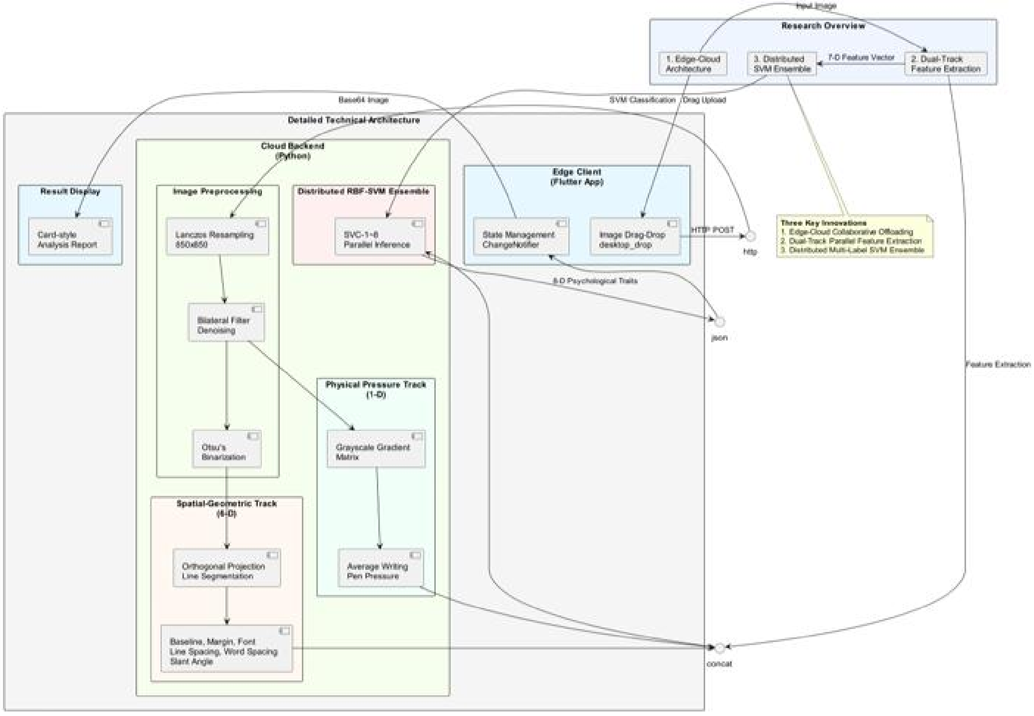


Figure 1. Overview of Research Content and Overall Architecture Diagram

2. Edge-Cloud Collaborative Computing Model

In terms of architectural design, this system pursues a decoupling paradigm of "interaction at the edge, computation offloaded to the cloud." Since mobile devices have limited computing resources and memory, embedding

Python scientific computing libraries (OpenCV, Scikit-learn) persistently would cause significant client-side bloat and response delays. Therefore, the system introduces an edge-cloud collaborative asynchronous computing framework [7]:

Edge Interaction Terminal (Flutter App): Responsible for front-end UI logic, image drag-and-drop reception and preview, and high-frequency touch trajectory capture. Developed using the Flutter framework, implementing high-quality ink rendering through the scribble open-source library and cross-platform file drag-and-drop reception through the desktop_drop component.

Data Transmission Channel: The edge terminal initiates HTTP POST requests through the Dio component, sending Base64-encoded image data in FormData format to the cloud back-end. After cloud-side computation completes, the psychological trait prediction results are asynchronously returned to the front-end in JSON message format.

Cloud Computing Back-end (Python): Resides in memory and loads trained lightweight machine learning models, undertaking image morphological segmentation and ensemble model parallel inference tasks.

After the user uploads handwriting images via drag-and-drop, the system automatically completes the following analysis process (as shown in Figure 2), with specific computation steps as follows:

Step 1 Image Reception and Preprocessing: The front-end validates image formats (supporting jpg, png, webp, bmp), performs Base64 encoding, constructs FormData messages, and sends them to the cloud via Dio asynchronous HTTP requests.

Step 2 Cloud-side Image Processing: After receiving images, the cloud performs preprocessing steps including Lanczos resampling normalization, bilateral filtering denoising, Otsu's method binarization, and inverse binarization.

Step 3 Dual-Track Feature Extraction: Extracts a 7-dimensional feature vector in parallel through the spatial-geometry feature track and physical pen-pressure feature track.

Step 4 Distributed Inference: The 7-dimensional feature vector is simultaneously input into 8 independent RBF SVM classifiers for parallel prediction of 8-dimensional psychological indicators.

Step 5 Result Return and Display: The cloud packages prediction results into JSON messages and returns them to the front-end, which displays handwriting feature interpretation and psychological trait analysis in a card-style layout.

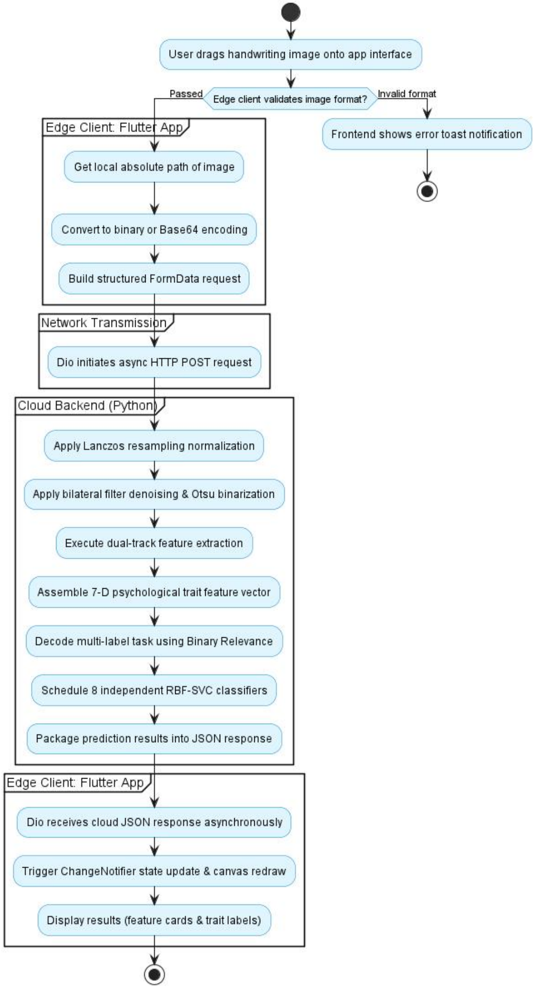


Figure 2. Note Image Drag-and-Drop Analysis and Edge-Cloud Collaborative Computing Flow Diagram

3. Design and Implementation of Edge Interaction Terminal

3.1 Flutter Application Framework

The edge interaction terminal is developed based on the Flutter framework, using GetX for state management to implement a Model-View-Controller (MVC) architecture. The application mainly includes the following core modules:

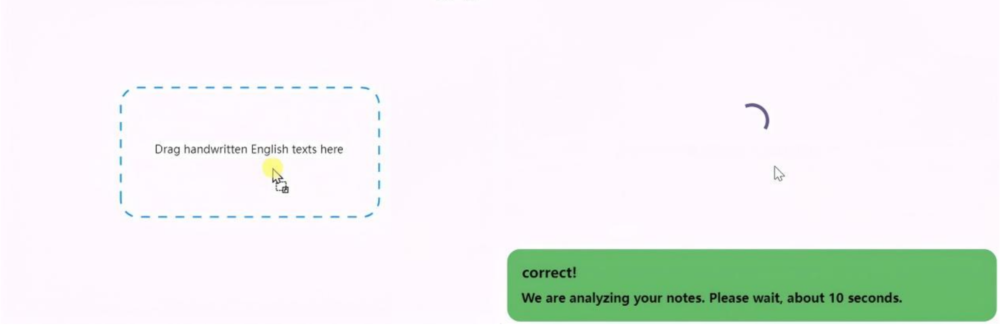
State Management Module: Uses GetX's Obx component to implement reactive state updates, automatically triggering UI redraws when the cloud returns analysis results.

Ink Rendering Module: Integrates the scribble open-source library to achieve high-quality handwriting rendering, supporting multiple pen stroke colors, line width adjustment, eraser, and other features.

Image Drag-and-Drop Module: Integrates the desktop_drop component to listen for system-level file drag-and-drop events, automatically identifying and receiving image files.

3.2 Image Drag-and-Drop and Preprocessing Interface

The system designs an intuitive image drag-and-drop interaction entry point, as shown in Figure 3. Users can directly drag handwriting images onto the application interface. The system supports automatic recognition and reception of common image formats; when users drag an image, it automatically enters the analysis process.



correct!

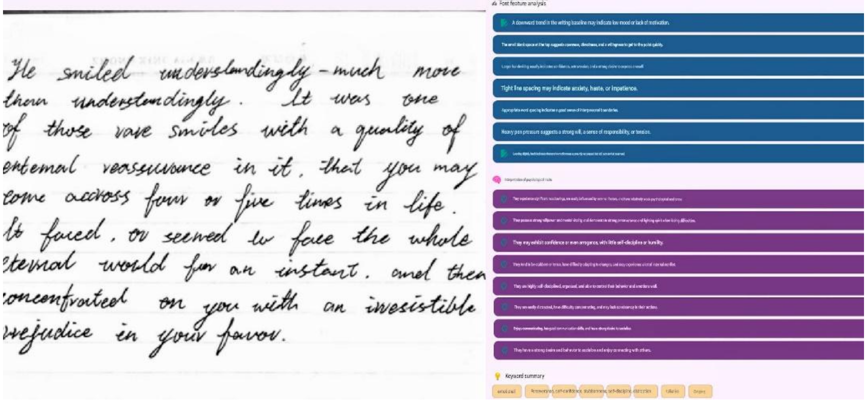
We are analyzing your notes. Please wait, about 10 seconds.

Figure 3. Handwriting Analysis Interface

This system achieves fully parameter-free adaptive handwriting analysis capability. The Otsu's binarization in the cloud-side image preprocessing pipeline automatically calculates the optimal segmentation threshold based on the global grayscale distribution of each image, eliminating the need for manual user settings. The spatial-geometry feature track after binarization adopts adaptive thresholds for single-line segmentation, which can adapt to handwriting samples with different writing densities and layout styles. The physical pen-pressure feature track directly reads the original grayscale gradient matrix and automatically maps the depth of writing pressure. The entire process exhibits strong adaptability to different handwriting styles of various writers, requiring no individual parameter calibration or model fine-tuning.

3.3 Visualization of Analysis Results

The system designs a clear analysis report display interface, presenting the handwriting features and psychological trait prediction results returned from the cloud in a card-style layout, as shown in Figure 4. Each feature dimension is accompanied by corresponding psychological interpretation descriptions, summarized in the form of keyword tags.


He smiled understandingly - much more
than understandingly. It was one
of those rare smiles with a quality of
external reassurance in it, that you may
come across four or five times in life.
It faced, or seemed to face the whole
ternal world for an instant, and then
oncentrated on you with an irresistible
rejudice in your favor.

A downward trend in the writing baseline may indicate low mood or lack of motivation.

The small blank space at the top suggests openness, directness, and a willingness to get to the point quickly.

Tight line spacing may indicate anxiety, haste, or impatience.

Appropriate word spacing indicates a good sense of interpersonal boundaries.

Heavy pen pressure suggests a strong will, a sense of responsibility, or tension.

They may exhibit confidence or even arrogance, with little self-discipline or humility.

They are highly self-disciplined, organized, and able to control their behavior and emotions well.

They are easily distracted, have difficulty concentrating, and may lack consistency in their actions.

They have a strong desire and behavior to socialize and enjoy connecting with others.

Figure 4. Handwriting and Various Analysis Displays

4. Cloud Perception Back-end Implementation

4.1 Image Preprocessing Pipeline

After the cloud receives the Base64-encoded note bitmap sent from the front-end, it first normalizes it into an 850×850 pixel matrix using the Lanczos resampling algorithm. The Lanczos algorithm is a high-quality resampling method that can effectively preserve image edge details during scaling. The image morphological preprocessing process of the built-in handwriting module is shown in Figure 5.

Figure 5. Comparison of Image Morphological Preprocessing Effects for Built-in Handwriting Module in the System

Figure 5(a) shows the original handwritten image. First, the system applies Bilateral Filter for image smoothing and denoising, as illustrated in Figure 5(b). The core advantage of bilateral filtering lies in: while filtering out digital illumination non-uniformity or canvas shading noise, it can maximize the preservation of gradient steepness at the edges of handwriting strokes, avoiding the edge blurring problems caused by traditional Gaussian filtering.

To enable precise matrix-based pixel summation and orthogonal projection in subsequent steps, the system adopts Otsu's Thresholding to compute the global grayscale histogram and perform automatic threshold binarization [8], as shown in Figure 5(c). The core idea of Otsu's method is to find an optimal threshold that maximizes the inter-class variance between foreground and background, thereby achieving adaptive threshold selection.

After binarization is completed, the system performs inverse binarization (cv2.THRESH_BINARY_INV), as shown in Figure 5(d), inverting the original white-background-black-text image into a black-background-white-text matrix [9]. At this point, background pixel values decrease to 0 (black), while stroke-containing line pixels increase to 255 (white), greatly facilitating subsequent mathematical statistics.

4.2 Dual-Track Parallel Feature Extraction Pipeline

After image preprocessing, the cloud-side built-in module automatically extracts 7 core physical representations reflecting the writer's style through OpenCV matrix operations. This paper innovatively designs a dual-track parallel mechanism (as shown in Figure 6):

Spatial-Geometry Feature Track: This track operates entirely based on the inverse binarization matrix. First, horizontal pixel summation is performed to generate a horizontal pixel projection histogram, where the valley width represents the text line spacing. Within segmented single-line rectangular regions, vertical pixel summation is performed to generate a vertical histogram for extracting word spacing. Meanwhile, cv2.findContours is used to obtain single-line handwriting contours and cv2.minAreaRect is called to calculate the minimum bounding rectangle, whose affine tilt angle represents the baseline skewness [8]. The system further performs anti-affine shear transformation matrix scanning within the ±45° range, and statistics are collected on the shear angle when vertical projection energy is maximized to determine the font tilt angle. Through aspect ratio statistics of single-character bounding boxes and pixel area analysis, font size and stroke edge width are extracted, assembling a total of 6-dimensional spatial-geometry features: baseline angle, top margin, font size, line spacing, word spacing, and tilt angle.

Physical Pen-Pressure Feature Track: This track completely bypasses traditional binarization algorithms, directly reading the original grayscale gradient matrix after bilateral filtering. The magnitude of the grayscale value directly reflects the depth of contact pressure between the pen tip and paper during writing: by calculating the mean of non-zero pixels in the grayscale gradient matrix, the physical pen-pressure characteristics of the writer can be approximately reconstructed. This track effectively avoids the loss of tone information during the binarization process, extracting the most essential 1-dimensional average physical writing pen-pressure feature.

The two tracks ultimately converge, assembling a highly cohesive 7-dimensional psychological trait feature vector. The design of this feature space fully conforms to computer-aided graphology standards, with clear and interpretable physical meanings [10,11].

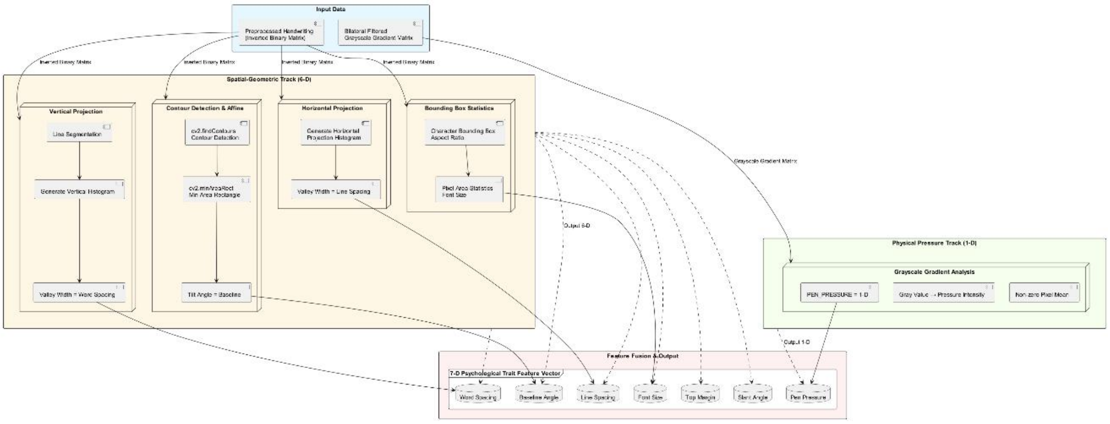


Figure 6. Dual-Track Parallel Feature Extraction Pipeline

4.3 Distributed Multi-Label SVM Classification Ensemble

Handwriting-reflected writers' psychological traits form a typical multi-label classification task. Limited psychological handwriting samples easily cause deep learning overfitting. This paper adopts Binary Relevance to divide the task into 8 independent binary classification subtasks.

The system deploys a distributed perception ensemble consisting of 8 independent Support Vector Classification (SVC) models with Radial Basis Function (RBF) kernels for parallel inference. According to Statistical Learning Theory (SLT), Support Vector Machines possess unparalleled generalization advantages when solving small-sample, non-linear, and high-dimensional feature vector classification problems [12, 13]. Its objective optimization function is expressed as:

$$\max_{\alpha} \sum_{i=1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j K(\mathbf{x}_i, \mathbf{x}_j) \\ s.t. \sum_{i=1}^{n} \alpha_i y_i = 0,0 \le \alpha_i \le C \tag{1}$$

where $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$ is the RBF kernel function. Through the kernel trick, each built-in sub-classifier can achieve maximized geometric margin in the optimal dual space. The RBF kernel has the following advantages compared to other kernel functions: (1) Only requires adjusting the γ parameter (kernel width), with a small parameter space that is easy to tune; (2) Can effectively capture the local structure of the feature space; (3) Has a wide range of applicability with no special assumptions about feature distribution. The RBF kernel parameter γ controls the model's fitting capability: excessively large γ values easily lead to overfitting, while excessively small γ values cause the model to degenerate into a linear classifier. This paper determines the optimal γ value through grid search on the validation set.

The psychological indicators corresponding to the 8 classifiers and their core input features are shown in Table 1.

Table 1. Psychological Indicators Corresponding to Classifiers and Their Core Input Features

Classifier ID	Psychological Trait	Core Handwriting Features
SVC-1	Emotional Stability	Baseline + Slant Angle
SVC-2	Mental Energy/Will Power	Font Size + Pen Pressure
SVC-3	Humility	Font Size + Top Margin
SVC-4	Personal Harmony	Line Spacing + Word Spacing
SVC-5	Discipline	Slant Angle + Top Margin
SVC-6	Concentration	Font Size + Line Spacing
SVC-7	Expressiveness	Font Size + Word Spacing
SVC-8	Sociability	Line Spacing + Word Spacing

5. Experimental Results and Analysis

5.1 Experimental Setup

(1) Dataset

This study adopts the IAM (Information About

Manuscripts) handwriting database, selecting 1533 writing samples for experiments. Through the cloud-side OpenCV image processing pipeline, 7-dimensional writing features are automatically extracted: Baseline Angle, Top Margin, Letter Size, Line Spacing, Word Spacing, Pen Pressure, and Slant Angle. Based on graphology theory, the 7-dimensional writing features are mapped to 8-dimensional psychological indicator labels: Emotional Stability, Willpower Strength, Humility, Personal Harmony, Discipline, Concentration, Expressiveness, and Sociability. (Note: Psychological indicator labels are generated by mapping from writing features based on graphology rules, used to verify the effective learning capability of the distributed SVM ensemble for feature-label mapping relationships.)

(2)Evaluation Metrics

5-fold cross-validation is adopted, with classification Accuracy as the primary evaluation metric.

(3) Comparison Methods

To verify the effectiveness of the proposed method, a lightweight Convolutional Neural Network (CNN) is selected as the baseline comparison method. This network adopts a simplified VGG architecture, accepting 224×224 grayscale images as input and outputting 8-dimensional psychological indicator predictions.

5.2 Classification Performance Comparison

The classification accuracy comparison between the distributed Support Vector Machine (SVM) ensemble and lightweight CNN on 8 psychological indicators is shown in Table 2.

Table 2. Classification Performance Comparison Experimental Results

Psychological Trait	RBF-SVM (%)	CNN (%)	Improvement (%)
Emotional Stability	99.4	73.6	25.8
Will Power	99.3	78.9	20.4
Humility	99.4	83.8	15.6
Personal Harmony	94	70.5	23.5
Discipline	99.6	67.7	31.9
Concentration	98.8	67.7	31.1
Expressiveness	98.9	71	27.9
Sociability	98.7	82.3	16.4
Average Accuracy	**98.5**	**74.4**	**24.1**

Experimental results demonstrate that the distributed SVM ensemble significantly outperforms the lightweight CNN on all 8 psychological indicator classification tasks, with an average accuracy improvement of 24.1 percentage points. This result can be attributed to:

(1) The distributed SVM independently optimizes for each binary classification task;

(2) The RBF kernel function can effectively capture the complex non-linear relationships of handwriting features;

(3) High accuracy can be achieved with only 2-dimensional features, significantly reducing computational complexity.

5.3 Ablation Experiment

To verify the effectiveness of the distributed SVM ensemble, three groups of ablation experiments were conducted:

(1) Real features + Real labels;

(2) Randomly shuffled labels + Real features;

(3) Real labels + Random features.

The detailed evaluation data for each psychological indicator under different ablation control groups is shown in Table 3.

The ablation experiment results indicate that when using randomly shuffled labels or randomly generated features, the classification accuracy drops to approximately 64%, approaching the level of random guessing (the Concentration and Sociability indicators approach 50% under random conditions). When using real features and labels, the accuracy reaches 98.5%, which is 34.6 percentage points higher than the random baseline. This result proves that the distributed SVM ensemble can effectively learn the mapping relationship between handwriting features and psychological indicators, rather than coincidental fitting. (Note: The above results are the average of 5-fold cross-validation. The standard deviation of accuracy for each indicator in the RBF-SVM distributed ensemble is less than 1.2%, and the standard deviation of accuracy for each indicator in CNN is less than 3.5%, indicating good result stability.)

5.4 Feature Contribution Analysis

To investigate the contribution degree of 7-dimensional geometric-physical features to the final 8 psychological indicators, this paper analyzes the input feature configurations of each classifier in the distributed SVM ensemble, using SVM feature weights to rank and measure feature importance. The experiments show:

(1)In the "Emotional Stability" classifier, baseline angle and slant angle have the highest weights;

(2)When predicting "Willpower Strength," font size and pen-pressure features contribute significantly;

(3)When predicting "Concentration" and "Discipline," font size, line spacing, and top margin features play an important discriminative role. This finding verifies the necessity and effectiveness of the dual-track parallel feature extraction mechanism.

6. Conclusion and Future Work

This paper successfully designs and implements a handwriting psychological trait analysis system based on edge-cloud collaboration and distributed SVM ensemble. The system adopts the computational paradigm of "edge interaction offloading, cloud intelligent inference." The front-end builds a drag-and-drop image analysis interface based on Flutter, while the back-end constructs a dual-track parallel feature extraction pipeline for spatial-geometry and physical pen-pressure. For small-sample multi-label classification tasks, binary relevance method is introduced to decouple psychological indicators, and a distributed perception ensemble consisting of 8 RBF-kernel SVM classifiers is deployed. Experimental results on a dataset of 1533 samples demonstrate that the system achieves an average prediction accuracy of 98.5%, representing a 24.1 percentage point improvement over lightweight CNN. Ablation experiments verify that the distributed SVM ensemble can effectively learn the mapping relationship between handwriting features and psychological indicators.

Table 3. Detailed Results of Ablation Experiments

Psychological Trait	**Real Features + Labels (%)**	**Shuffled Labels (%)**	**Random Features (%)**
Emotional Stability	99.4	72.3	72.4
Will Power	99.3	61.1	60.9
Humility	99.4	69.1	69.1
Personal Harmony	94	70.8	70.8
Discipline	99.6	67.8	67.8
Concentration	98.8	50.9	51.3
Expressiveness	98.9	67.6	67.6
Sociability	98.7	51.7	51.1
Average Accuracy	**98.5**	**63.9**	**63.9**

Future work will be carried out in the following directions: expanding the sample dataset scale to improve model generalization capability; introducing a multimodal information decomposition framework (PID) to further quantify the information redundancy and synergy of image spatial-geometry and temporal touch pen-pressure in mapping psychological traits; exploring the integration of the system into daily digital note-taking applications to build a more lightweight and adaptive intelligent note interaction ecosystem.

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