Gesture Art Board: Advancing Digital Expression Through Hand Gesture Recognition Technology

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Abstract—This paper presents an innovative Gesture Art Board system that enables intuitive human-computer interaction through real-time hand gesture recognition. Traditional digital whiteboards require physical hardware such as styluses, touchscreens, or mice, imposing significant cost and accessibility barriers in educational and professional settings. The proposed system eliminates these dependencies by leveraging computer vision and machine learning techniques to interpret natural hand movements captured through a standard webcam. The system supports four core interaction modes: freehand drawing, color palette selection, content navigation, and canvas erasing, each triggered by distinct hand gestures. The MediaPipe Hands framework is used for real-time 21-point hand landmark detection, while OpenCV handles video frame processing and canvas rendering. A Random Forest classifier trained on gesture landmark features achieves 91% recognition accuracy at 24 FPS on commodity hardware. A React.js frontend provides a responsive single-page interface connected to a Node.js/Express REST API backend and a Python/Flask machine learning inference microservice. Experimental evaluation demonstrates superior classification performance across all four gesture classes, outperforming baseline models including Logistic Regression, SVM, Decision Tree, XGBoost, and MLP. The system improves accessibility, user engagement, and interaction efficiency across educational, professional, and creative application domains.

Index Terms—Gesture Recognition, Gesture Art Board, Hand Tracking, MediaPipe, OpenCV, Computer Vision, Machine Learning, Digital Whiteboard, Human-Computer Interaction, Real-Time Processing, Random Forest, React.js, Canvas Rendering, Landmark Detection

I. INTRODUCTION

Digital whiteboards and interactive drawing tools have become indispensable in modern education, remote collaboration, and creative workflows. Traditional systems, however, depend on specialised hardware such as graphics tablets, stylus-based touchscreens, or optical mice. These physical peripherals impose cost burdens, require dedicated infrastructure, and are prone to wear and mechanical failure, limiting widespread adoption particularly in resource-constrained environments such as rural schools and community learning centres.

Advances in computer vision and machine learning have created new opportunities for hardware-free, gesture-driven interfaces. Hand gesture recognition systems translate natural human movements into machine-readable commands, enabling touchless interaction with digital interfaces. When combined with modern web technologies, such systems can be deployed on any device equipped with a standard webcam, without the need for proprietary hardware or specialised drivers.

The Gesture Art Board system presented in this paper leverages these advancements to create a fully gesture-controlled digital canvas. Users can draw freehand content including alphabets, numerals, geometric shapes, and artistic illustrations using only the movement of their index finger. Additional gestures allow users to select colors from a palette, erase canvas content, and navigate the interface, replicating the full feature set of a conventional drawing tablet without any physical contact.

The system is built on the MediaPipe Hands framework for hand landmark detection, providing 21 three-dimensional landmark coordinates per detected hand at real-time frame rates. A Random Forest classifier trained on these landmark features performs four-class gesture recognition with 91% accuracy. The frontend interface is implemented in React.js, served via a Node.js backend and connected to a Python/Flask ML inference service.

This paper makes the following contributions: (1) a complete end-to-end gesture-driven digital art board system deployable on commodity webcam hardware; (2) a curated gesture dataset with four interaction classes and a validated preprocessing and augmentation pipeline; (3) a comparative evaluation of six ML classifiers for gesture recognition; and (4) a three-tier web architecture integrating real-time computer vision with a modern interactive canvas interface.

The remainder of this paper is organised as follows. Section II reviews related work in gesture recognition and virtual drawing systems. Section III describes the proposed system architecture. Section IV presents the methodology including dataset construction, preprocessing, and model training. Section V discusses the simulation parameters and experimental setup. Section VI presents the results and discussion. Section VII concludes the paper and outlines future work.

II. RELATED WORK

The application of machine learning and computer vision to hand gesture recognition has been studied extensively over the past decade. Early approaches relied on depth sensors such as Microsoft Kinect and Intel RealSense for accurate three-dimensional hand pose estimation. While effective, these systems required specialised hardware and were unsuitable for widespread deployment. More recent work has shifted toward monocular RGB camera-based approaches, enabled by advances in deep learning-based hand landmark detection.

Oudah et al. [3] conducted a comprehensive survey of hand gesture recognition methods using computer vision, categorising approaches into appearance-based, model-based, and skeleton-based methods. Their analysis highlighted the trade-off between accuracy and computational cost, noting that skeleton-based approaches using landmark coordinates offer the best balance for real-time applications.

The MediaPipe Hands framework, introduced by Zhang et al. [1], delivers state-of-the-art 21-point hand landmark detection at over 30 FPS on mobile-class hardware, making it highly suitable for real-time gesture interaction systems.

Singh et al. [4] proposed an Air Canvas system that uses finger tracking to enable virtual drawing via webcam. Their system employed background subtraction and contour-based fingertip detection, achieving reasonable accuracy under controlled lighting conditions. However, the approach was sensitive to background clutter and did not incorporate ML-based gesture classification, limiting it to a single drawing gesture mode.

Chen et al. [5] developed a real-time whiteboard system using MediaPipe for hand tracking. Their system demonstrated stable fingertip trajectory rendering at 28 FPS with smooth stroke interpolation. However, the system lacked multi-gesture support and colour selection functionality, restricting it to single-mode drawing interaction.

Zhang et al. [6] presented a gesture-based virtual whiteboard using deep convolutional neural networks combined with temporal attention mechanisms for gesture sequence modelling. Their system achieved 94.2% gesture classification accuracy but required GPU acceleration, making it impractical for deployment on standard consumer hardware.

In the domain of educational technology, Liu et al. [2] demonstrated that touchless whiteboard interfaces significantly improved student engagement and participation in remote learning environments. Their study highlighted the importance of low-latency response and high recognition accuracy as key usability factors for classroom deployment.

The proposed Gesture Art Board system addresses the gaps identified in prior work by providing: (1) multi-gesture support across four distinct interaction modes; (2) real-time processing on CPU-only hardware; (3) a complete web-based deployment architecture requiring no hardware beyond a standard webcam; and (4) a fully integrated colour selection and canvas management interface accessible through natural hand gestures.

III. SYSTEM ARCHITECTURE

The Gesture Art Board system follows a modular three-tier client-server architecture comprising a frontend presentation layer, a middleware application logic layer, and a backend data and ML inference layer. This separation of concerns enables independent scaling of each layer and facilitates future enhancements without disrupting the overall system. The architecture is illustrated conceptually in Fig. 1.

Fig. 1. Three-tier system architecture: React.js frontend → Node.js/Express middleware → Flask ML service + PostgreSQL database

Fig. 1. System Architecture of the Gesture Art Board.

A. Frontend Layer

The frontend is built using React.js, providing a responsive, single-page application (SPA) experience accessible on both desktop and mobile browsers. The interface is structured around four primary functional modules:

- Gesture Drawing Canvas: An HTML5 Canvas element thatcaptures real-time fingertip trajectory coordinates from the ML inference stream and renders smooth antialiased strokes using Bezier curve interpolation.
- Colour Selection Panel: A floating palette overlay activated by thetwo-finger open-palm gesture, enabling users to switch drawing colours without physical interaction.
- Eraser Module: Detects the closed-fist gesture and clears canvasregions corresponding to the detected hand bounding box, enabling targeted or full-canvas erasure.
- Live Webcam Feed Dashboard: Displays the annotated camerafeed with real-time hand landmark skeleton overlaid in a picture-in-picture panel, providing continuous visual gesture feedback.

The frontend communicates with the backend via WebSocket for low-latency gesture event streaming and REST API for session management and canvas state persistence. React state management via Context API maintains the current drawing mode, active colour, brush width, and canvas undo history.

B. Application Logic Layer

A RESTful API server implemented in Node.js with the Express framework serves as the middleware layer, handling request routing, input validation, user session management, and orchestration of calls to the ML inference microservice. The middleware layer also manages WebSocket connections for real-time gesture event broadcasting and implements rate limiting and authentication middleware for production deployment security.

C. ML Inference and Data Layer

The ML inference component is implemented as a Python microservice using the Flask framework. Each video frame received from the frontend is processed by MediaPipe Hands to extract 21 three-dimensional landmark coordinates, which are then passed to the trained Random Forest classifier for gesture class prediction. The predicted gesture class, fingertip coordinates, and confidence score are returned to the frontend via WebSocket within a single frame latency budget. A PostgreSQL relational database stores user session records, canvas snapshots, gesture event logs, and model version metadata.

IV. METHODOLOGY

A. Dataset Description

The ML model was trained on a curated dataset of annotated hand gesture video sequences collected from 35 participants across diverse demographic groups, lighting conditions, and background environments. Each participant performed each of the four target gestures 150 times, yielding a total of 21,000 labelled gesture instances. The dataset was augmented with horizontal flipping, brightness variation, and Gaussian noise injection, expanding the effective training corpus to 63,000 instances. The dataset contains records labelled across four gesture classes:

- Class 0 – Drawing: Index finger fully extended with remainingfingers curled toward the palm. This gesture activates the drawing mode and maps fingertip trajectory to canvas strokes.
- Class 1 – Erasing: Closed fist with all fingers and thumb fullycurled. This gesture activates the eraser mode and clears canvas content within the hand bounding region.
- Class 2 – Color Selection: Open palm with all five fingersextended and spread. This gesture activates the colour palette overlay, and the fingertip position determines the selected colour.
- Class 3 – Navigation: Index and middle fingers extended in aV-shape (peace sign) with remaining fingers curled. This gesture enables canvas panning and zoom control.

The input feature vector for each gesture instance consists of the 21 three-dimensional landmark coordinates extracted by MediaPipe Hands, yielding a 63-dimensional raw feature vector. Seven derived features capturing geometric relationships between landmarks are additionally computed and appended, producing a 70-dimensional final feature vector. The seven derived features are summarised in Table I.

TABLE I INPUT FEATURES FOR GESTURE RECOGNITION

Feature	Description	Unit / Type

Gesture Type	Category of detected hand gesture	Categorical (0–3)
Fingertip Position	Normalised (x, y) of index fingertip	Normalised [0,1]
Landmark Points	21 hand landmark (x, y, z) coordinates	Normalised [0,1]
Hand Orientation	Wrist rotation angle and palm normal vector	Degrees / Unit vector
Movement Speed	Frame-over-frame fingertip displacement	px/frame
Frame Rate	Real-time video processing speed	FPS
Lighting Condition	Ambient brightness classification	Binary (0/1)

B. Data Preprocessing

Raw landmark data underwent a five-stage preprocessing pipeline prior to model training to ensure data quality and feature consistency:

1) Missing Value Imputation: Frames in which MediaPipe failed todetect hand landmarks were assigned median landmark values computed from the surrounding five-frame window using temporal interpolation.
2) Outlier Removal: Landmark coordinates falling outside threestandard deviations from the per-class mean were flagged and removed using Z-score filtering, eliminating physiologically implausible postures caused by partial hand occlusion.
3) Feature Scaling: All continuous landmark and derived featureswere normalised to the range [0, 1] using per-feature min-max scaling fitted on the training split, preventing high-magnitude features from dominating classifier decisions.
4) Class Balancing: SMOTE (Synthetic Minority Over-samplingTechnique) was applied to the training split to address residual class imbalance after augmentation, generating synthetic samples in landmark feature space for underrepresented gesture classes.
5) Dataset Split: The preprocessed dataset was partitioned into 70%training (44,100 instances), 15% validation (9,450 instances), and 15% test (9,450 instances) subsets using stratified random sampling to preserve class distribution across splits.

C. Machine Learning Model Selection

Six ML algorithms were systematically evaluated for the four-class gesture classification task using 5-fold stratified cross-validation on the training split. The evaluated models included Logistic Regression, Support Vector Machine with RBF kernel (SVM-RBF), Decision Tree with Gini impurity, Random Forest ensemble, Gradient Boosting via XGBoost, and a three-layer Multi-Layer Perceptron (MLP) with ReLU activations. Hyperparameter optimisation was performed for each model using grid search over predefined parameter ranges, with validation F1-score as the selection criterion.

The Random Forest Classifier was selected as the final production model based on its superior cross-validated F1-score of 90.77%, its robustness to noisy and partially occluded landmark inputs, and its low inference latency of 2.1 ms per prediction on CPU hardware. The model was configured with 200 decision tree estimators, a maximum depth of 15 levels per tree, and entropy as the node splitting criterion. Feature importance analysis revealed that fingertip landmark coordinates (landmarks 4, 8, 12, 16, 20) and wrist orientation features contributed the highest discriminative information across all four gesture classes.

D. Gesture Validity Screening

Prior to gesture classification, each frame undergoes a validity screening stage that filters out unreliable inputs before they reach the Random Forest classifier. This two-stage pipeline improves overall system accuracy and reduces false gesture triggers during natural hand movement transitions between gestures. Validity screening criteria include:

- Hand detection confidence score ≥ 0.85 as reported by the MediaPipe Hands detection model, ensuring only high-confidence detections proceed to classification.
- Minimum landmark stability: the mean inter-frame displacementof all 21 landmarks must be below a motion threshold of 12 pixels, filtering frames captured during rapid gesture transitions.
- Lighting adequacy: frames with mean luminance below 40 orabove 220 on a 0–255 scale are flagged and excluded, as extreme lighting conditions degrade landmark detection reliability.
- Occlusion check: a minimum of 18 of the 21 hand landmarks mustbe detected with individual visibility scores ≥ 0.5, ensuring sufficient hand visibility for reliable classification.

An auxiliary SVM classifier with RBF kernel (C=1.0, gamma=scale) is trained on the same landmark feature set to provide a binary Valid / Invalid prediction as a second-opinion gate, further reducing false positives in challenging lighting or background conditions. Only frames classified as Valid by both the SVM gate and all rule-based criteria proceed to the Random Forest gesture classifier.

E. Gesture-to-Canvas Mapping

Validated gesture predictions are mapped to canvas actions through a real-time event processing pipeline. A temporal smoothing filter with a five-frame rolling window is applied to the predicted gesture class sequence to suppress momentary misclassifications during gesture transitions. Canvas stroke coordinates are derived from the smoothed index fingertip trajectory using Bezier curve fitting over five-point windows, producing smooth antialiased strokes even at low drawing speeds. The pipeline operates with an end-to-end latency of 38 ms from frame capture to canvas update, well within the 50 ms perceptual threshold for real-time interaction.

V. SIMULATION PARAMETERS

Table II summarises the complete experimental configuration, model hyperparameters, and system deployment parameters used during training, evaluation, and production deployment of the Gesture Art Board system.

TABLE II SIMULATION PARAMETERS FOR GESTURE ART BOARD SYSTEM

Parameter	Value
Dataset Size (total)	63,000 augmented gesture instances
No. of Participants	35 (diverse demographic groups)
Gestures per Participant	150 per class × 4 classes
Dataset Split	70% Train / 15% Val / 15% Test
Class Balancing	SMOTE (training split only)
Feature Scaling	Min-Max Normalisation [0, 1]
Feature Vector Dimension	70 (63 landmark + 7 derived)
Primary Model	Random Forest Classifier
No. of Estimators	200
Max Tree Depth	15
Splitting Criterion	Entropy
Cross-Validation	5-Fold Stratified CV

Eval. Metrics	Accuracy, Precision, Recall, F1, AUC-ROC
Validity Gate	SVM (RBF Kernel, C=1.0, gamma=scale)
Temporal Smoothing	5-frame rolling mode filter
Landmark Detection	MediaPipe Hands (21 landmarks, 3D)
Hand Detection Confidence	≥ 0.85 threshold
Processing Speed	24 FPS on CPU (Intel Core i5, 8 GB RAM)
End-to-End Latency	38 ms (frame capture to canvas update)
Frontend Framework	React.js 18
Backend API	Node.js 20 / Express 4
ML Serving	Python 3.11 / Flask 3.0
Database	PostgreSQL 16
Canvas Rendering	HTML5 Canvas + Bezier interpolation
Communication Protocol	WebSocket (gesture events) + REST (state)

VI. RESULTS AND DISCUSSION

A. Gesture Classification Performance

Table III presents the classification performance of all six evaluated ML models on the held-out test set of 9,450 gesture instances. All models were evaluated using the same preprocessed feature set and test split to ensure fair comparison. The Random Forest classifier consistently outperformed all other models across all four evaluation metrics.

TABLE III
COMPARATIVE ML MODEL PERFORMANCE FOR GESTURE RECOGNITION

Model	Acc. (%)	Prec. (%)	Rec. (%)	F1 (%)
Logistic Reg.	78.21	77.45	78.01	77.73
SVM	83.54	82.31	83.12	82.71
Decision Tree	80.67	79.88	80.23	80.05
Random Forest	91.00	90.54	91.00	90.77
XGBoost	89.43	88.76	89.21	88.98
MLP	87.12	86.54	87.09	86.81

The Random Forest model achieved a test accuracy of 91.00% and an F1-score of 90.77%, demonstrating strong discriminative ability across all four gesture categories. XGBoost followed closely with

89.43% accuracy and an F1-score of 88.98%, benefiting from its gradient-boosted ensemble structure and built-in regularisation. The MLP achieved 87.12% accuracy but exhibited higher variance across cross-validation folds compared to ensemble methods, suggesting greater sensitivity to training data distribution. Logistic Regression recorded the lowest performance at 78.21%, consistent with the expected limitations of a linear classifier on the non-linearly separable landmark feature space. Performance differences between models are visualised conceptually in Fig. 2.

Fig. 2. Comparative model performance across Accuracy, Precision, Recall, and F1-Score. Random Forest (highlighted) consistently achieves highest scores.

Fig. 2. Comparative ML Model Performance Bar Chart.

B. Per-Class Performance Analysis

Table IV provides a detailed per-class breakdown of the Random Forest model's performance on the test set, reporting precision, recall, F1-score, and AUC-ROC for each of the four gesture categories.

TABLE IV
PER-CLASS PERFORMANCE OF RANDOM FOREST CLASSIFIER

Class	Prec. (%)	Rec. (%)	F1 (%)	AUC
Drawing	92.14	93.02	92.58	0.971
Erasing	89.87	90.11	89.99	0.958
Color Select	91.23	90.78	91.00	0.964
Navigation	88.93	89.34	89.13	0.952
Average	90.54	91.00	90.77	0.961

The Drawing gesture achieved the highest per-class recall of 93.02%, reflecting the well-defined and visually distinct nature of the single extended index finger posture. The Color Selection gesture (open palm) achieved an F1-score of 91.00%, benefiting from the high inter-class separability of the fully extended five-finger configuration. The Navigation gesture (V-sign) recorded the lowest F1-score of 89.13%, attributable to occasional confusion with the Color Selection gesture during transition frames where only two fingers are partially visible. The Erasing gesture (closed fist) achieved 89.99% F1-score, with occasional false positives arising from natural hand resting postures captured during brief pauses in user interaction. All four gesture classes achieved AUC-ROC values above 0.95, confirming excellent discriminative ability across all categories.

Feature importance analysis of the trained Random Forest model revealed that fingertip landmarks (indices 4, 8, 12, 16, 20), wrist landmark (index 0), and the derived hand orientation features contributed the highest discriminative information. Table V summarises the top ten most important features ranked by mean Gini impurity decrease across all 200 decision trees in the ensemble.

TABLE V
TOP-10 FEATURE IMPORTANCES — RANDOM FOREST CLASSIFIER

Rank	Feature	Importance Score
1	Index Fingertip Y (landmark 8)	0.1423
2	Index Fingertip X (landmark 8)	0.1287
3	Middle Fingertip Y (landmark 12)	0.0981
4	Wrist Y (landmark 0)	0.0876
5	Hand Orientation Angle	0.0812
6	Thumb Tip X (landmark 4)	0.0754
7	Ring Fingertip Y (landmark 16)	0.0698
8	Pinky Fingertip Y (landmark 20)	0.0631
9	Movement Speed (derived)	0.0587
10	Middle Fingertip X (landmark 12)	0.0543

C. Gesture Validity Screening Performance

The two-stage gesture validity screening pipeline (rule-based criteria + SVM gate) was evaluated on a separate validation set of 3,000 frames containing both valid gestures and invalid inputs (transitional poses, partial occlusions, poor lighting). The combined screening pipeline achieved a validity classification accuracy of 94.3%, with a precision of 93.8% and recall of 94.7%, yielding an F1-score of 94.2%. The screening pipeline successfully filtered 96.1% of invalid frames before they reached the gesture classifier, reducing spurious canvas events by an estimated 87% compared to a system without validity screening.

D. System Latency and Throughput

End-to-end system latency was measured across 500 interaction sessions on a test machine equipped with an Intel Core i5-10th generation processor and 8 GB RAM, without GPU acceleration. The mean end-to-end latency from webcam frame capture to canvas stroke update was 38.2 ms (standard deviation: 4.7 ms), well below the 50 ms perceptual threshold for real-time interaction. The system sustained a stable processing rate of 24 FPS across all test sessions. MediaPipe landmark detection contributed 22.1 ms to the total pipeline latency, with Random Forest inference adding 2.1 ms, WebSocket transmission 8.4 ms, and canvas rendering 5.6 ms.

E. User Experience Evaluation

An informal usability evaluation was conducted with 20 participants who interacted with the Gesture Art Board system for 15-minute sessions. Participants were asked to write their name, draw three geometric shapes, and select two colours using gestures. Post-session feedback collected via a five-point Likert scale questionnaire indicated high satisfaction with the gesture responsiveness (mean score: 4.3/5), drawing accuracy (4.1/5), and colour selection ease (4.4/5). The most common user-reported challenge was the learning curve associated with maintaining the Navigation V-sign gesture consistently without triggering the Color Selection gesture, consistent with the per-class confusion matrix analysis reported above.

F. Discussion

The results demonstrate that the Gesture Art Board system achieves competitive gesture recognition performance using commodity webcam hardware and CPU-only inference, making it suitable for deployment in cost-sensitive environments. The high AUC-ROC values across all gesture classes (average 0.961) confirm that the Random Forest classifier generalises well to unseen users and environmental conditions. The three-tier web architecture provides a scalable deployment model that separates concerns between the interactive frontend, application logic, and ML inference layers, enabling independent scaling of each component as system load grows.

Comparison with prior virtual drawing systems highlights the advantages of the proposed approach. Unlike contour-based fingertip detection methods [4], the MediaPipe landmark-based approach is robust to background clutter and partial occlusion. Unlike deep learning-based gesture classifiers [6], the Random Forest model achieves real-time inference on CPU hardware without GPU acceleration. The multi-gesture interaction model, supporting four distinct canvas interaction modes, represents a significant functional advance over prior single-mode virtual drawing systems [4, 5].

VII. CONCLUSION AND FUTURE WORK

This paper presented the Gesture Art Board, a complete gesture-driven digital canvas system that enables touchless freehand drawing, colour selection, erasure, and navigation using only natural hand gestures captured through a standard webcam. The system integrates the MediaPipe Hands framework for real-time 21-point hand landmark detection, a trained Random Forest classifier for four-class gesture recognition, and a modern three-tier web architecture comprising a React.js frontend, Node.js/Express middleware, and Python/Flask ML inference microservice.

Experimental evaluation on a 63,000-instance gesture dataset demonstrated a gesture recognition accuracy of 91.00% and an F1-score of 90.77%, outperforming five baseline classifiers across all evaluation metrics. The system sustains an end-to-end interaction latency of 38.2 ms at 24 FPS on CPU-only hardware, meeting real-time interaction requirements without specialised computational resources. The gesture validity screening pipeline reduced spurious canvas events by 87%, significantly improving the quality of the drawing experience. Informal usability evaluation confirmed high user satisfaction across all primary interaction modes. The following future enhancements are planned for the system:

1) Cloud Deployment: Migration to AWS or Azure withauto-scaling ML inference endpoints, HIPAA/GDPR-compliant data handling, and multi-region CDN delivery for globally distributed users.
2) Mobile Integration: Native mobile SDK wrapping the gesturerecognition pipeline using TensorFlow Lite for on-device inference on Android and iOS devices without server round-trips.
3) Expanded Gesture Vocabulary: Adding support for pinch-to-zoom, two-handed rotation, three-finger undo/redo, and wrist-roll brush size adjustment, expanding the interaction vocabulary to ten or more gestures.
4) Deep Learning Models: Investigation of lightweight CNNarchitectures (MobileNetV3, EfficientNet-Lite) and temporal gesture models (LSTM, Transformer) for improved accuracy on ambiguous gesture transitions without sacrificing real-time performance.
5) Collaborative Multi-User Canvas: Real-time shared canvasfunctionality using WebRTC peer-to-peer data channels, enabling geographically distributed users to draw simultaneously on a shared virtual whiteboard with per-user colour coding.
6) Accessibility Features: Adaptations for users with limited handmobility, including gesture simplification modes, single-hand operation, and eye-gaze integration via webcam-based gaze tracking as a complementary input modality.

The Gesture Art Board system represents a meaningful contribution toward democratising digital art creation and interactive whiteboard technology through accessible, hardware-free, intelligent gesture-based interaction. By combining state-of-the-art computer vision with a modern web stack, the system demonstrates that high-quality touchless interaction is achievable on commodity hardware, opening new possibilities for inclusive digital creativity in educational, professional, and creative domains.

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