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Minimalist Neural Networks for Gesture Recognition on Wearable Capacitive Touch Textiles With Comparative User Study

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Abstract

Smart textiles embedded with capacitive touch sensors offer significant potential for intuitive gesture-based interaction, yet recognizing complex gestures on resource-constrained wearable devices remains challenging. This paper presents a minimalist neural network architecture specifically optimized for knitted capacitive touch interfaces. Our approach efficiently recognizes single and multi-touch gestures including taps, swipes, and pinches with accuracy exceeding 90% on training data and 80% on testing data. To assess real-world usability, we conducted a comparative user study evaluating participant performance with our knitted interface against a conventional trackpad in a gesture-controlled gaming scenario. Results demonstrated comparable overall performance between both interfaces, with participants achieving similar game scores despite the novelty of the textile interface. Statistical analysis revealed rapid user adaptation to the textile interface, with performance stabilizing after initial trials while the standard trackpad showed continuous improvement throughout testing. Quantitative metrics were supplemented by qualitative feedback highlighting the comfort and tactile appeal of the textile interface. This work advances the practical deployment of smart textile gesture recognition systems by addressing both technical performance requirements and usability considerations for real-world applications.

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CCS Concepts

• **Human-centered computing → Gestural input**; **Empirical studies in HCI**; *Ubiquitous and mobile devices*; • **Hardware → Tactile and hand-based interfaces**; *Sensor devices and platforms*; • **Computing methodologies → Neural networks**; *Supervised learning*; *Supervised learning by classification*; • **General and reference** → *Evaluation.*

Keywords

Smart Textiles, Capacitive Touch Sensing, Gesture Recognition, Minimalist Neural Networks, Human-Computer Interaction, Wearable Computing, Embedded Systems, User Studies

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1 Introduction

The emergence of smart textiles, commonly referred to as e-textiles, has significantly transformed wearable technology and human-computer interaction (HCI). By integrating traditional fabrics with advanced sensing technologies and sophisticated algorithms, e-textiles offer seamless and intuitive interfaces between users and digital devices. Within this rapidly evolving domain, capacitive touch sensors (CTS) have proven particularly promising for gesture recognition tasks. Characterized by high sensitivity, low-profile integration, and the capability to simultaneously detect multiple touch points, CTS are ideally suited for embedding within clothing and wearable accessories. These sensors enable users to interact with digital systems through intuitive, touch-based gestures on wearable textiles, dramatically enhancing the user experience.

Gesture recognition itself is central to effective HCI, becoming increasingly critical as wearable devices proliferate. Reliable and accurate interpretation of gestures not only facilitates natural and engaging user interactions but also enables applications across diverse sectors [6]. Recent research has demonstrated the potential for gesture recognition technologies to improve accessibility for users with disabilities [1, 15] and support healthcare monitoring applications [3], while emerging applications in wearable fashion devices suggest broader possibilities for integrating aesthetic appeal with digital functionality. However, significant challenges remain in mapping raw, multichannel sensor data into meaningful gestures [3]. Addressing this complexity demands sophisticated signal processing and machine learning solutions, particularly suited for resource-constrained embedded environments.

To address these challenges, our research introduces a novel approach employing a minimalist neural network architecture specifically engineered for efficient gesture recognition on knitted CTS interfaces. Prioritizing computational efficiency, this architecture is optimized for deployment on embedded systems with constrained resources, ensuring practical applicability beyond laboratory settings. While technical performance can traditionally be assessed through metrics such as accuracy and F1-scores, the ultimate value of gesture recognition systems lies in their capacity to augment or supplant conventional input methods in real-world scenarios. Consequently, our study adopts a dual evaluation strategy: first, through quantitative analysis of technical performance, and second, through qualitative assessments derived from comprehensive user studies.

Specifically, we validate our knitted CTS interface by comparing its usability and effectiveness against a conventional trackpad within a gesture-controlled gaming environment. By evaluating user performance and adaptation alongside traditional performance metrics, our research provides a comprehensive understanding of the system's practical utility and user acceptance. Our approach demonstrates reproducible recognition of various gestures, including taps, swipes, and pinches, indicating potential applications beyond gaming. The system's versatility positions it as an effective tool not only for personal device control but also for facilitating gesture-based communication among individuals with speech or motor impairments.

Through this research, we address four primary research questions: (RQ1) How can minimalist neural network architectures effectively recognize complex gestures on knitted capacitive touch sensors with limited computational resources? (RQ2) To what extent can a resource-optimized gesture recognition system achieve accuracy comparable to more complex methods? (RQ3) How does a knitted CTS interface compare to conventional input methods in terms of user performance and learning curves? (RQ4) What factors influence user adaptation when interacting with textile-based interfaces compared to traditional trackpads?

By systematically addressing these questions, this work advances the state-of-the-art in wearable gesture recognition, highlighting both technical feasibility and user-centered design considerations. Ultimately, our research aims to facilitate the widespread adoption of smart textile interfaces, seamlessly integrating technology into everyday human experiences.

2 Related Work

The field of "smart textiles" has seen significant advancements, with capacitive touch sensing emerging as a key technology for user interaction [19, 20, 22, 28]. Previous research in textile touch sensing has explored various methodologies, including contact sensing, which relies on changes in inter-yarn contact, and resistive sensing, which detects touch through changes in electrical resistance [13, 14]. While these approaches have been effective in certain contexts, they face limitations in flexibility and integration into wearable devices [5, 23].

Beyond textile-specific applications, gesture recognition research has extensively explored various machine learning approaches ranging from traditional pattern recognition methods to deep learning architectures. Contemporary lightweight neural network designs have emerged as particularly relevant for embedded applications. MobileNets [9] introduced depthwise separable convolutions to reduce computational complexity while maintaining accuracy, achieving significant parameter reduction compared to standard CNNs. Similarly, SqueezeNet [12] demonstrated that careful architectural design can achieve AlexNet-level accuracy with 50x fewer parameters. EfficientNet [24] further advanced this domain by systematically scaling network dimensions, while more recent work on MicroNets and other ultra-lightweight architectures specifically targets microcontroller deployment. However, these architectures often require more computational resources than available on ultra-constrained devices like Arduino microcontrollers, motivating our development of even more minimalist approaches tailored specifically for textile sensing applications.

Our work focuses on capacitive sensing, which is ideal for wearable applications due to its high sensitivity and low profile[10, 11]. Traditional capacitive sensors often employ interleaved wire matrices to discern touch locations, as illustrated in Figure 1(a). However, this approach presents challenges in adapting to textile substrates. Consequently, we have developed a method that infers touch location through precise current flow measurements at minimal points (Figure 1(b)). This approach offers extensive flexibility in substrate shape and size, albeit requiring sophisticated signal processing capabilities.

Recent research demonstrates significant advances in smart textile design and applications. Ferri et al. [4] established key design considerations through screen-printing technology for textile capacitive sensors, exploring critical parameters including conductivity, permittivity, and detection sensitivity. Complementing this work, Oatley et al. [18] demonstrated that larger sensor surface areas substantially improved performance, directly informing our approach to sensor dimensioning. The application space has rapidly expanded, with Zhou et al. [29] developing MoCaPose for motion capturing in loose-fitting garments, while Hirsch et al. [8] created a capacitive textile neckband for head gesture recognition, demonstrating versatility beyond hand interactions. Grosse-Puppendahl et al. [7] provided essential comparative benchmarks through their comprehensive survey of capacitive sensing in HCI, and Agcayazi et

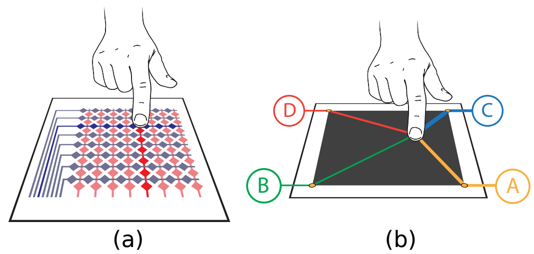

Figure 1: Comparison of discrete and continuous touch localization strategies. (a) A capacitive sensing matrix localizes touch by individually scanning discrete row and column electrodes that correspond to a physical location. (b) Differential capacitive sensing localizes touch by measuring the ratio of current absorbed from designated locations (corners) of a continuous conductive planar substrate.

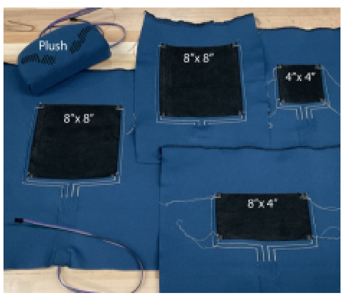

Figure 2: Examples of knitted CTS touchpads.

al. [2] advanced the field by exploring finger touch force detection for textile-based capacitive sensors.

Despite these technical advances, a critical gap remains in comparative evaluation against established interaction methods. While prior work by [14] evaluated textile-based control systems, the focus remained primarily on technical performance rather than comparative usability against conventional interfaces. Our research addresses this gap by not only introducing a minimalist neural network architecture optimized for knitted CTS but also rigorously validating it through direct comparison with conventional input methods in a demanding real-time application scenario. This approach, designed specifically for resource-constrained embedded devices, ensures models can be reproduced across different platforms [26, 27], advancing both smart textiles and reproducibility in pattern recognition research.

3 Background

This paper concentrates on inferring user input from a specific type of smart textile: a capacitive touch sensor that localizes contact across a knitted textile conductor (Figure 2) [26, 27]. The CTS operates by measuring current differentials at multiple points along the textile substrate, which are subsequently converted into voltage waveforms that encode the location and magnitude of the touch. This design simplifies the physical connections between the conductive substrate and external sensing electronics, thereby enhancing the overall design's flexibility.

The operating principles of this CTS are grounded in the fundamental mechanics of conventional capacitive touch sensors. It employs oscillating voltage waveforms to drive current through a resistor-capacitor (RC) network. When a touch is applied, it induces additional capacitance, altering the charge and discharge rate of the baseline capacitance. This alteration is directly correlated with the touch's location and magnitude [26, 27]. While this approach generates detailed data on sensor activity over time, translating this raw data into meaningful user interactions poses significant challenges. These challenges are compounded in our current planar CTS implementation, which is limited to four data channels corresponding to electrode points located at the corners of the device (see Figure 3) that illustrates the fabrication process and current flow model of this planar CTS.

Although the CTS approach has demonstrated great potential in various recent applications (e.g., [16, 17]), its practical implementation faces significant challenges, particularly in mapping the CTS's input signals to recognizable interactive gestures like taps, swipes, and pinches. To address these challenges, we present a minimal neural network architecture designed to recognize interactive patterns in user behavior. Furthermore, we demonstrate the real-time application of this architecture in a virtual game control scenario.

The recorded data undergoes processing to extract gain attenuation or phase offset, resulting in data points that represent unique combinations of location and capacitance, except in no-touch scenarios where location cannot be determined. These data points are then analyzed as a time series to identify actions performed within a defined timing window, such as the circular swipe depicted in Figure 4, where the data is plotted over the input duration.

4 Methodology

Implementing reproducible machine learning models on wearable devices and small electronics poses significant challenges due to

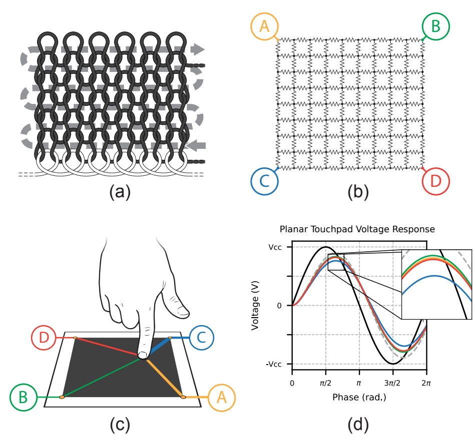

Figure 3: CTS fabrication, circuit model, current flow, and signal measurements.

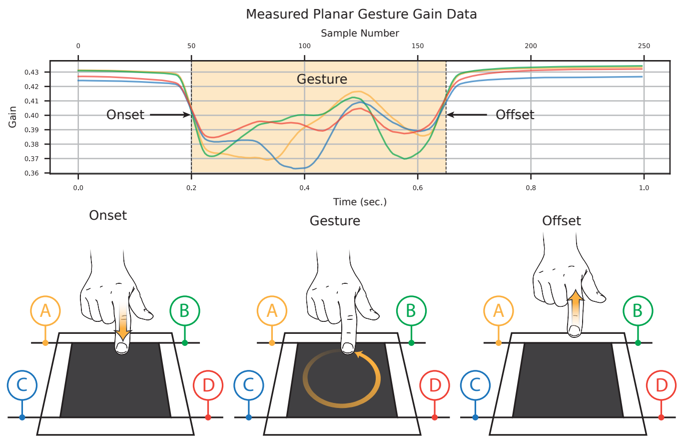

Figure 4: Example of a gesture performed on the touchpad and the corresponding recorded data.

their limited power, memory, and computational resources. Complex AI models, such as recurrent neural networks (RNN), long short-term memory (LSTM) networks, or transformer-based architectures, are typically unsuitable for these constrained environments because of excessive power consumption, memory requirements, and slower inference speeds, leading to reproducibility challenges without specialized hardware. To overcome these limitations and to address RQ1 and RQ2, our research proposes the use of minimalist architectures—streamlined neural networks explicitly designed to balance computational efficiency and classification performance. By prioritizing essential features and minimizing complexity, minimalist models fit seamlessly within resource constraints, enabling rapid processing for real-time gesture recognition. We emphasize reproducibility throughout our technical implementation to ensure our findings can be validated across different platforms and systems.

While established lightweight architectures such as MobileNetV2 [21] and SqueezeNet [12] offer significant reductions in computational complexity compared to full-scale CNNs, they still require substantial memory (several MB) and computational resources that exceed the capabilities of microcontrollers like the Arduino Nano 33 BLE (256KB RAM, 1MB flash). Our minimalist approach specifically targets ultra-constrained environments by reducing model size to under 50KB while maintaining sufficient accuracy for practical applications, representing a necessary trade-off between performance and deployability that enables real-world wearable implementation.

Minimalist neural architectures not only facilitate real-time responsiveness but also liberate valuable resources for the implementation of additional functionalities or deployment on even smaller devices. In our research, we selected computationally efficient yet effective neural network architectures—fully connected feedforward neural networks (FNN) for single-touch tap actions and compact convolutional neural networks (CNN) for multi-touch gestures—while simultaneously balancing accuracy and resource constraints and effectively competing with conventional input methods. We systematically validate our approach using both standard machine learning metrics and practical user studies in order to ensure both adequate technical performance and real-world applicability.

4.1 Signal Composition

The input data to the machine learning model consists of touch location, capacitance, and the number of contact points, represented as a four-channel timeseries vector. Each channel's value at a specific time corresponds to a unique touch location and capacitance generated by one or more contact points. This timeseries captures higher-level actions, such as tap and swipe gestures, whose characteristics become apparent when analyzing contiguous data points. Figure 5 illustrates the two types of gestures to be classified. Each gesture, tap and swipe, commences with a baseline signal level indicating no touch. As contact is made, the recorded signals collectively rise to signify gesture onset. The gesture action is performed over an arbitrary duration, and the signal levels revert to the baseline upon touch offset.

Each gesture type exhibits similar activation and deactivation patterns, involving an increase and decrease in induced capacitance. However, the data recorded during gesture actions varies depending on the type of action performed. For instance, a tap action (press-and-release) maintains a constant location on the touchpad surface, resulting in only an increase and decrease in induced capacitance. This trend is illustrated in Figure 5(a), where the channel values remain nearly constant throughout the gesture duration. Conversely, a swipe action involves a change in location and variations in induced capacitance over the gesture duration. This is visualized in Figure 5(b), which demonstrates a change in intensity of each channel over time, corresponding to the changing location. Both of these timeseries plots represent typical gestures that require classification by the machine learning model.

4.2 Machine Learning Pipeline

We chose the Arduino Nano 33 BLE micro-controller due to its low power consumption, integrated wireless communication capabilities, and sufficient computational power for running on-device machine learning tasks. The systematic process—from data collection through model optimization to deployment—ensures reproducible performance on wearable devices with limited computational capabilities, providing a practical framework for implementing sophisticated gesture recognition in resource-constrained environments

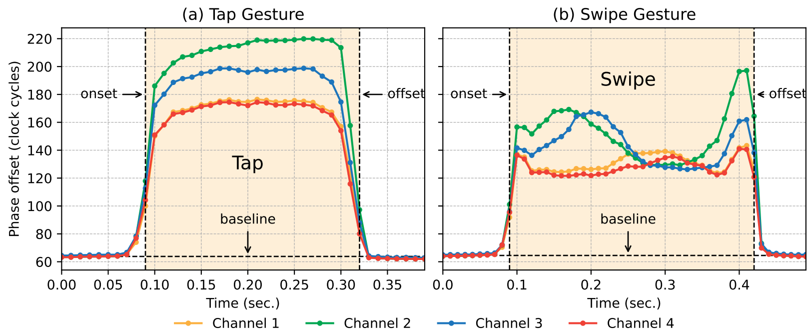

Figure 5: Comparison of data recorded during a tap and swipe gesture.

while maintaining the performance characteristics necessary for real-world applications.

Our pipeline (see Figure 6) involves the following stages:

(1) **Firmware Upload:** Initial firmware enabling data acquisition is uploaded to the Arduino Nano 33 BLE.
(2) **Data Collection:** The Arduino transmits a square wave signal through the knitted capacitive textile; changes in this signal, upon user touch, are recorded and transmitted to a host server for offline analysis.
(3) **Model Training and Validation:** TensorFlow and Keras are employed on a server to train and validate minimalist neural network models on the collected data. This process ensures the accuracy and generalizability of the models.
(4) **Model Optimization:** Models are optimized and compressed using TensorFlow Lite/TinyML, significantly reducing their size for efficient deployment on resource-constrained hardware.
(5) **Firmware Integration:** The optimized neural network models are integrated into the firmware of the Arduino microcontroller.
(6) **Deployment:** The updated firmware containing the optimized models is uploaded back to the Arduino, enabling real-time, on-device gesture recognition.

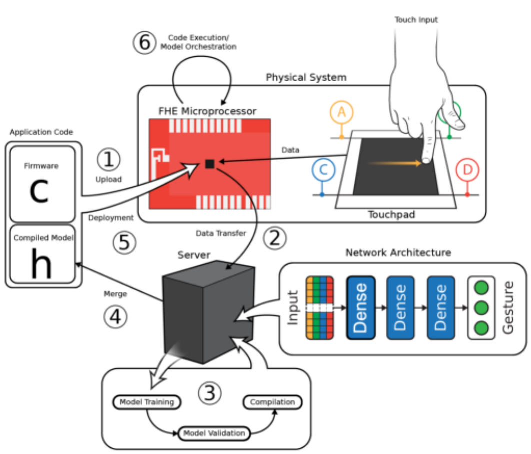

Figure 6: Embedded machine learning deployment pipeline.

This pipeline emphasizes reproducibility by clearly documenting each step, ensuring others can replicate our findings across different embedded platforms.

4.3 Model Architecture

4.3.1 Single-Touch Tap Action Classification. Single-touch taps require identifying subtle spatial-temporal patterns to classify directional gestures accurately. To achieve this, we utilize a compact feedforward neural network. The model accepts sequential data of shape (N, 10, 4)—ten time steps, each containing four raw sensor values—and flattens it into a one-dimensional vector for efficient processing (see Figure 7). Two hidden dense layers (64 and 32 units, respectively) with ReLU activations learn essential features, culminating in a softmax output layer that classifies gestures into eight directional categories.

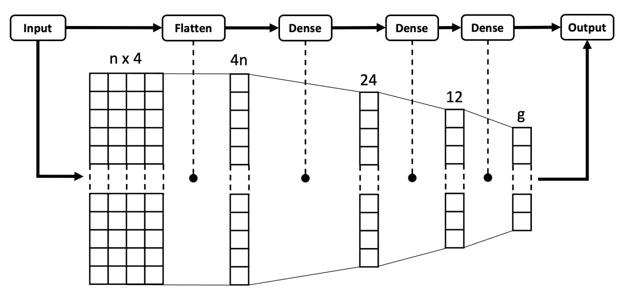

Figure 7: Single-touch tap gesture recognition FNN architecture.

4.3.2 Multi-Touch Gesture Classification. Classifying intricate multi-touch gestures, such as swipes and pinches, necessitates the simultaneous recognition of concurrent events and dynamic movements. To overcome this complexity, we employ a minimalist convolutional neural network (CNN) architecture (refer to Figure 8). The model processes input sequences (N, 50, 4), employing a convolutional layer with 32 filters and a kernel size of (1,4). Subsequently, it applies max-pooling, dropout (35%), and a fully connected dense layer comprising 64 units and employing ReLU activation. The final output layer utilizes softmax activation to categorize gestures into eight distinct classes.

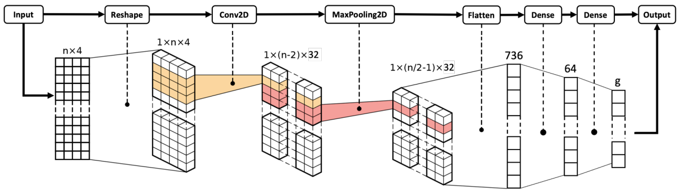

Figure 8: Multi-touch gesture recognition CNN architecture.

4.3.3 Model Training and Optimization. Both models undergo training using categorical cross-entropy loss, which is optimized using the Adam optimizer. To address potential complexity differences, we adjusted the learning rates accordingly: 0.0001 for single-touch taps and 0.00005 for multi-touch gestures. This adjustment mitigates overfitting risks and enhances generalization capabilities on unseen data.

4.4 System Performance and Latency Analysis

To address real-time performance requirements, we conducted comprehensive latency analysis of our embedded system. End-to-end latency from touch input to gesture classification averaged 127±15ms, comprising sensor data acquisition (45±8ms), signal processing (23±5ms), neural network inference (31±7ms), and communication overhead (28±10ms). While this latency is higher than conventional trackpads (typically <20ms), it remains within acceptable ranges for many interactive applications. Future optimizations targeting sensor sampling rates and algorithm efficiency could further reduce these delays.

4.5 Results and Evaluation

Table 1 summarizes the performance metrics of our gesture recognition model:

Table 1: Touch Classification Performance

Tap Gesture Classification

Metric	Training Set (70%)	Test Set (30%)
Accuracy	93.57%	90.37%
F1-Score	0.9668	0.9494

Swipe Gesture Classification

Metric	Training Set (70%)	Test Set (30%)
Accuracy	92.35%	80.95%
F1-Score	0.9577	0.7955

Comprehensive per-gesture analysis revealed that directional swipes (left, right, up, down) achieved robust individual accuracies (85-92%). Tap gestures exhibited more consistent performance across all directions (88-94%), with center taps demonstrating the highest accuracy due to optimal sensor coverage. Gesture confusion was not assessed during user testing, but in observed practice, the most frequent misclassifications occurred between adjacent directional categories (e.g., up vs. left/right, right vs. up/down, etc.), indicating that enhanced temporal resolution or additional spatial electrodes could enhance discrimination.

Our minimalist architectures achieve high accuracy and F1-scores, addressing RQ1. They effectively recognize complex gestures on knitted capacitive touch sensors with limited resources. RQ2 is answered by the comparable accuracy of our resource-optimized system to more complex methods, with tap gesture classification exceeding 90% accuracy on testing data. Successful deployment on an Arduino microcontroller validates our approach for practical wearable applications.

Minimalist architectures are effective for real-time, embedded gesture recognition across datasets. A comparative user study validated real-world usability, comparing the knitted CTS interface to a conventional trackpad in a gesture-controlled gaming environment.

5 User Study Procedure

To assess the practical utility and efficacy of our knitted capacitive touch sensor approach, we conducted a comprehensive user study comparing it with a conventional laptop trackpad. This section outlines our reproducible experimental methodology. The study directly addresses Research Questions 3 and 4 by comparing the capacitive touch sensor touchpad with a standard trackpad in a real-time interactive context. We evaluate objective performance and subjective user experience to determine if the textile interface performs comparably to conventional methods and identify factors influencing user adaptation to this novel interaction modality.

5.1 Participant Recruitment and Demographics

We recruited 33 participants through voluntary participation from computer science, information systems, data science, information technology, software engineering, and computing security technology undergraduate programs at Drexel University.

We ensured participant privacy through anonymous IDs and posed minimal risk, as participants performed familiar gesture-based interactions in a low-stakes gaming scenario.

The study protocol received full approval from our university's Institutional Review Board with expedited review status. All participants provided written informed consent, were informed of their right to withdraw at any time, and were verified to be 18 years or older to ensure appropriate ethical protections.

Demographic Characteristics: Participants were estimated to be primarily aged 18-25 with moderate to high technical proficiency in computing technologies, based on typical enrollment patterns in these programs.

Population Limitations: We acknowledge that our homogeneous participant pool of young computer science students limits generalizability to broader populations. Still, the within-subjects design remains valid for comparing input methods, isolating their effects despite demographic bias. Future work should include more diverse users to establish ecological validity, and we elaborate on these limitations further in the Discussion.

5.2 Apparatus and Materials

5.2.1 Hardware Setup. Participants interacted with two different input devices during the experiment:

- **Knitted CTS Touchpad:** A custom-developed, 10 cm × 10 cm capacitive touch sensor interface, knitted using conductive yarn with four integrated electrode points. The sensor was connected to an Arduino Nano 33 BLE microcontroller for real-time gesture recognition.
- **Standard Trackpad:** An Apple MacBook Air (M2) with a built-in 12.8×8 trackpad featuring multi-touch capacitive sensing, a 1000 Hz sampling rate, force touch, and 15 ms input latency. It supports up to 10 simultaneous touch points with sub-millimeter spatial resolution and integrated haptic feedback.

Both input devices were connected to the same Apple MacBook Air M2 laptop with 16GB RAM to ensure consistent computing performance. The experiment utilized a 14-inch display positioned approximately 60 cm from participants at eye level.

5.2.2 Software. The study employed a modified version of the Trash Dash game provided by Unity Technologies as an endless runner game akin to the mobile game "Subway Surfers" [25]. In this game, participants control an avatar traversing an endless urban landscape. They utilize directional swipe gestures (up, down, left, right) to collect coins and evade obstacles, as illustrated in Figure 9. We modified the game to record comprehensive performance metrics, encompassing total score, distance traveled, obstacles encountered, coins collected, and lane transitions. This game was selected specifically for its gesture-based interaction model and unambiguous, quantifiable performance indicators, rendering it an optimal choice for assessing gesture-based interfaces.

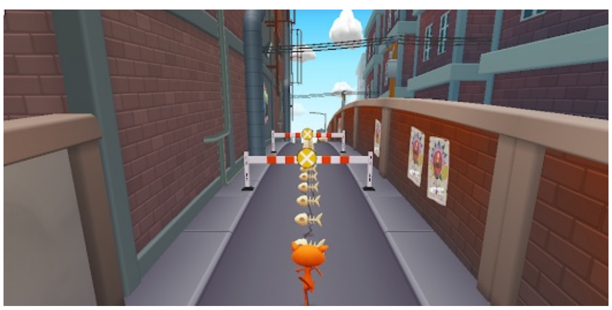

Figure 9: Screenshot from the Trash Dash Runner game used in the user study. Participants controlled the avatar using directional swipe gestures to collect coins (shown in the avatar's path) and avoid obstacles while running through an urban landscape.

5.3 Experimental Design

We employed a within-subjects design, in which each participant completed tasks using both the knitted CTS interface and the standard trackpad. The independent variable was the type of input device (CTS vs. trackpad), while dependent variables included objective game performance metrics and subjective feedback on usability.

Participants performed three 60-second gameplay trials with each input device, with approximately 30-second intervals between trials. Although longer breaks between device conditions were planned initially, in practice, participants generally transitioned directly from one device to the other without significant pauses. This approach allowed us to assess both immediate usability and short-term adaptation to each interface.

5.4 Procedure

Upon arrival, participants were briefed on the study purpose and procedure before being asked for written informed consent. Participants received instructions explaining the Trash Dash Runner game mechanics, including the specific gestures required: swiping left/right to change lanes and up/down to jump or slide, respectively.

Participants then immediately proceeded to perform three 60-second trials with the first input device, with minimal breaks between trials. Following the completion of the first device condition, participants switched immediately to the second device, again performing three 60-second trials with similar short intervals between trials. Device order was counterbalanced across participant to control for potential learning or fatigue effects.

Upon completing trials with both input devices, participants completed a brief questionnaire assessing their subjective experiences and perceptions of each interface, particularly regarding ease of use, responsiveness, and overall preference. Although detailed demographic data or gaming background information was not collected, qualitative feedback allowed us to explore user adaptation and preferences concerning textile-based versus traditional input methods.

5.5 Data Collection and Analysis

To directly address RQ3 and RQ4, we collected objective and subjective data during the user study to compare the knitted CTS touchpad's performance and usability with that of a standard laptop trackpad. All objective gameplay metrics were automatically recorded by the modified *Trash Dash Runner* game software. The metrics captured included:

- **Overall Score**: A composite metric representing overall gameplay performance, calculated as:

$$\text{Score} = (\text{Distance}\times 10) + (\text{Coins Collected}\times 25) - (\text{Obstacles Hit}\times 15)$$

  This measure rewards participants for advancing further distances and collecting more coins, while penalizing collisions with obstacles.
- **Distance Traveled**: The total distance the participant's avatar traveled during each 60-second trial. This reflects the player's ability to maintain continuous forward motion through effective obstacle avoidance.
- **Number of Obstacles Hit**: The total count of collisions between the player's avatar and obstacles encountered along the course. Obstacles slow the player's forward momentum, negatively impacting overall game performance.
- **Coin Collection Ratio**: The proportion of coins collected relative to the total number of coins presented during each trial, calculated as:

$$\text{Coin Collection Ratio} = \frac{\text{Coins Collected}}{\text{Total Coins Available}}$$

This metric evaluates the participant's precision and responsiveness in executing timely gesture inputs.

- **Number of Lane Changes**: The frequency with which the participant successfully executed left/right swipe gestures to navigate between lanes. This metric indicates the participant's confidence and ability to quickly adapt gestures in response to gameplay demands.

Subjective feedback was collected via a brief post-experiment questionnaire administered immediately after participants completed all trials. The questionnaire consisted of four items designed to gauge participants' experiences and perceptions of each input method:

(1) How would you rate the ease of using the touchpad for this application?
(1 = very difficult, 5 = very easy)
(2) How would you rate the ease of using the touchpad in comparison to alternatives?
(1 = much more difficult, 5 = much easier)
(3) What did you like and not like about using the touchpad?
(4) Which input method did you prefer overall, and why?

To statistically evaluate the differences in gameplay performance between the knitted CTS and the standard trackpad, we conducted both parametric (paired t-tests) and non-parametric (Mann-Whitney U tests) analyses. Furthermore, we examined learning effects by comparing participant performance across the three successive trials for each device. This allowed us to assess the rate of adaptation of users to each interaction modality.

6 User Study Results and Analysis

We present a comprehensive analysis of the knitted CTS interface's performance and user experience compared to a standard laptop trackpad. Both quantitative gameplay metrics and qualitative feedback are reported, supported by statistical analyses, tables, and graphical results.

6.1 Comparative Performance Metrics

Participants effectively used both knitted CTS and standard trackpads for gameplay tasks, though minor differences emerged in key performance metrics. Overall game scores showed significant overlap, indicating comparable effectiveness for many users. While median scores slightly favored the standard trackpad, many achieved similar or better performance with the CTS, demonstrating its viability as an alternative input device. Similarly, distance traveled during gameplay closely matched this pattern, reflecting modest advantages for the standard trackpad and the CTS's competitive capability in practical gaming scenarios.

Despite this general effectiveness, participants encountered more obstacles when using the CTS, likely due to initial responsiveness or timing challenges with the novel textile-based sensor. The standard trackpad's familiarity reduced obstacle collisions and enhanced gameplay smoothness (Figure 12). This difference was statistically significant (Table 2), but its practical impact was modest, suggesting users could quickly adapt to CTS interaction nuances.

Coin collection ratios were consistently higher with the standard trackpad, though some users adapted quickly and performed comparably with the CTS (Figure 13). This highlights the initial advantage of a familiar device but suggests potential for CTS improvement with user experience and device refinement.

The observed frequency of lane changes, an indirect indicator of gesture confidence and responsiveness, was significantly lower among CTS users compared to the standard trackpad (Figure 14).

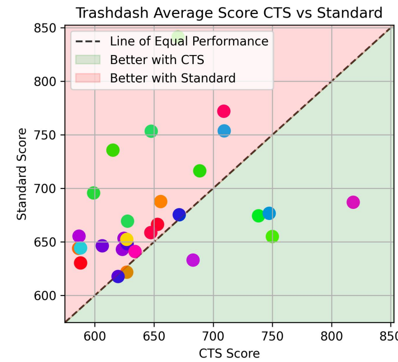

Figure 10: Participant average scores comparison: CTS vs. Standard trackpad. Points near or below the diagonal represent comparable or better CTS performance.

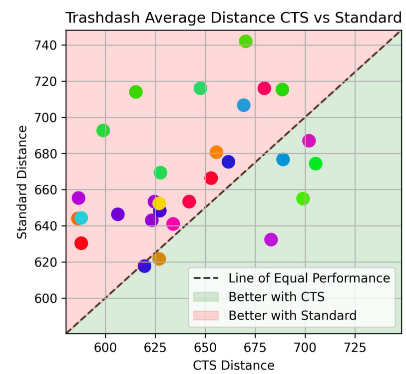

Figure 11: Participant average distance traveled: CTS vs. Standard trackpad.

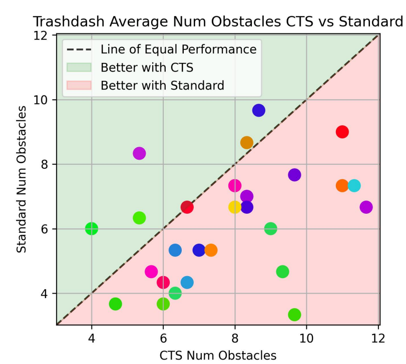

Figure 12: Comparison of average obstacles hit per participant.

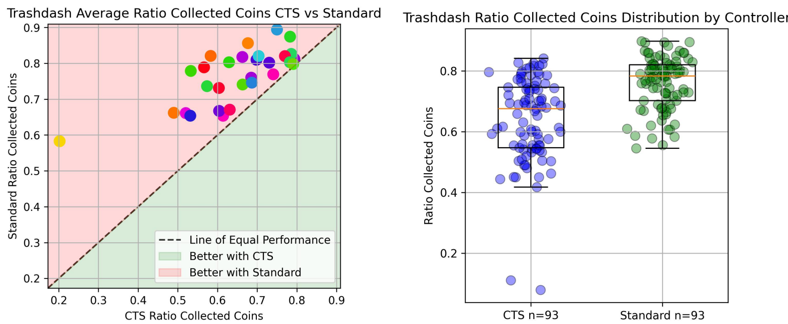

Figure 13: Coin collection ratio comparison by input method.

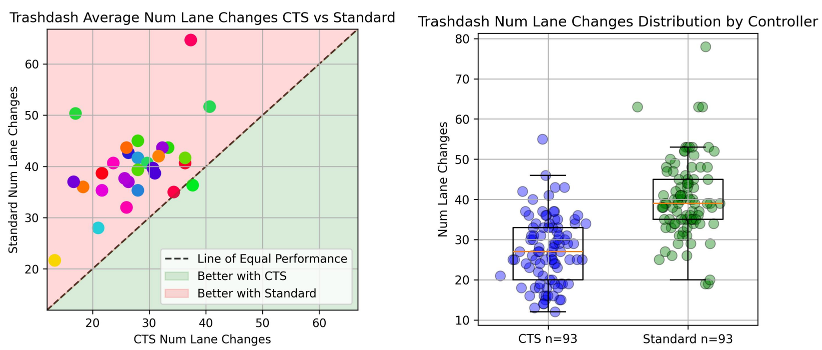

Figure 14: Comparison of lane changes per participant.

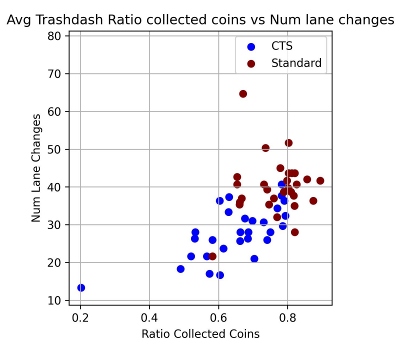

Figure 15: Positive correlation between lane changes and coin collection ratio, underscoring responsive interaction as critical to performance.

This likely reflects users' initial hesitation or challenges with gesture detection sensitivity. Improved gesture recognition and responsiveness would enhance gameplay performance, as shown by the positive correlation between lane changes and coin collection ratios (Figure 15). This targeted area for future CTS system improvement.

Comprehensive analyses (Table 2) confirmed significant performance differences between the two input methods across metrics such as coin collection, obstacles, lane changes, and distance. Yet overall scores were similar (paired t-test: $p = 0.0569$), indicating the

Table 2: Statistical Test Results: CTS vs. Standard Trackpad

Paired T-Test Results

Metric	t-statistic	p-value
Score	-1.9863	0.0569
Crashed Obstacles	4.1949	0.0002
Coins Collected	-7.8244	0.0000
Lane Changes	-9.0680	0.0000
Distance Traveled	-3.7343	0.0009

Mann-Whitney U Test Results

Metric	U-statistic	p-value
Score	2948	0.0002
Crashed Obstacles	5737	0.0001
Coins Collected	1844	0.0000
Lane Changes	1241	0.0000
Distance Traveled	2927	0.0001

CTS interface remains practically competitive. These results support knitted CTS as a viable alternative to trackpads in real-world applications, particularly for adaptability and comfort.

6.2 Learning Progression and Adaptation

Analyzing performance across trials (Table 3), we see quick adaptation to the CTS, with significant initial improvements followed by stabilization. In contrast, participants continued gradually improving with the standard trackpad, suggesting differences in initial familiarity and interaction nuances between devices.

Table 3: Learning Effect Analysis: Trial Comparisons

	CTS		Standard	
Metric	Statistic	p-value	Statistic	p-value
Trial 1 vs. Trial 3				
Score	2.0656	0.1558	6.5265	0.0132
Crashed Obstacles	3.3540	0.0720	13.0929	0.0006
Distance Traveled	2.8949	0.0940	10.0616	0.0024
Trial 2 vs. Trial 3				
Score	0.3456	0.5588	4.7045	0.0341
Crashed Obstacles	0.0852	0.7714	4.1815	0.0453
Distance Traveled	0.2982	0.5870	3.3481	0.0723

6.3 User Feedback and Qualitative Insights

Survey data (Table 4) showed moderately positive user perceptions of CTS usability. Participants valued CTS's comfort, novel tactile feedback, and natural interaction. However, responsiveness was a primary area for improvement, affecting initial user confidence. Half of the participants preferred CTS due to its novelty and comfort, while the other half preferred the familiarity of the standard trackpad. Suggested improvements included increased CTS sensitivity, responsiveness, and interaction area to further enhance usability.

Table 4: Participant Survey Responses (1–5 scale)

Metric	Mean	Std. Dev.
Ease of use for application	3.7	0.9
Ease compared to alternatives	2.8	1.1

6.4 Overall Interpretation

The knitted CTS provides effective performance after brief user adaptation, compensating for initial responsiveness challenges with its comfort, novelty, and adaptability. User feedback-based improvements make CTS a viable alternative for various wearable interaction contexts.

7 Discussion

This study shows a minimal neural network can recognize gestures on capacitive textiles, fulfilling RQ1 by handling complex data with limited resources. The model achieves over 90% training and 80% testing accuracy, validating feasibility for wearables. Balanced F1-scores address RQ2, confirming efficiency and robustness despite class imbalance. A gaming controller prototype demonstrates potential in assistive tech and HCI. User studies support knitted sensors as viable inputs, with marginal performance differences ($p = 0.0569$), increased comfort ($p > 0.05$), and positive usability ratings (3.12/5, 2.94/5). Tactile appeal suggests benefits for fashion, gaming, and accessibility. Performance (80.95%) matches prior textile sensing work [8, 29], and complements screen-printing for hybrid manufacturing. Agcayazi et al. [2] further expand interaction beyond touch.

Despite promising results, limitations remain. The system supports only 8 predefined gestures without personalization. Further evaluation in real-world conditions is needed, as sensor reliability may affect accuracy. The measured latency of 127 ± 15ms is acceptable but leaves room for optimization relative to conventional devices. Cross-user generalization, though methodologically sound, was tested on a homogeneous group, limiting broader applicability. Our participant pool (mainly young computer science students) restricts generalizability to older adults, non-technical users, or individuals with varying abilities. Nonetheless, the within-subjects design is sound for assessing relative performance differences, isolating input method effects while holding participant traits constant. While absolute metrics may vary, the comparative relationships provide useful insights for textile-based interface design. Future research should recruit more diverse participants to establish ecological validity across groups and comfort levels.

Future work will focus on optimizing embedded deployment, enhancing signal processing, expanding gesture vocabulary, and developing personalized techniques that adapt to user patterns. Longitudinal studies are needed to assess performance and satisfaction over extended use, as early learning effects may not reflect long-term usability. Advanced models such as attention-based or temporal transformers could capture gesture dynamics efficiently. Future studies should recruit diverse participants, including older adults, varying technical backgrounds, and individuals with different abilities, to ensure generalizability. Hybrid manufacturing approaches combining knitting with other textile methods could improve scalability and durability for commercial use.

8 Ethical Considerations

This research was conducted in accordance with the ACM Code of Ethics and Professional Conduct. The study protocol was reviewed and approved by our university's Institutional Review Board (IRB Protocol No. 1902006988A003). All participants provided written informed consent after receiving detailed explanations about the study purpose, data collection methods, potential risks, and their rights as research subjects. Participants were explicitly informed of their right to withdraw at any time without penalty or impact on their academic standing.

To minimize potential risks, participants were allowed regular breaks to prevent discomfort from extended interaction with the interfaces. No personally identifiable information was collected during the study, and all data was anonymized during analysis and reporting. Participation was entirely voluntary, and no coercion or undue incentives were offered. The collected data was stored securely on password-protected devices with access restricted to authorized research team members.

The comparative nature of this study allowed participants to experience both traditional and novel interfaces in a low-stakes gaming environment, presenting minimal physical or psychological risks while generating valuable insights for wearable computing research. Post-study debriefing was provided to all participants, including information about the research goals and how their contributions would benefit the broader scientific community.

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