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Smart Wireless Wearable Glove Keyboard

M. J. F. Aasifa, M. F. S. Ahamed and M. Pravina

Department of Electrical and Electronic Engineering, Faculty of Engineering, University of Jaffna, Sri Lanka
aasifajawsi@gmail.com, ahamedshimak99@gmail.com, and pravina@eng.jfn.ac.lk

Abstract. In the rapidly evolving technological landscape, smart wearable devices have become integral to daily life. The Smart Wireless Wearable Glove Keyboard (SWWGK) introduces an innovative method of interaction by enabling users to type effortlessly in mid-air using finger movements. Unlike conventional keyboards that restrict user mobility, the SWWGK translates finger gestures into English text with an accuracy of 89.74%, a latency of 500 milliseconds, and a battery life of up to six hours per charge. This technology is particularly valuable for presenters, educators, and professionals, as it transforms presentations into more interactive and engaging experiences. By allowing users to naturally engage with screens while their gestures are seamlessly converted into written text, the device enhances both learning and participation. The SWWGK is designed to provide a user-friendly interface supported by optimized hardware and software to ensure extended battery life and precise gesture recognition. By removing the limitations of physical keyboards, this innovation redefines communication and interaction within educational and professional environments, offering a powerful tool to enhance connectivity with smart devices and improve information delivery.

Keywords: Smart Wireless Wearable Glove Keyboard (SWWGK), Support Vector Machine (SVM), Bluetooth Low Energy (BLE), Human-Computer Interaction (HCI), Recurrent Neural Network (RNN).

1 Introduction

In the context of rapid technological advancements, the smart wireless wearable glove keyboard (SWWGK) represents a significant breakthrough in human-computer interaction. This device allows users to type effortlessly by moving their fingers in the air, freeing them from the constraints of traditional physical keyboards. The glove interprets hand movements into English letters with high accuracy, providing a seamless typing experience. Current devices primarily focus on American Sign Language (ASL) recognition or push-button input methods. They often overlook the potential of recognizing handwritten gestures [1], [2]. Moreover, most existing smart gloves are designed for medical or gaming applications and lack features tailored for educational purposes [3], [4]. Addressing these gaps requires education-specific features to enhance usability in learning environments.

The SWWGK is designed for presenters, educators, and professionals. It enables dynamic interaction with presentation screens, enriching the learning experience and fostering a stronger connection between human expression and technology. Traditional presentation methods often require physical movement to operate keyboards and pointers, which can disrupt the flow of lectures. The SWWGK provides a more intuitive and convenient input method.

The primary aim of this research is to design and develop a Smart Wireless Wearable Glove Keyboard (SWWGK) that accurately recognizes hand gestures and translates them into English letters. To achieve seamless interaction, a user-friendly interface with a pop-up writing window is incorporated, while optimizing battery life through hardware and software improvements enhances practicality for prolonged usage. The main contributions of this work are as follows:

- Developing an intuitive user interface with a pop-up writing window.
- Implementing robust gesture recognition algorithms for accurate translation of finger trajectory path movements.
- Integrating the SWWGK with presentation software for direct slide interaction through hand gestures.
- Evaluating the performance and effectiveness of the SWWGK in enhancing presentation interactions and user experience.

2 Related Work

In our project, gesture recognition plays a pivotal role in enabling typing or writing on the pop-up window during presentations. Various methods have been explored in previous studies, including push-button glove keyboards, virtual reality keyboards, EEG-based typing, and gesture recognition techniques [1], [5] – [8]. We have chosen gesture recognition due to its effectiveness in facilitating accurate input without requiring physical contact.

Gesture recognition algorithms are critical for converting hand movements into digital commands, enabling intuitive control of presentation software. Key approaches include air gesture mode, fingertip detection, and handwriting detection algorithms. Air gesture mode captures hand movements in mid-air, allowing interaction with presentation software without physical contact. Fingertip detection algorithms track fingertip positions to execute commands with precision. Handwriting detection algorithms interpret handwritten gestures into text, with Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) demonstrating particular effectiveness [5], [6], [9] – [14].

Significant studies have explored various technologies for gesture recognition, including modular data gloves equipped with accelerometers and gyroscopes [5], MyoWare Muscle Sensors for detecting muscle activation [6], and devices utilizing gyroscopes and accelerometers for air-written character recognition [7]. Advanced methods include CNN-based frameworks for gesture recognition [9], [13], and combinations of Support Vector Machine (SVM) with RNNs for text display [14]. Additionally, some researchers have employed MATLAB plotting techniques to visualize gestures [7]. Our choice of air gesture mode, fingertip detection, and handwriting detection is motivated by their demonstrated accuracy and practicality in interactive presentation settings.

To address limitations identified in previous research, we selected the SVM algorithm for handwriting detection, preferring it over CNNs and other machine learning methods. SVM offers several advantages, including efficiency with small datasets, effective handling of high-dimensional feature spaces, and memory efficiency stemming from its reliance on support vectors. Additionally, SVMs manage non-linear decision boundaries effectively, making them well-suited for complex sensor data and diverse user inputs. Their strong generalization capability ensures reliable performance across varied real-world conditions.

Wearable sensors play an increasingly vital role in enhancing Human-Computer Interaction (HCI) by providing intuitive and immersive interfaces. These sensors facilitate the translation of natural hand movements into digital commands, thereby creating a more seamless interaction experience. Effective system design requires not only user-friendly interfaces but also the integration of visual cues and feedback mechanisms to improve gesture recognition accuracy and user comprehension.

In this context, the study presented in [8] demonstrates a real-time wearable system for finger air-writing recognition. The system utilizes an Arduino Nano 33 BLE Sense and employs TensorFlow Lite for on-device recognition and classification of characters. Users can write characters including digits and English lowercase letters in three-dimensional space through finger movements. Motion data captured by Inertial Measurement Units (IMUs) and processed by a microcontroller enables the recognition and interpretation of 36 characters, highlighting the potential for advanced HCI applications in wearable technology.

A smart wireless wearable glove keyboard uses Bluetooth technology to connect wirelessly with devices like laptops, smartphones, and projectors. This enables seamless, cable-free control of presentation software, enhancing user mobility and ensuring reliable communication.

In [15], hand gestures captured by smart gloves with embedded sensors are converted from analog to digital signals using the voltage divider rule. These signals are processed by a PIC microcontroller and transmitted wirelessly via Radio Frequency (RF), incorporating error correction mechanisms at the receiver end. Similarly, in [2], strain sensors detect knuckle positions by converting them into variable resistance values, which are then transformed into voltage signals through voltage dividers. The Teensy microcontroller processes these voltages to generate a binary key representing the knuckle states, which is subsequently transmitted wirelessly.

3 Methodology

The methodology (Fig. 1) for developing the Smart Wireless Wearable Glove Keyboard (SWWGK) integrates hardware design, software development, data collection, and machine learning analysis. This comprehensive approach ensures accurate gesture recognition, reliable system performance, and seamless user interaction.

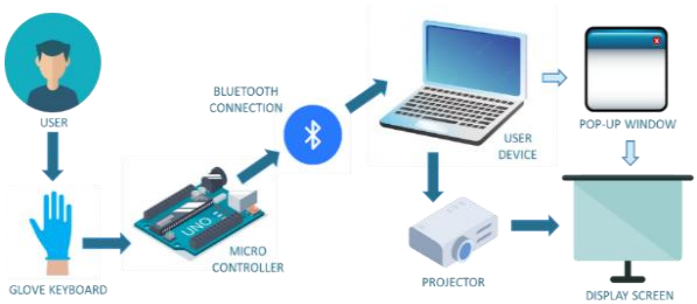

Fig. 1. Working process of smart wireless wearable glove keyboard.

3.1 Hardware Implementation

The hardware system is built around a 3D-printed glove that houses all electronic components, prioritizing user comfort and usability. The ESP32 Dev Kit is employed as the microcontroller due to its compact size, low power consumption, ease of programming, and integrated wireless communication capabilities (Fig. 2). Motion tracking is facilitated by the MPU-6050 sensor, while the TTP223 touch sensor enables intuitive fingertip input. Power is supplied by a 3.7 V LiPo battery, managed through a TP4056 charging module, and controlled via an ON/OFF push button serving as the main switch. The circuit design process begins with schematic development followed by prototyping on a breadboard.

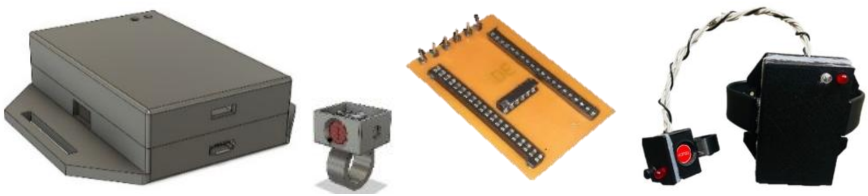

Fig. 2. The stages of hardware development progress.

The hardware and software components are integrated by programming the ESP32 to interface with sensors and establish Bluetooth connectivity with smart devices. Comprehensive testing and validation are conducted to evaluate gesture recognition accuracy and system reliability. The glove is designed in SolidWorks for ergonomics, then 3D printed. The PCB is created using EasyEDA and fabricated on a copper shield. After assembling all components, the system undergoes thorough testing for functionality and wireless communication. Usability testing with volunteers helps refine performance based on feedback.

3.2 Gesture Recognition Software Design

The software design process begins with dataset collection, preprocessing, and augmentation. Data representing 26 alphabet letters were collected from volunteers, with 25 samples recorded for each letter. Each gesture was saved as a text file, creating a structured dataset for model training. To address the limited dataset size, a data augmentation algorithm was applied to extend and diversify the samples, improving model robustness. The Arduino IDE was used to program the ESP32 for Bluetooth connectivity, facilitating communication between the glove and a PC. Python scripts, developed within the Anaconda Jupyter

Notebook environment, supported data collection, preprocessing, and machine learning model development. Gesture-to-text mapping was implemented to translate detected fingertip trajectories into their corresponding characters.

Support Vector Machine (SVM) was selected as the classification algorithm due to its strong performance in trajectory-based recognition. The model was trained on the collected dataset to capture fingertip movement patterns corresponding to each English letter. Training, prediction, and evaluation of the SVM model were carried out in the Jupyter Notebook environment using Python scripts for letter prediction and output, providing an interactive platform for coding and analysis. The user interface was developed in Python using Tkinter, featuring a pop-up writing window that displays recognized text in real time. This interface also supports training data collection and integrates with presentation software, enabling seamless interaction during live sessions. Usability testing was conducted to assess system performance and guide refinements to enhance the user experience.

4 Results and Discussion

The Smart Wireless Wearable Glove Keyboard (SWWGK) demonstrates significant potential as an innovative mid-air text input device. By interpreting hand gestures, the glove enables users to input text without relying on physical surfaces, offering a practical alternative to conventional keyboards. A pop-up writing window provides real-time feedback, enhancing usability in dynamic environments (Fig. 3).

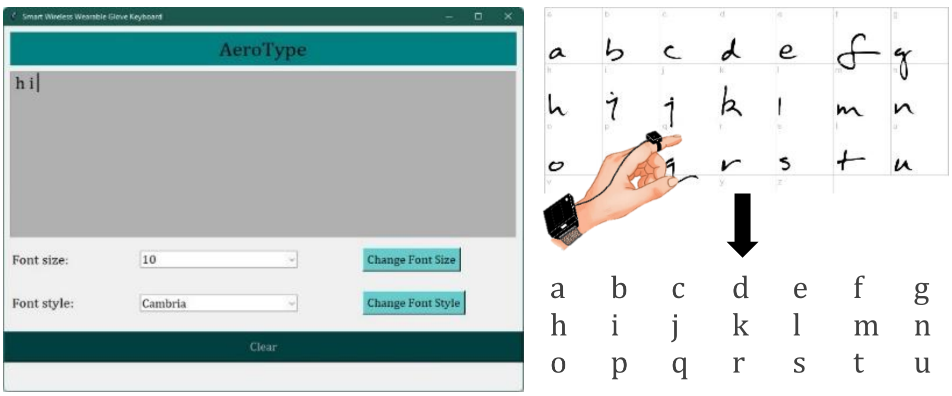

Fig. 3. A sample design of pop-up window with handwritten letter converting process.

The device operates via Bluetooth 4.2 (BLE) with a stable indoor range of up to 10 meters, making it well-suited for settings such as classrooms and conference rooms. From an ergonomic perspective, the glove's dimensions (23 × 26 × 36 mm and 70 × 60 × 20 mm) and weight (100 g) ensure user comfort during extended use. Additionally, its 3.7 V DC battery delivers up to six hours of continuous operation, with a recharge time of 1 to 2 hours.

The glove collects accelerometer and gyroscope data to predict letters, which are displayed in the pop-up window (Fig. 3), enabling continuous mid-air writing. This integration of advanced sensing technology, ergonomic design, and efficient power management renders the SWWGK both user-friendly and versatile.

4.1 Algorithm Overview

Support Vector Machines (SVM) are supervised learning algorithms commonly employed for classification tasks. Their primary objective is to identify an optimal hyperplane that separates data points of different classes within a high-dimensional feature space. This hyperplane is selected to maximize the margin, which is defined as the distance between the hyperplane and the closest data points from each class, known as support vectors. Maximizing this margin typically enhances the model's generalization ability (Fig. 4).

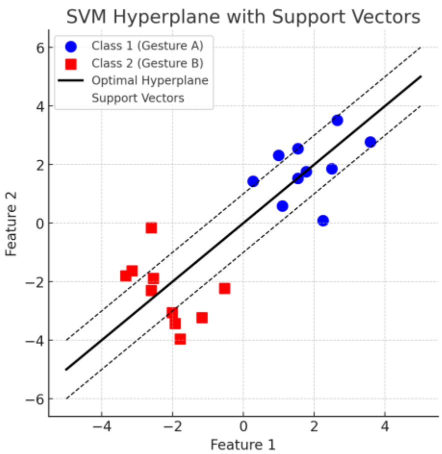

Fig. 4. Illustrates the working principle of SVM, where the optimal hyperplane separates two classes with maximum margin, and the nearest points to the margin are identified as support vectors.

For datasets that are not linearly separable, SVM utilizes kernel functions to map the input data into a higher-dimensional feature space, enabling the algorithm to capture complex, non-linear decision boundaries. Commonly used kernels include linear, polynomial, and Radial Basis Function (RBF), each tailored to suit different classification scenarios.

In this work, the SVM algorithm was applied to classify fingertip trajectory data collected from glove sensors. The feature set was constructed using hand orientation and motion data corresponding to 26 English alphabet gestures. A grid search over the parameters 'C = [0.001, 0.01, 0.1, 1, 10, 100]' and 'kernel = [linear, rbf, poly]' was performed to identify the optimal model configuration. The best performance was achieved using the RBF kernel with C set to 10.

The best-performing SVM model utilized the Radial Basis Function (RBF) kernel with a regularization parameter C=10. Additionally, key hyperparameters included break_ties = False, a cache size of 200 MB, no class weighting (class_weight = None), and coef0 = 0.0. The decision function employed a one-vs-rest (ovr) scheme for multi-class classification, with a polynomial degree of 3 (applicable if a polynomial kernel is used). The gamma parameter was set to 'scale', allowing automatic adjustment based on the data. The model allowed unlimited iterations with max_iter = -1, enabled probability estimates (probability = True), and used the shrinking heuristic (shrinking = True). The tolerance for stopping criteria was set to 0.001, no specific random state was fixed, and verbose output was disabled (verbose = False).

The RBF kernel was selected due to its effectiveness in capturing non-linear relationships within fingertip trajectory data, enabling the model to accurately distinguish complex gesture patterns. The gamma parameter was set to 'scale', allowing automatic adjustment of the influence of individual data points based on the number of features. This provides a balanced trade-off between bias and variance, ensuring stable generalization performance across all 26 gesture classes.

The model was trained and evaluated using a stratified 75–25 train-test split to maintain class distribution consistency. The SVM achieved strong performance metrics, including an accuracy of 89.74%, precision of 0.92, recall of 0.90, and an F1-score of 0.89, demonstrating its robustness in recognizing gesture-based inputs. Such findings resonate with the known advantages of RBF kernels in gesture recognition tasks, where their capacity to model intricate, multi-dimensional data patterns supports high classification accuracy, especially in wearable sensor applications.

4.2 Model Performance Analysis

The confusion matrix (Fig. 5) shows that most letters were classified correctly, as evidenced by the strong diagonal pattern. A detailed classification report in Table 1 provides precision, recall, and F1-score metrics for each letter individually. For benchmarking, a Recurrent Neural Network (RNN) with two Long Short-Term Memory (LSTM) layers was implemented. The performance comparison between the SVM and RNN models is summarized in Table 2. The results indicate that the SVM outperforms the RNN on the current dataset, likely due to its better handling of high-dimensional, structured gesture data and its effectiveness with smaller sample sizes.

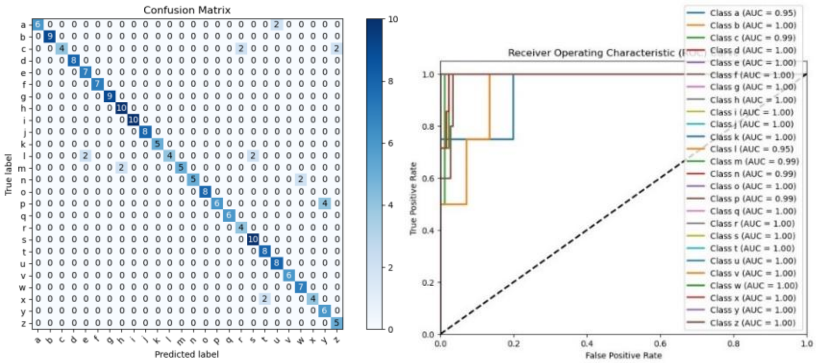

Fig. 5. Confusion matrix & ROC curve displaying classification performance across all 26 letters.

Table 1. Classification report for each letter class using SVM.

Letters	Precision	Recall	F1-score	Letters	Precision	Recall	F1-score
a	1.00	0.75	0.86	n	1.00	0.71	0.83
b	1.00	1.00	1.00	o	1.00	1.00	1.00
c	1.00	0.50	0.67	p	1.00	0.60	0.75
d	1.00	1.00	1.00	q	1.00	1.00	1.00
e	0.78	1.00	0.88	r	0.67	1.00	0.80
f	1.00	1.00	1.00	s	0.83	1.00	0.91
g	1.00	1.00	1.00	t	0.80	1.00	0.89
h	0.83	1.00	0.91	u	0.80	1.00	0.89

i	1.00	1.00	1.00	v	1.00	1.00	1.00
j	1.00	1.00	1.00	w	0.78	1.00	0.88
k	1.00	1.00	1.00	x	1.00	0.67	0.80
l	1.00	0.50	0.67	y	0.60	1.00	0.75
m	1.00	0.71	0.83	z	0.71	1.00	0.73

Table 2. Performance comparison between SVM and RNN.

Model	Accuracy (%)	Precision	Recall	F1-score
SVM	89.74	0.92	0.90	0.89
RNN	69.74	0.72	0.70	0.69

5 Conclusions

The SWWGK demonstrates considerable progress in mid-air handwriting recognition by integrating precise gesture recognition, reliable Bluetooth 4.2 connectivity with an effective indoor range of up to 10 meters, and an ergonomic design optimized for comfort and extended use. Its lightweight structure (approximately 100 g) and compact dimensions ensure user comfort, while a 3.7 V battery enables up to six hours of continuous operation. The SVM model employed delivers strong performance on small, high-dimensional datasets, outperforming alternative models such as CNN and RNN for this application. However, the study's limitations include a relatively small dataset of 25 samples per letter and limited diversity in hand orientation, gesture speed, and environmental conditions, which could impact robustness and generalization. Subtle misclassifications among similar gesture trajectories persist. Future work will focus on expanding the dataset with more diverse users and movement variations, exploring deep learning and hybrid models for improved accuracy, refining hardware design for better ergonomics and power efficiency, and implementing hand gestures for essential keyboard functions such as backspace, enter, delete, and spacebar. Furthermore, extending recognition to include numbers alongside English letters will broaden the system's applicability, ultimately aiming to deliver a more versatile, reliable, and scalable solution for mid-air text input applications.

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