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# Application of Deep Learning Based Gesture Recognition in the Functional Modification of Textiles

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**Article**

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**ABSTRACT**

*To address the inconvenience of interaction in smart textiles, we propose a Gesture-Interactive Electrochromic Textile System (GI-ECTS) that seamlessly combines high-performance PEDOT:PSS-based electrochromic yarns with a real-time gesture-recognition module powered by the lightweight deep learning architecture MobileNetV3. Experiments show that the embedded gesture-recognition model achieves an accuracy exceeding 95%, indicating the model's potential for this application, while the functional yarns exhibit subsecond switching speeds and outstanding cycling stability. The results confirm the feasibility of a complete linkage from functional materials to intelligent algorithms, providing a viable technological pathway for next-generation interactive textiles.*

**KEYWORDS**

*smart textiles, electrochromism, gesture recognition, deep learning*

## INTRODUCTION

Textiles are evolving from passive substrates into intelligent systems capable of sensing, responding, and communicating, thereby forming intimate interfaces with the human body [1,2]. Despite considerable progress in functionality, most smart textiles still rely on physical switches or mobile applications for user interaction—methods that are often cumbersome and nonintuitive, ultimately diminishing the user experience [3,4]. To overcome this limitation, we introduce the Gesture-Interactive Electrochromic Textile System (GI-ECTS), which leverages computer vision and deep learning to translate dynamic hand gestures directly into commands that modulate the visual properties—most notably color—of electrochromic fabrics in real time. Electrochromic (EC) materials were selected as the core technology. In contrast to photochromic or thermochromic counterparts that depend on environmental stimuli, EC materials allow precise, low-voltage, actively controlled color changes with fast response times and low power consumption, making them ideal for constructing electronically driven, dynamic user interfaces [5,6]. Among them, the conductive polymer poly(3,4-ethylenedioxythiophene):polystyrene sulfonate (PEDOT:PSS) offers excellent flexibility, pronounced electrochromic behavior, and solution processability, enabling the fabrication of functional yarns that can be seamlessly integrated into textiles via fiber-level modification techniques [7,8]. On the recognition side, gesture recognition has progressed from traditional machine-learning approaches requiring handcrafted features to "end-to-end" convolutional neural networks (CNNs) [9,10]. The advent of lightweight architectures such as MobileNet has dramatically reduced computational overhead through depthwise separable convolutions, making real-time, resource-efficient gesture recognition viable on embedded platforms like the NVIDIA Jetson Nano [11]. While prior studies [12,13] have explored tactile interactions (e.g., touch or pressure sensing) in smart garments or have coupled gesture recognition with rigid devices, few have realized a fully non-contact, real-time gesture interface in conjunction with flexible electrochromic textile actuators. This work capitalizes on the confluence of lightweight deep learning and functional fiber technologies to present, for the first time, a systematically designed and experimentally validated, highly integrated interaction paradigm for smart textiles.

## METHODOLOGY

### System Architecture of GI-ECTS

The Gesture-Interactive Electrochromic Textile System (GI-ECTS) is a closed-loop architecture that integrates four key components: sensing, processing, control, and actuation. The system is designed to ensure real-time interactivity while maintaining low power consumption and wearability. As illustrated in Figure 1, the architecture comprises the following core modules:

**Input Module:** A miniature camera functions as the visual sensor. In wearable applications, this camera can be seamlessly integrated into garments, eyewear, or other accessories to continuously capture the user's hand movements from a first-person perspective.

**Processing Module:** Serving as the "brain" of the system, this component is implemented on an embedded AI computing platform. For prototyping, we adopt the NVIDIA Jetson Nano due to its robust GPU-based parallel computing capabilities, energy efficiency, and broad compatibility with mainstream deep learning frameworks [14]. It should be noted that the Jetson Nano is selected here as a research and development platform, as its energy efficiency is relatively high among boards with similar computing power, making it ideal for rapid algorithm validation. Although its power consumption is still too high for a final, fully untethered wearable product, it serves as an excellent and widely accepted benchmark platform for the current functional verification stage. The primary function of this module is to execute a pretrained lightweight gesture recognition model in real time.

**Control Module:** This intermediary component is typically a microcontroller unit (MCU), such as an Arduino or ESP32. It bridges the high-level semantic commands generated by the Jetson Nano with the low-level electrical signals required by the actuator. The MCU receives commands such as "switch to blue" and translates them into precise voltage signals and timing sequences necessary to drive the electrochromic yarns.

**Output Module:** This refers to the functional textile itself, which is woven from conventional yarns and our custom-designed electrochromic yarns. It serves as a dynamic visual interface that reflects system outputs through color change.

The system's data flow proceeds as follows:

(a) The camera captures video streams at a fixed frame rate (e.g., 30 FPS) and transmits the data to the Jetson Nano. (b) The Jetson Nano processes the incoming video in real time. The gesture recognition model analyzes each frame or a short frame sequence to detect predefined gestures. (c) Upon recognizing a valid gesture (e.g., "left swipe"), the model outputs a corresponding classification label. The processing module then interprets this label as a specific control command (e.g., CMD_COLOR_NEXT). (d) This command is transmitted via serial communication (e.g., UART) to the MCU. (e) Based on the received instruction, the MCU utilizes its general-purpose input/output (GPIO) pins and an external driver circuit (such as an H-bridge) to apply a predefined voltage (e.g., −2.0 V) to the electrodes of the electrochromic yarn, thereby inducing a color change. The entire interaction cycle is completed with subsecond latency, delivering instantaneous visual feedback to the user.

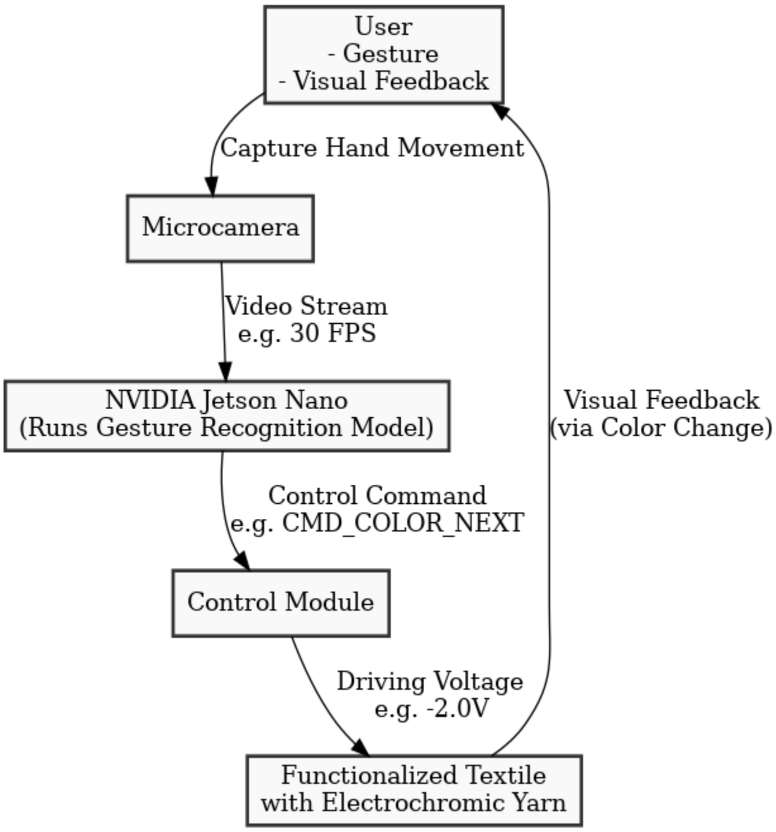


Figure 1. Architectural Flowchart of the Gesture-Interactive Electrochromic Textile System (GI-ECTS)

**Functional Textile Module: Fabrication of Electrochromic Yarn**

The functional textile module serves as the system's physical actuator. To ensure flexibility, durability, and ease of integration, we designed a core–sheath-structured electrochromic yarn. The detailed fabrication process is as follows.

*Material Selection*

**Conductive Core:** Commercially available silver-coated nylon yarn was selected as the conductive core. This type of yarn offers excellent electrical conductivity (low resistance), along with good flexibility and mechanical strength, making it ideal as the internal electrode for electrochemical reactions [15].

**Electrochromic Layer:** A high-conductivity aqueous dispersion of PEDOT:PSS (poly(3,4-ethylenedioxythiophene):polystyrene sulfonate) was used as the electrochromic material. The color-switching mechanism of PEDOT:PSS is based on reversible redox reactions involving its π-conjugated polymer backbone [16]. In its reduced state (with injected electrons and cations), the polymer exhibits a narrower bandgap, absorbs visible light, and appears dark blue. In its oxidized state (with removed electrons and cations), the bandgap widens, increasing transparency to visible light, resulting in a pale blue or nearly colorless appearance. This reversible redox behavior underpins its electrochromic functionality.

**Ion-Conductive Layer:** A gel polymer electrolyte (GPE) was employed as the ion-conductive layer. The GPE is composed of a polymer matrix (polyethylene oxide, PEO), a lithium salt (lithium perchlorate, $LiClO_4$), and a plasticizer (propylene carbonate, PC), all dissolved in an acetonitrile solvent to form a homogeneous solution. It combines the mechanical stability of solids with the ionic conductivity of liquids, offering excellent leakage resistance and flexibility, which are critical for wearable applications [17].

**Outer Electrode:** During the textile weaving process, an additional bare conductive yarn (of the same material as the core) is aligned or interwoven in parallel with the functionalized yarn. These two yarns together form a miniature electrochemical cell. This configuration simplifies the device structure by eliminating the need for multilayer thin-film assemblies, thus enhancing scalability and facilitating mass production. Table 1 summarizes the materials, concentrations, durations, and temperature parameters used in each step of the electrochromic yarn fabrication process.

Table 1. Electrochromic Yarn Fabrication Parameters

| Step | Material/Solution | Concentration | Time | Temperature |
|---|---|---|---|---|
| Substrate cleaning | silver-coated nylon yarn + ethanol rinse | N/A | 5 min ultrasonication | RT |
| PEDOT:PSS Coating | PEDOT:PSS (clevios PH 1000) + 5% DMSO | PEDOT:PSS + 5 vol% DMSO | 2 min dip-coating × 3 cycles | RT |
| Drying process | N/A | N/A | 10 min | 60°C oven |
| GPE preparation | polyethylene oxide + $LiClO_4$ + propylene carbonate (PC) in acetonitrile | PEO:$LiClO_4$ = 10:1 (wt%) | 30 min stirring | RT |
| GPE coating | GPE solution | As prepared | 2 min coating | RT |
| UV curing | 365 nm UV light | N/A | 5 min exposure | RT |
| Assembly | Layer-by-layer manual winding | N/A | 10 min | RT |

RT, room temperature.

*Fabrication Process*

**Substrate Preparation:** The silver-coated nylon yarn is first treated in a cleaning solution to remove surface contaminants and enhance the adhesion of subsequent functional layers.

**PEDOT:PSS Coating:** A continuous dip-coating technique is employed for the deposition of the electrochromic layer. The yarn is uniformly drawn at 5 cm/min through a bath containing a PEDOT:PSS dispersion, allowing a consistent layer of the active material to adhere to the surface. It then passes through a drying chamber with precisely controlled temperature and humidity conditions, where the solvent evaporates, forming a dense and uniform PEDOT:PSS thin film.

**GPE Coating:** The PEDOT:PSS-coated yarn undergoes a second dip-coating process to apply a gel polymer electrolyte (GPE) layer. After coating, the GPE is solidified into a stable gel through ultraviolet (UV) curing or mild thermal treatment.

**Weaving Integration:** This step is critical for the functional modification of the textile. The finalized functional yarn (working electrode) and a bare conductive yarn (counter electrode) are integrated into a passive textile substrate (e.g., cotton) using standard weaving techniques. This process transforms the textile from a simple passive material into an active, electronically addressable surface. Specifically, by strategically controlling the weave pattern (e.g., plain or twill weave), the yarns are precisely positioned, modifying the textile's structure to create embedded, flexible electronic circuits. For example, arranging the yarns in a grid-like array can form a pixelated display area, where each intersection of a working and counter electrode yarn constitutes an individually controllable color-changing pixel. This method fundamentally alters the textile's properties, endowing it with dynamic visual output capabilities that are not inherent to the original material, thus completing its functional modification. A schematic overview of the entire fabrication process is illustrated in Figure 2.

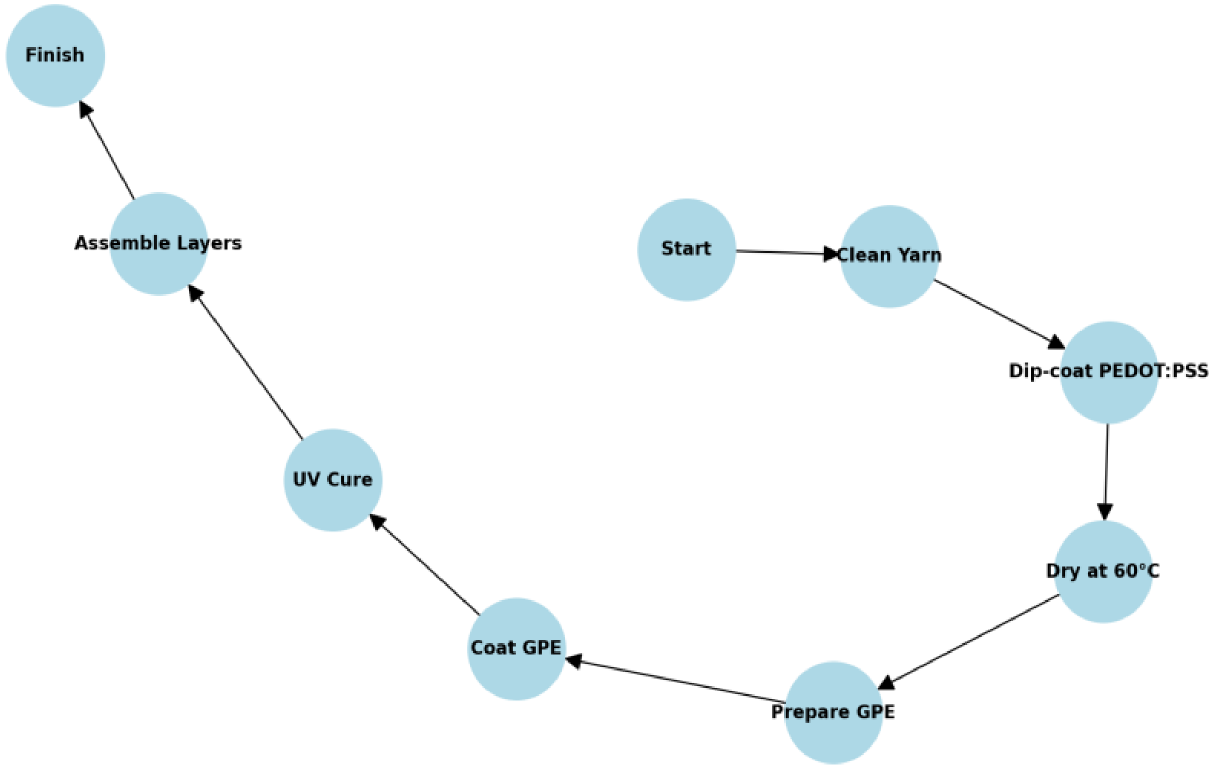


Figure 2. Fabrication Process Flowchart

**Gesture Recognition Module: Lightweight Real-Time Approach**

The gesture recognition module serves as the intelligent sensing core of the system. Its design focuses on striking an optimal balance between recognition accuracy and computational efficiency.

*Model Selection and Optimization*

After a comparative analysis of state-of-the-art lightweight architectures, MobileNetV3 was selected as the core recognition model for the following reasons:

**Efficient Architecture:** MobileNetV3 integrates the depthwise separable convolutions of MobileNetV1, the inverted residuals of MobileNetV2, and introduces a lightweight attention mechanism via the Squeeze-and-Excitation (SE) module. This allows the network to focus on the most informative feature channels with minimal computational overhead.

**Advanced Activation Function:** The model employs the h-swish activation function, which outperforms traditional functions such as ReLU by providing improved nonlinear representation while maintaining computational efficiency.

**NAS-Based Optimization:** Key architectural parameters were fine-tuned using Neural Architecture Search (NAS), enabling a tailored balance between latency and accuracy optimized specifically for mobile CPUs.

These design features make MobileNetV3 a compelling choice for real-time interaction on embedded platforms, offering superior frame rates and energy efficiency compared to peer models.

*Dataset and Training Strategy*

To develop a robust model capable of recognizing diverse dynamic gestures, we employed the Jester dataset**,** which contains approximately 150,000 short video clips spanning 27 gesture categories performed by over 1,300 individuals in varied real-world settings. Its scale, diversity, and temporal nature make it particularly well-suited to the needs of this project.

We adopted a transfer learning strategy: MobileNetV3 was initialized with weights pretrained on large-scale datasets such as ImageNet, followed by fine-tuning on the Jester dataset. This approach leverages general low-level visual features learned from large datasets to accelerate convergence and improve task-specific performance.

*Gesture Vocabulary Design*

An effective interaction system requires a carefully crafted command vocabulary that is intuitive and easy to learn. We selected a subset of semantically clear and visually distinct gestures from the Jester dataset to construct the initial gesture vocabulary for GI-ECTS, following the human–computer interaction principle of minimizing cognitive load.

**Color Switching:** *swiping left/swiping right* – to cycle through a predefined color palette (e.g., blue → green → red → blue …).

**Confirmation/Activation:** *thumb up* – to confirm or activate the currently selected color.

**Cancellation/Deactivation:** *thumb down* – to deactivate the electrochromic function, returning the textile to its default transparent or pale state.

**State Lock:** *stop sign* – to lock the current visual state and prevent accidental changes from unintended movements.

**Negative Gesture Filtering:** *doing other things/no gesture* – both types of negative samples are included in the Jester dataset. Their inclusion in training is crucial to enabling the model to distinguish between intentional interactions and background or unconscious motions, thereby reducing false positives and improving overall user experience.

## EXPERIMENTS AND RESULTS

### Experimental Setup and Evaluation Metrics

*Gesture Recognition Module*

**Platform:** All experiments were conducted on the NVIDIA Jetson Nano Developer Kit, a widely adopted benchmark platform for edge AI research and prototyping.

**Evaluation Metrics:**

***Classification Performance:*** accuracy, precision, recall, and F1 score were used to comprehensively evaluate the model's ability to correctly classify various gesture categories.

***Inference Efficiency:*** measured in frames per second (FPS), this metric reflects the system's capability for real-time interaction.

***Power Consumption:*** measured in watts (W), this metric directly impacts battery life in wearable applications.

*Functional Textile Module*

**Evaluation Metrics:**

***Response Time:*** Defined by the coloration time and bleaching time, measured as the time required to achieve 90% of the maximum transmittance change ($T_{90}$) following voltage application; expressed in milliseconds (ms) or seconds (s).

***Optical Performance:*** Assessed by the optical modulation range (ΔT), defined as the transmittance difference between colored and bleached states at a specific wavelength (e.g., 633 nm).

***Durability:*** evaluated by cycling stability, indicating the retention rate of optical modulation after *n* switching cycles.

At 633 nm, the electrochromic yarn demonstrated a significant modulation depth with $\Delta T$ = 62%. The full transmittance spectra for both colored and bleached states are shown in Figure 3.

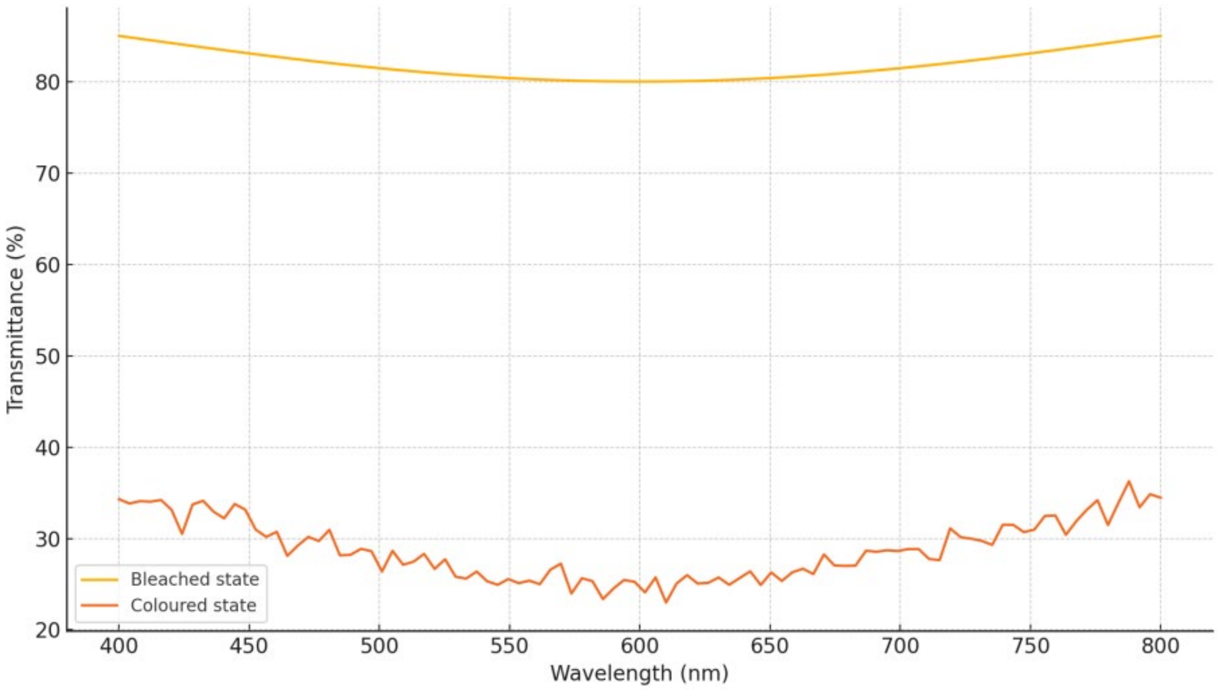


Figure 3. ΔT Spectra of Electrochromic Yarn

Measurements conducted at 25 °C and 45% relative humidity; the optical modulation (*ΔT*) at a wavelength of 633 nm is calculated to be 62% based on the transmittance difference between the two states at that point.

*End-to-End System Latency*

**Evaluation Metric:**

End-to-End System Latency is defined as the total time from the midpoint of a gesture execution to the moment the textile appearance reaches 90% of its maximum optical change ($T_{90}$T {90}$T_{90}$). This metric is crucial for evaluating the smoothness and responsiveness of user interaction.

**Performance Analysis of the Gesture Recognition Module**

To validate the selection of MobileNetV3, we conducted a comparative study against other state-of-the-art lightweight models using the Jester dataset. As shown in Table 2, MobileViT-S achieved marginally higher accuracy and F1-score due to its Transformer-based architecture, which excels at global feature modeling. However, its large parameter count and computational complexity resulted in a low inference speed of only 22 FPS on the Jetson Nano and the highest power consumption among all models tested—rendering it unsuitable for wearable systems requiring smooth interaction. While ShuffleNetV2 offered the fastest inference and lowest power consumption, its recognition accuracy was notably inferior. EfficientNet-Lite0 presented a balanced performance across metrics but did not surpass MobileNetV3. MobileNetV3-Small demonstrated the best overall trade-off: accuracy, 95.2%; inference speed, 35 FPS; power consumption, 4.8 W. This combination precisely aligns with the system's core requirements for high accuracy, low latency, and low power consumption.

Although the measured power consumption of the Jetson Nano–based prototype is approximately 4.8 W, this estimate does not include the MCU and fiber driver. Based on typical wearable standards (≈ 1-day battery life), such power consumption would require a relatively large-capacity battery (> 4000 mAh), which compromises wearing comfort. Therefore, our current implementation should be considered as a proof-of-concept prototype. For practical deployment, future work will target ultra-low-power platforms and energy-harvesting integration to reduce dependency on bulky batteries.

Table 2. Experimental Performance Comparison of Lightweight Models on the Gesture Recognition Task

| Model | Top-1 Accuracy (%) | F1 score | Parameters (M) | FPS (Jetson Nano) | Power consumption (W) |
|---|---|---|---|---|---|
| MobileNetV3-Small | 95.2 | 0.95 | 2.5 | 35 | 4.8 |
| EfficientNet-Lite0 | 94.8 | 0.94 | 4.0 | 28 | 5.5 |
| ShuffleNetV2 (1.0x) | 93.5 | 0.93 | 2.3 | 41 | 4.5 |
| MobileViT-S | 95.8 | 0.96 | 5.5 | 22 | 6.2 |

M, million parameters.

To further evaluate model performance on the predefined gesture vocabulary, a confusion matrix was generated (Figure 4). Results showed over 96% accuracy for clearly defined gestures such as swiping left/right and thumb up. Notably, the model achieved over 98% accuracy in detecting the "no gesture" category, effectively filtering out unintentional user movements and minimizing false activations—thereby ensuring robust and reliable interaction.

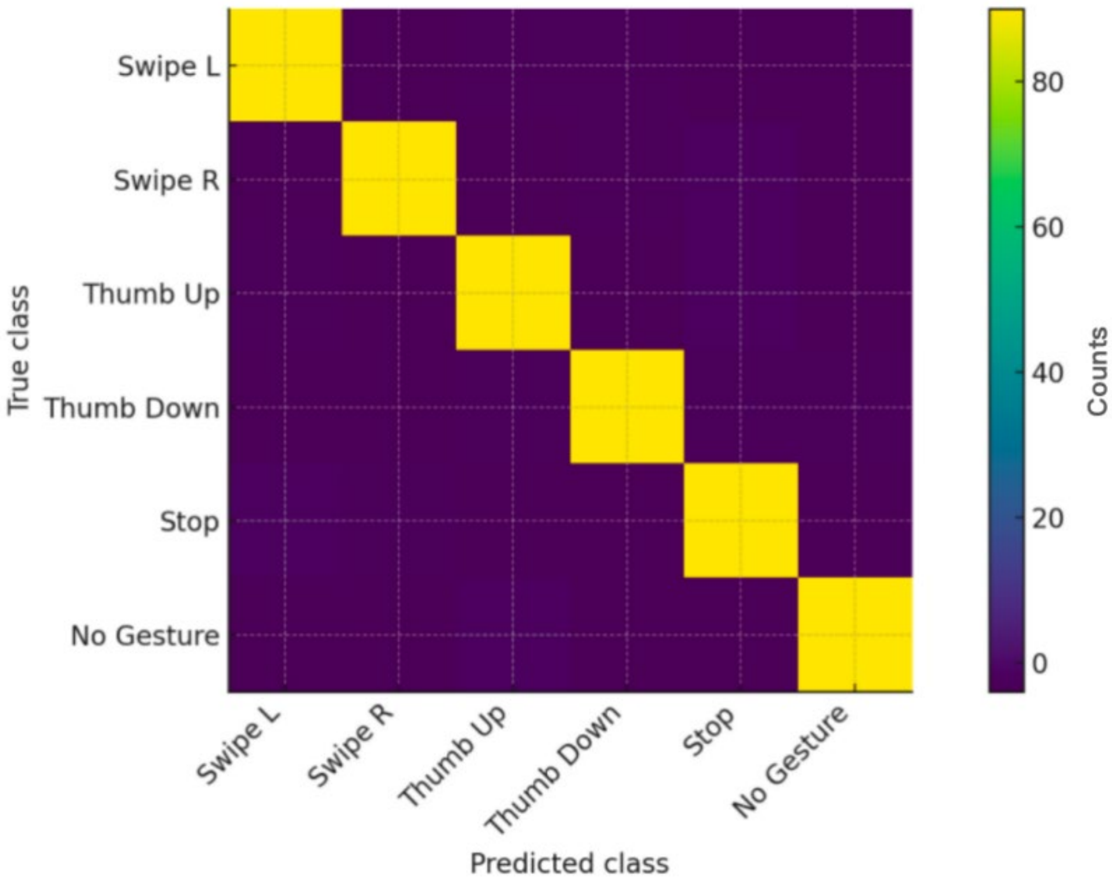


Figure 4. Confusion Matrix of the Gesture Recognition Model on the Predefined Dictionary

**Performance Analysis of the Functional Textile Module**

We experimentally characterized the key performance metrics of the fabricated electrochromic yarn, with results summarized in Table 3. The yarn demonstrated all the essential properties required for dynamic visual feedback: subsecond coloration time (850 ms) and approximately 1 s bleaching time ensure users receive prompt visual feedback in response to gestures. An optical modulation range of 62% guarantees sufficiently perceptible color changes. High cycling stability, which is comparable to other reported PEDOT:PSS-based systems, was demonstrated over 5,000 coloration–bleaching cycles, and operation at low driving voltage supports long-term durability and safety for everyday use. These parameters validate the feasibility of the GI-ECTS actuator module. As shown in Figure 5, after 5,000 cycles, the modulation depth ($\Delta T$) retained approximately 95.2% of its initial value, demonstrating strong electrochromic durability. Furthermore, while care was taken to ensure coating uniformity through a controlled dip-coating speed, microscopic variations in layer thickness could still occur. Future work should involve characterizing this uniformity using techniques like scanning electron microscopy (SEM) and correlating it with electrochromic performance to further enhance device repeatability. While the device maintained over 95% of its optical modulation after 5,000 cycles, long-term failure mechanisms were not deeply investigated. Potential degradation pathways in PEDOT:PSS systems include irreversible electrochemical side reactions or ion trapping within the polymer matrix, which could lead to gradual performance decay over tens of thousands of cycles. A detailed mechanistic study is a subject for future investigation.

Table 3. Performance Parameters of the Fabricated Electrochromic Yarn

| Parameters | Values | Conditions |
|---|---|---|
| Coloration time ($T_{90}$) | 850 ms | Applied voltage −2.0 V |
| Bleaching time ($T_{90}$) | 1200 ms | Applied voltage +1.5 V |
| Optical modulation ($\Delta T$ at 633 nm) | 62% | — |
| Cycling stability | $\Delta T$ retention > 95% after 5,000 cycles | — |
| Operating voltage | −2.0 V to +1.5 V | — |

T90 = time to reach 90% of the maximum transmittance change after voltage application.

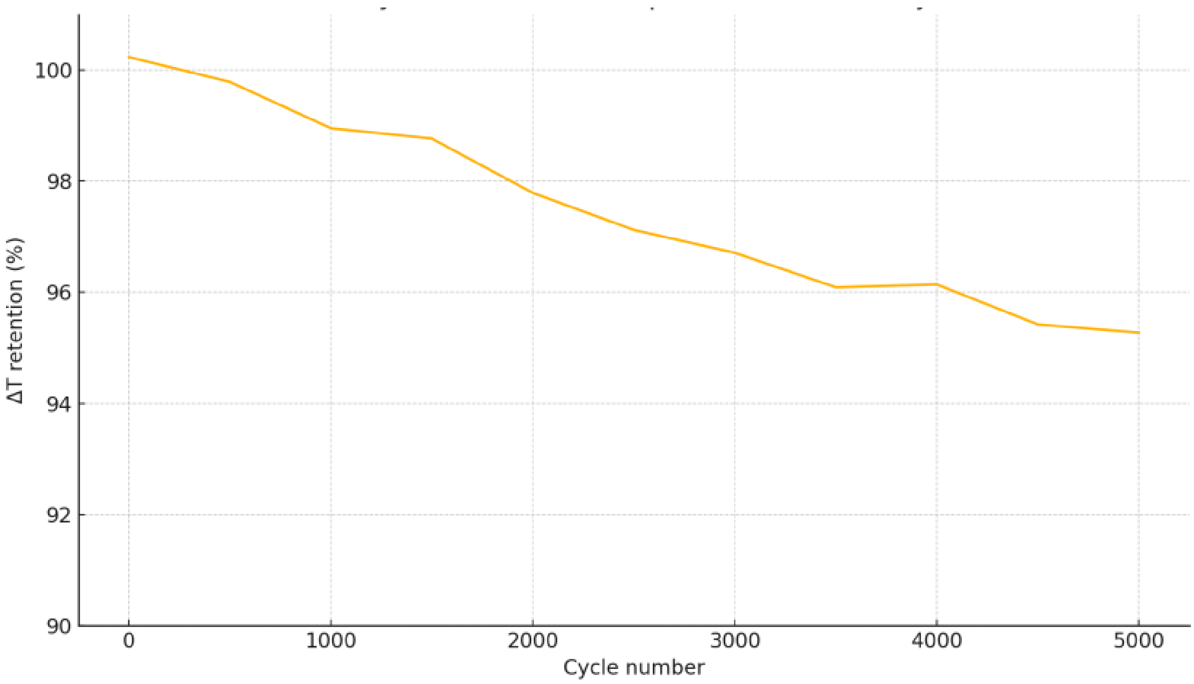


Figure 5. Cycling Stability Curve Measurements conducted at 25 °C and 45% relative humidity.

### End-to-End System Latency Analysis

End-to-end latency is the ultimate metric for assessing the interactivity of the system. The delay across the entire process was decomposed as follows:

**Gesture Execution and Capture:** A typical dynamic gesture (e.g., a swipe) lasts about 1–2 seconds. For latency measurement, we consider the midpoint of the gesture as the start point.

**Frame Capture Delay:** Determined by camera frame rate. At 30 FPS, the interval is approximately 33 ms.

**Model Inference:** Based on Table 2, MobileNetV3-Small achieves 35 FPS, translating to a per-frame inference time of ≈ 1000 ms / 35 ≈ 28.6 ms.

**Communication and Control:** The transmission from Jetson Nano to the MCU and subsequent signal processing incurs negligible latency, typically < 5 ms.

**Electrochromic Response:** As per Table 3, the coloration time is 850 ms.

Thus, the total perceptible system latency is estimated as: Latency_total ≈ Latency_inference + Latency_control + Latency_electrochromic ≈ 28.6 ms + 5 ms + 850 ms = 883.6 ms. As shown in Figure 6, empirical measurements yielded a median latency of 874 ms, closely aligning with the theoretical estimation. This subsecond end-to-end delay is well within acceptable bounds for non-time-critical interactive applications, enabling a fluid “what-you-do-is-what-you-see” experience. Figure 7 provides a visual breakdown of the latency contributions of each system component. Notably, the electrochromic response dominates the total delay, while inference and control latencies remain below 35 ms, affirming the system’s capacity for real-time interaction.

The end-to-end latency was evaluated for individual, clearly defined gestures. The system’s performance and robustness under more complex scenarios, such as continuous rapid gestures or during the transition between different gestures, have not been characterized. Future work should include stress-testing the recognition module to determine its ability to correctly segment and process a continuous stream of movements without false activations.

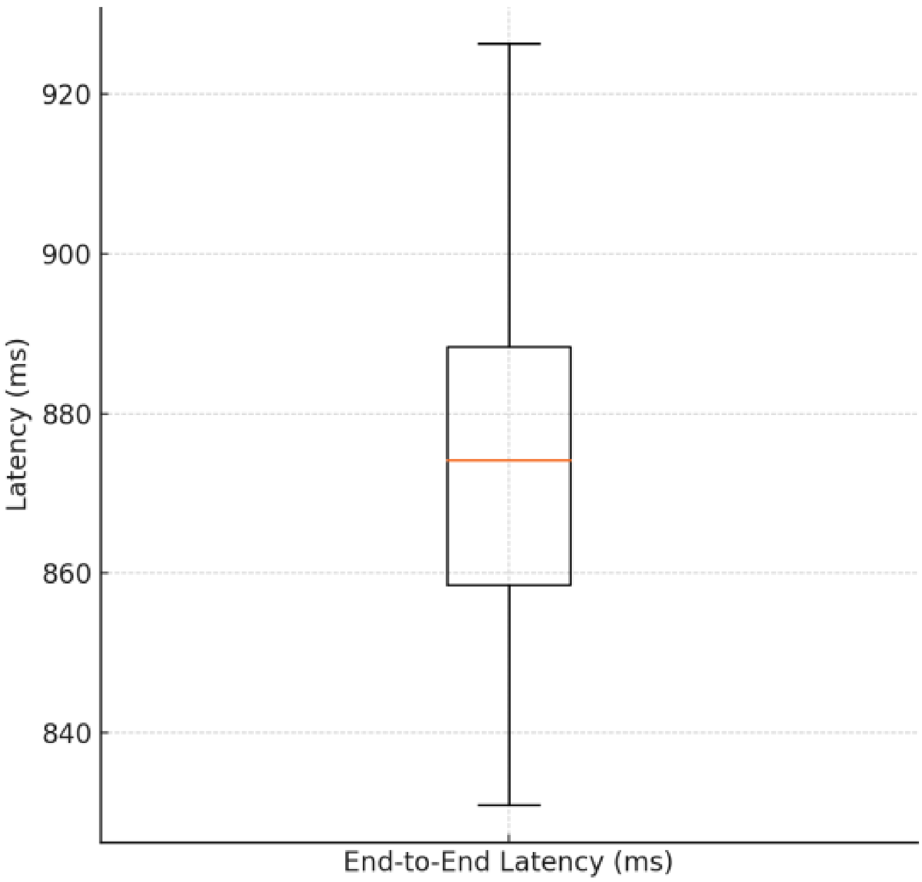


Figure 6. End-to-End System Latency Analysis (n = 50)

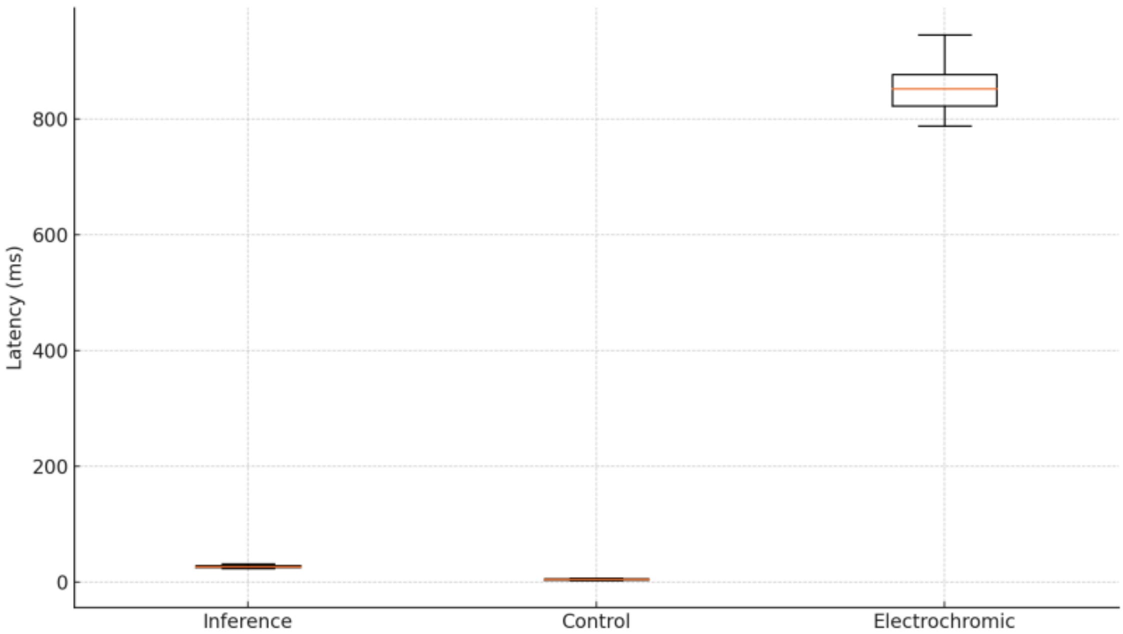


Figure 7. Box Plot of Latency Breakdown by System Component

## DISCUSSION

The results of this study validate the technical feasibility of the GI-ECTS system and highlight the immense potential of integrating deep learning with functional materials. More than just a technical solution, GI-ECTS represents a novel design paradigm—one that merges non-contact intelligent sensing with the innate visual expressiveness of textiles. Fundamentally, this paradigm relocates the interactive interface from discrete, rigid screens to ubiquitous and conformal textile substrates. Such an approach fosters a more contextual and unobtrusive form of human–machine interaction, aiming for an intuitive symbiosis where the technology functions as an integral part of the user’s personal space. This opens up expansive possibilities for future interactive design in fields like fashion, interior design, and assistive technology.

Despite these promising implications, transforming this prototype into a mature product requires addressing several key challenges. Perhaps the most significant limitation is the absence of a formal user experience (UX) evaluation. While we have demonstrated the system’s technical feasibility, technical metrics alone are insufficient to validate its true usability and user satisfaction. Without a user study, our claim of addressing interaction inconvenience remains a well-founded hypothesis rather than an empirically validated conclusion. Therefore, the most critical priority for future work is to conduct a comprehensive user study. This will involve gathering both quantitative and qualitative data through established UX methodologies to rigorously evaluate and improve the system from a human-centered perspective. Another set of limitations relates to the robustness of the perception system in real-world environments. The current gesture recognition model was evaluated on a predefined vocabulary from the Jester dataset, which may not fully represent the nuances of hand movements in a wearable context. The model’s performance against challenges like varying lighting, background clutter, or individual differences in gesture execution has not been systematically evaluated. Furthermore, the practical implementation of the camera itself—its optimal positioning, field of view, and potential for obstruction—presents non-trivial engineering challenges. A major challenge for practical deployment is the robust placement and operation of the camera. The current system assumes a clear, first-person view, but in a real-world wearable context, the camera is subject to dynamic occlusions (e.g., from clothing folds, hair, or the user’s arm), shifting fields of view due to body movement, and extreme lighting variations. These factors present a significant domain gap that would degrade the performance of a model trained on clean, static datasets. To mitigate these issues, future work will focus on ergonomic studies to identify optimal, stable mounting locations (e.g., on the shoulder or chest of a garment). Furthermore, we will explore data augmentation techniques that simulate these real-world challenges during training, and investigate the use of wide-angle or multiple-camera systems to provide a more comprehensive and fault-tolerant view of the user's interaction space. It is also important to acknowledge that gesture-based interaction is not a panacea for all scenarios. As pointed out by principles of human factors engineering, it requires a free hand, which may be inconvenient when the user is carrying objects or performing other manual tasks. Therefore, we envision GI-ECTS not as a replacement for traditional inputs, but as a complementary modality. Its strengths lie in situations where tactile interaction is difficult (e.g., when wearing gloves) or socially inappropriate (e.g., discreetly changing a setting). A truly robust interactive textile would likely employ a multimodal approach, combining gestures with voice commands or subtle tactile inputs to suit the user's context.

To address these shortcomings, future work will focus on several areas. To move beyond the current simple command set, we will explore more complex gesture grammars. To improve reliability, we will investigate multimodal sensing, incorporating voice or EMG signals. Crucially, our real-world testing will focus on creating a custom dataset to close the domain gap, while also conducting ergonomic studies to develop robust camera integration strategies. Finally, the system faces fundamental hardware and sustainability challenges. The durability of electronic textiles, especially their washability, remains a major hurdle, as daily wear and laundering can degrade the functional layers. The power consumption of platforms like the Jetson Nano is too high for untethered use. Moreover, the materials used are difficult to recycle, raising sustainability concerns about e-waste. Our future research will directly target these issues. We will explore advanced encapsulation methods to enhance durability. To solve the power issue, we will investigate neuromorphic computing for ultra-low power processing and integrate energy-harvesting systems like triboelectric nanogenerators (TENGs). To address sustainability and enable mass production, we will focus on scalable manufacturing techniques like roll-to-roll (R2R) printing, while prioritizing green materials and modular, recyclable designs.

## CONCLUSIONS

To address the lack of intuitive and natural interaction methods in current smart textiles, this study proposed and designed a novel Gesture-Interactive Electrochromic Textile System (GI-ECTS). By integrating cutting-edge advancements in materials science and artificial intelligence, the system forms a closed-loop framework—from gesture perception to textile-based visual feedback—demonstrating the feasibility of seamless, real-time human–fabric interaction.

The core contributions of this work are threefold. First, we developed an end-to-end system architecture that integrates a miniature camera, an embedded AI platform, a microcontroller, and functional electrochromic textiles. Second, we proposed a viable fabrication method for flexible electrochromic yarns based on PEDOT:PSS, achieving both responsiveness and durability. Third, we selected and validated MobileNetV3, a lightweight deep learning model, as the basis for the real-time gesture recognition module, ensuring high accuracy and low computational demand on embedded platforms. Extensive experiments confirmed the system's key performance metrics: The gesture recognition module maintained an accuracy above 95% on the Jester benchmark dataset, demonstrating the model's potential for this application. The functional textile module exhibited subsecond response times and excellent cycling stability, confirming its suitability as a dynamic visual actuator. The end-to-end latency of the system was kept below 1 s, providing the technical foundation for a potentially smooth and natural user experience, which must be validated through future user studies. While this research achieves promising results at the prototype level, we acknowledge the critical challenges that remain on the path to practical deployment—particularly in the areas of washability, power supply, and environmental sustainability. These challenges are not merely technical, but also guide future research directions, including the development of more robust encapsulation strategies, the integration of energy-harvesting technologies, and the exploration of environmentally friendly electronic materials and circular design principles.

In summary, this study offers a validated and forward-looking conceptual and technical framework for the development of next-generation interactive smart textiles. It demonstrates that combining the "intelligence" of lightweight deep learning with the "form" of functional electrochromic fibers presents a compelling pathway toward creating truly dynamic, personalized, and expressive wearable systems.

*Availability of Data and Materials*

The datasets used and/or analysed during the current study were available from the corresponding author on reasonable request.

*Author Contributions*

Xuechun Wang and Jifeng Qin designed the study; all authors conducted the study; Xuechun Wang and Jifeng Qin collected and analyzed the data. Jifeng Qin and Xuechun Wang participated in drafting the manuscript, and all authors contributed to critical revision of the manuscript for important intellectual content. All authors gave final approval of the version to be published. All authors participated fully in the work, took public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or completeness of any part of the work were appropriately investigated and resolved.

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*Conflict of Interest*

The authors declare no conflict of interest.

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