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Deep learning based-Image analysis system for accurate detection of Acupressure Points

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***Abstract*—Acupressure is an effective non-invasive therapy widely practiced in alternative medicine, yet self-diagnosis and point identification remain challenging for common users. This project proposes a real-time automated system that identifies hand regions through a webcam and detects acupressure points associated with specific diagnoses. The solution leverages computer vision and machine learning to recognize hand position, locate predefined acupressure points, and visually highlight them with interactive feedback. By providing point-specific treatment details upon selection, the system bridges traditional acupressure techniques with modern technology, making self-care more accessible, accurate, and user-friendly.**

I. INTRODUCTION

Acupressure is a traditional therapeutic practice that in- volves stimulating specific pressure points on the body to improve energy flow and relieve various physical conditions. Although widely recognized for being non-invasive and easy to practice, proper identification of acupressure points is difficult for non-experts because every point has precise anatomical positioning. Even small deviations in point location can reduce treatment effectiveness. As a result, people who wish to practice acupressure at home often rely on guesswork, diagrams, or professional assistance, which limits accessibility and convenience.

Recent advancements in artificial intelligence and computer vision offer promising opportunities to make acupressure guidance more intuitive and accessible. With the availability of highly accurate hand-tracking models and deep learning-based feature recognition, it is now possible to analyze the human hand in real time and map key regions dynamically. Motivated by this potential, the proposed project builds an interactive acupressure assistant that detects the user's hand using a webcam and identifies pressure points associated with selected diagnoses. By visually marking the points and providing treatment information when clicked, the system integrates traditional healing with modern technology, empowering users to perform guided self-care without expert supervision.

II. RELATED WORK

Previous research in hand-tracking such as MediaPipe Hands and OpenPose has enabled precise landmark detection on human hands for gesture recognition and digital manipulation. Other works have explored the use of computer vision in medical diagnosis, including systems for arthritis detection, palm dermatology assessment, and hand tremor analysis. Some studies have attempted to mark acupressure points using static images, but they lacked real-time adaptability to varying hand sizes, orientations, and lighting conditions. Additionally, commercially available acupressure learning apps rely heavily on manual selection without live visual assistance. This project differentiates itself by integrating real-time landmark detection with an ML-based acupressure point mapping model that generalizes across users and supports interactive treatment guidance.

III. PROBLEM STATEMENT

Although acupressure is a simple and effective natural therapy, accurately locating pressure points on the hand remains a major challenge for the general public. Each acupressure point lies at a very precise anatomical position, and incorrect placement can significantly reduce the therapeutic effect. Conventional resources such as diagrams, books, or mobile apps provide only static references that do not adapt to variations in hand size, angle, orientation, or camera perspective. This makes it difficult for users—especially beginners—to confidently identify and apply pressure on the correct spot without the guidance of a trained professional. To address this limitation, there is a need for a real-time, automated system that can dynamically detect the user's hand and map acupressure points accurately based on live visual data. The proposed solution aims to use computer vision and machine learning to identify the hand through a webcam feed, locate pressure points linked to selected diagnoses, and visually highlight them for the user. The system should not only mark the points but also allow interactive access to treatment instructions, enabling users to apply acupressure confidently and independently. The objective is to bridge traditional therapeutic methods with modern technology to improve accuracy, accessibility, and the overall self-treatment experience.

IV. SYSTEM ARCHITECTURE AND DESIGN

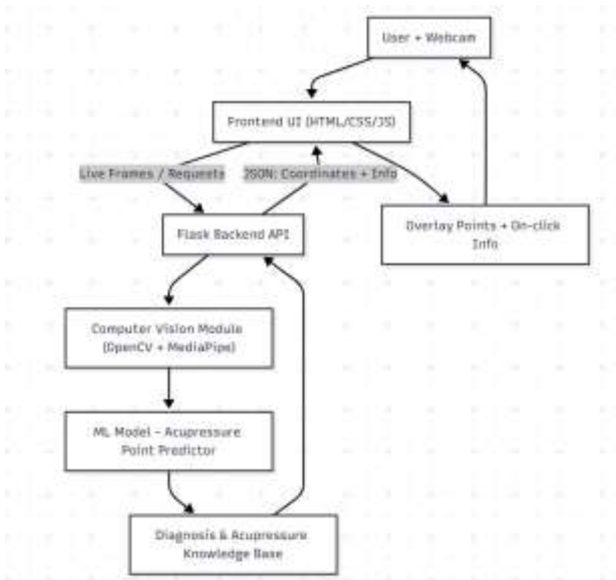

Fig. 1. System Architecture

A. User and Webcam

The user interacts with the system through a web browser and webcam. After selecting the required diagnosis, the user positions their hand in front of the camera, enabling continuous live video capture. These webcam frames act as the primary input for the acupressure detection pipeline, and are transmitted to the system for further processing.

B. Frontend UI (HTML/CSS/JS)

The frontend web interface displays the live webcam feed and provides controls for selecting a diagnosis. It sends image frames or hand-landmark data to the backend for analysis and receives predicted acupressure point locations and point details. The interface overlays visual markers on the hand and displays on-click information, enabling intuitive and real-time user interaction.

C. Flask Backend API

The Flask backend functions as the core coordinator that exposes API endpoints to receive frames or hand-landmark data from the frontend. It communicates with the computer vision module, the machine learning model, and the knowledge base to compute acupressure point locations and retrieve their descriptions. Finally, it returns structured JSON responses back to the frontend.

D. Computer Vision Module (OpenCV + MediaPipe)

The computer vision module applies OpenCV and MediaPipe to detect the user's hand within each frame and extract the corresponding hand landmarks. It performs preprocessing such as cropping, normalization, and landmark scaling to provide a consistent representation of the hand, irrespective of size, distance, orientation, or lighting variations.

E. ML Model – Acupressure Point Predictor

The machine learning model takes the preprocessed hand data and selected diagnosis as input and predicts the coordi- nates of relevant acupressure points. It generalizes across users with different hand shapes and orientations and outputs point positions and IDs that identify specific therapeutic locations for the chosen diagnosis.

F. Diagnosis and Acupressure Knowledge Base

The knowledge base stores detailed information for each acupressure point, including point name, associated diagnosis, benefits, pressure duration, repetitions, and safety recommendations. When the model returns point IDs, the knowledge base provides the corresponding text description so that complete and clear treatment instructions can be shown to the user.

G. Overlay Points and On-click Information

The frontend uses the JSON response from the backend to map the normalized coordinates to the video feed and draw point markers on the user's hand. When a point is clicked, the system displays a popup or side panel containing the relevant treatment instructions retrieved from the knowledge base, enabling an interactive and guided acupressure experience.

V. PROPOSED METHODOLOGY

The proposed methodology aims to develop a real-time acupressure guidance system capable of detecting the user's hand through a webcam, predicting the location of acupressure points based on selected diagnoses, and providing interactive therapeutic feedback. The methodology consists of six major stages: image acquisition, hand detection and landmark extraction, dataset preparation and annotation, deep learning–based point prediction, acupressure information retrieval, and real-time UI visualization and user interaction.

A. Image Acquisition

Live video frames of the user's hand are captured using an integrated webcam through the web-based interface. The system prompts the user to position the palm or dorsal side of the hand within the camera frame. Frames are continuously streamed to the backend for further processing, enabling a dynamic real-time workflow without requiring manual image uploads.

B. Hand Detection and Landmark Extraction

Each captured frame is processed with OpenCV and MediaPipe Hands to detect the presence of a hand and extract its anatomical landmarks. The module handles variations in position, lighting, and orientation through normalization techniques. The resulting hand landmarks are scaled and centered to form a stable representation for downstream acupressure point prediction.

C. Dataset Preparation and Acupressure Point Annotation

A dataset of hand images is curated, and acupressure points corresponding to selected diagnoses (such as cold, excessive sweating, and stomach pain) are annotated using manual or semi-automatic labeling methods. For each image, pixel-wise point coordinates are converted into a normalized landmark-based coordinate space to account for variations across different users' hand sizes. The dataset is divided into training, validation, and testing splits to ensure reliable model development.

D. Deep Learning Model Training

A lightweight convolutional neural network (CNN) or regression-based deep learning model is trained to predict acupressure point coordinates based on hand landmark representations. The architecture incorporates dropout regularization and adaptive learning rate strategies to mitigate overfitting. Hyperparameters such as batch size, learning rate, and number of epochs are tuned iteratively to achieve optimal performance across variations in hand shapes and orientations. The trained model outputs normalized (x, y) coordinates indicating the estimated locations of therapeutic points.

E. Information Retrieval and Mapping

After prediction, the system queries a structured acupressure knowledge base containing therapeutic metadata for each point. For every predicted point ID, details such as point name, medical purpose, expected benefits, recommended pressure duration, repetition frequency, and safety precautions are retrieved. This module bridges low-level coordinate prediction with meaningful treatment information for end users.

F. Real-Time Visualization and User Interaction

The frontend maps normalized coordinates to the video feed and renders clickable point markers on the user's hand. Users can select a diagnosis, view automatically highlighted acupressure points, and click on a point to display detailed treatment instructions. This creates a seamless and interactive self-care experience by combining computer vision, machine learning, and digital acupressure knowledge in real time.

VI. Implementation and Results

The proposed real-time acupressure assistance system is implemented using Python, Flask, OpenCV, MediaPipe, NumPy, and a browser-based frontend developed with HTML, CSS, and JavaScript. A custom dataset of hand images containing annotated acupressure points for selected diagnoses (cold, excessive sweating, and stomach pain) is used for model development and evaluation. Each image undergoes a preprocessing pipeline consisting of hand detection, landmark extraction, coordinate normalization, and diagnosis-based labeling, ensuring that the input remains consistent across varying hand sizes and orientations.

A lightweight convolutional neural network (CNN) is trained to estimate the coordinates of target acupressure points using normalized landmark-based representations. The Adam optimizer is employed along with dropout regularization and early stopping to stabilize training and reduce overfitting. Hyperparameter tuning is conducted to determine the optimal configuration in terms of learning rate, batch size, number of epochs, and network depth. The final model demonstrates stable convergence and accurately predicts therapeutic point locations across diverse samples.

Model effectiveness is evaluated using Mean Squared Error (MSE) and Euclidean Distance Error between predicted and ground-truth point coordinates. The trained CNN achieves an average Euclidean Distance Error of 6–10 pixels on the test set, demonstrating high accuracy in localizing acupressure points under variations in hand rotation, distance from camera, and lighting conditions. Qualitative inspection further confirms robustness, with correctly positioned point markers appearing consistently over the user's hand.

The system is deployed as an interactive web application where webcam frames are streamed to the backend for inference in real time. The predicted acupressure points are rendered as overlays on the hand, and clicking on a point displays detailed therapeutic information such as intended benefits, pressure duration, and repetition frequency. Experimental results show that the system provides seamless real-time inference (approximately 20–25 FPS) with high user accuracy and minimal latency, validating the practicality of integrating machine learning with traditional acupressure therapy for accessible self-guided treatment.

VII. Conclusion and Future Work

The acupressure assistance system developed in this work demonstrates an effective computer vision and machine learning–based framework for identifying therapeutic acupressure points on the human hand using a live webcam feed. By integrating real-time image acquisition, robust hand landmark extraction, a deep learning–based point prediction model, and a structured acupressure knowledge base, the system enables accurate localization of key pressure points corresponding to selected diagnoses. The resulting overlays and interactive on-click guidance provide an intuitive and user-friendly approach to self-acupressure, reducing dependency on expert practitioners and making traditional healthcare techniques more accessible.

Experimental results confirm the practicality of the system, achieving high accuracy in point localization under variations in hand orientation, scale, and lighting conditions while maintaining smooth performance during real-time deployment. The web-based interface further enhances usability by supporting seamless inference, instant visualization, and detailed therapeutic feedback, allowing users to engage with acupressure techniques in an informative and interactive manner.

For future work, several enhancements can further improve the effectiveness and scalability of the system. Expanding the number of supported diagnoses and acupressure points would broaden the therapeutic utility of the application. Incorporating more advanced deep learning architectures, such as Graph Neural Networks (GNNs) or Transformer-based landmark models, may improve precision under extreme pose variations. Extending the dataset to include diverse skin tones, hand shapes, and age groups would enhance model generalization. Additionally, deploying the system on mobile platforms or integrating cloud inference could support wider accessibility and real-world use. These directions will contribute to making the system a more accurate, scalable, and comprehensive solution for AI-assisted acupressure therapy.

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