Development of an assistive glove for precision handwriting

Nandhini S[1], *Raji* S[1], *Sakthi* Adhavan M[2] and *Sathiesh* Kumar V[3*]

[1]Student, Department of Electronics Engineering, Madras Institute of Technology, Anna University, Chennai, Tamil Nadu, India.
[2]Student, Department of Electronics Engineering, Madras Institute of Technology, Anna University, Chennai, Tamil Nadu, India.
[3]Assistant Professor (Sl. Gr.), Department of Electronics Engineering, Madras Institute of Technology, Anna University, Chennai, Tamil Nadu, India.
*Corresponding author: sathieshkumar@annauniv.edu

Abstract. Handwriting is one among the most fine-motor work which needs precision, stability and coordination. People with neural disorders have a difficulty in keeping their handwriting steady. This paper discusses the design and development of an assistive glove for precise handwriting. This wearable glove model uses deep learning for checking and improving fine-motor skills. The glove is integrated with two Inertial Measurement Unit (IMU) sensor, flex sensors, and pressure sensors to collect the data of wrist position, finger joint movement, and grip strength during handwriting. The collected data go through preprocessing, normalization, and feature extraction. They are then analysed through an LSTM network for learning sequences over time and classifying movements. The glove is then tested with ten users writing the English alphabets where each user has different speed, different style and different strokes. After training the model achieved an overall accuracy of 81% and a prediction accuracy of 93.7%. These results show that the glove can accurately identify and distinguish handwriting patterns. This framework shows the utilization of sensor integration and LSTM-based modelling for motor rehabilitation and analysing handwriting performance.

1 Introduction

Handwriting serves as an important indicator for motor coordination and neuromuscular control. Quantitative handwriting analysis provides insights about motion stability, trajectory consistency, and control accuracy, making it essential for applications in motor rehabilitation, neuro-assessment, and human–computer interaction.

This work presents a sensor-based handwriting analysis system designed to characterize wrist and finger dynamics into letters using inertial and tactile sensing modalities. The system integrates an Adafruit BNO055 Inertial Measurement Unit (IMU) for three axis acceleration and angular velocity measurement, flex sensors for finger joint displacement, and pressure sensors for pen-surface force measurement. Unlike traditional IMU-based setups which depends on magnetometer readings, this system estimates Euler orientation angles directly from accelerometer-gyroscope fusion, which doesn't get affected by magnetic interference and shows improved stability during continuous motion.

The acquired multi-sensor data is pre-processed to remove drift and noise, which is then used for extraction of temporal and spatial features representing motion smoothness, stroke velocity, and orientation change. Deep learning algorithms are used to classify handwritten alphabets and model temporal dependencies across stroke sequences. This proposed approach enables accurate recognition and detailed evaluation of handwriting behaviour.

2 Literature Survey

[1] Park, M. et al. (2024) developed a stretchable sensing glove for accurate and strong hand-pose reconstruction. Using liquid-metal strain sensors, the glove estimated finger bone lengths and joint angles without calibration. Experimental results showed high accuracy in pose reconstruction and real-time tracking performance across various hand motions.

[2] Zhu, Y. et al. (2022) developed a wearable soft robotic glove for hand rehabilitation and assistive grasping. The system made use of pneumatic actuators integrated with flexible strain sensors for motion detection and feedback. Experimental output demonstrated effective grasp assistance, improved hand mobility, and comfortable usage during rehabilitation exercises.

[3] Wu, C. et al. (2021) developed a low-cost wearable glove designed to capture finger joint angles accurately. The glove is designed with flexible bending sensors and an efficient signal-processing system for real-time motion tracking. Experimental results displayed high precision and stability. It is also cost-effective making it suitable for gesture recognition and rehabilitation applications.

[4] Filipowska, A. et al. (2024) developed a machine learning-based gesture recognition glove using flex sensors and IMUs for motion capture. This system employed machine learning algorithms to accurately

identify hand gestures in real time. Experimental evaluations demonstrated high recognition accuracy, robustness, and potentially stable for applications like human–computer interaction and assistive technologies.

[5] Bryantono, H.D. et al. (2025) developed soft gripper gloves with a mirroring system for hand rehabilitation. This design used pneumatic actuators to mirror healthy hand movements onto the impaired hand. Experimental results showed strong motion synchronization, improved rehabilitation efficiency, and enhanced user adaptability through intuitive bilateral control.

[6] Guo, Y. et al. (2025) proposed an approach for dynamic air-writing recognition using wearable wristbands. The system employed self-supervised learning to adapt to individual writing styles. Experimental results demonstrated improved recognition accuracy, robustness to user variation, and efficient real-time performance in writing tasks.

[7] Lim, D.Y.L., Lai, H.S. and Yeow, R.C.H. (2023) developed a bidirectional fabric-based soft robotic glove for assisting hand function in chronic stroke patients. The glove is incorporated with fabric pneumatic actuators enabling both flexion and extension. Experimental results showed improved grasp strength, movement range, and functional recovery during rehabilitation therapy.

[8] Hu, C., Neate, T., Luo, S. and Gionfrida, L. (2025) developed, a multimodal soft exoskeleton glove designed for transparent object grasping assistance. The system integrated motion, visual, and force sensors for adaptive control. Experimental results demonstrated improved grasp stability and precision in robotic assistive applications.

[9] Ridremont, T. et al. (2024) developed a soft robotic bilateral system for coordinated hand and wrist therapy. The system utilized pneumatic actuators and embedded sensors to copy the motion from the healthy limb to the impaired one. Experimental outcomes showed enhanced joint mobility, movement symmetry, and rehabilitation effectiveness.

[10] Harrison, A. et al. (2024) conducted a systematic evaluation of IMU sensors for smart glove applications in hand monitoring. Various IMU sensors were analysed for accuracy, stability, and drift. Results identified optimal sensor configurations, enhancing motion tracking precision and reliability in smart rehabilitation and monitoring systems.

[11] Bublin, M. et al. (2023) developed SensoGrip, a handwriting evaluation system using deep learning techniques. The device integrated pressure and motion sensors to capture detailed handwriting motions. Experimental results showed high accuracy in testing handwriting quality, grip pressure, and motion patterns, supporting rehabilitation and motor skill analysis.

[12] Park, W., Babushkin, V., Tahir, S. and Eid, M. (2021) developed a guidance system to support handwriting in children with cognitive and fine motor delays. The system provided real-time feedback through a stylus to guide writing motions. Experimental results showed improved handwriting accuracy, stability, and motor coordination.

[13] Fei, F. et al. (2021) developed a wearable glove system integrated with multiple sensors for collective hand kinematics assessment. The glove consists of flex, pressure, and IMU sensors to capture detailed finger and wrist movements. Experimental validation confirmed high accuracy and potential for rehabilitation and human–computer interaction applications.

[14] Xia, Q. et al. (2025) developed a wearable glove with improved sensitivity using push–pull optical fiber sensors. The system captured fine finger movements with high precision and fast response. Experimental results demonstrated improved motion detection accuracy, gesture recognition, making it suitable for rehabilitation.

[15] Ruppel, P. and Zhang, J. (2024) developed an elastic tactile sensor glove for dexterous teaching. The glove integrated soft tactile sensors to capture detailed finger forces and contact patterns. Experimental results showed accurate motion and force reading, enabling effective skill transfer and teaching in robotic manipulation tasks.

[16] Li, F. et al. (2023) developed a soft robotic glove consisting of sensing and force feedback for rehabilitation in virtual reality environments. The glove combined flex sensors and actuators to provide real-time motion tracking and haptic feedback. Experimental outcomes demonstrated enhanced engagement, accurate hand motion replication, and effective rehabilitation results.

[17] Kottink, A.I. et al. (2024) examined the therapeutic effects of a wearable assistive soft robotic glove on hand function during home use. The glove provided grip-strength support via soft actuators. Results showed improved hand strength, functional performance, demonstrating the glove's effectiveness for extended home-based rehabilitation.

[18] Zhu, Y. et al. (2022) developed a novel wearable soft glove for hand rehabilitation and assistive grasping. The glove is embedded with pneumatic actuators and flexible strain sensors for motion detection and adaptive assistance. Experimental validation demonstrated improved hand mobility, effective grasp support, improved user comfort and human-machine interaction during rehabilitation exercises.

3 Proposed Methodology

The proposed system aims to develop a robust, precise and adaptable assistive glove which is capable of accurately analysing handwriting patterns through multi-sensor data integration and deep learning. This model captures fine motor activity during writing to quantify motion characteristics, detect inaccuracies, and provide feedback for performance assessment and rehabilitation (Fig 1).

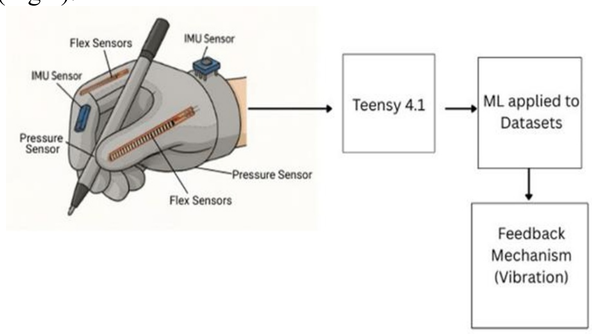

Fig 1. Block Diagram

Data collected from the Inertial Measurement Unit (IMU) sensor, flex sensors, and pressure sensors are integrated to get spatial and temporal representations of wrist and finger movements. The IMU sensor provides acceleration and angular velocity values for orientation estimation, flex sensors capture finger joint bends, and pressure sensors record pen-surface interaction forces.

A Long Short-Term Memory (LSTM) network is used to train temporal dependencies within the multi-sensor system. The LSTM processes time-series input to learn motion patterns associated with individual alphabets and individual writing behaviours, which then enables robust recognition and anomaly detection. This architecture provides high precision, adaptability, and reliability in handwriting pattern analysis for both assistive and rehabilitative applications.

3.1 System Architecture

The two primary domains of the assistive glove architecture are software and hardware. The hardware module is used for sensing, collecting data, and transmitting information. The software module manages feedback creation, machine learning-based classification, feature extraction, and signal conditioning. The microcontroller first processes the data collected by the sensors built into the glove, synchronizes the data, and then sends it to a computer or cloud interface for further analysis.

There are four primary steps for the entire workflow:

- Data acquisition: Using embedded sensors to record unprocessed motion, pressure, and orientation inputs.
- Preprocessing: Eliminating noise and outliers from the collected data by filtering and standardizing it.
- Feature Extraction: Extracting spatial and temporal properties from processed information.
- Analysis and Feedback: Performance indicators are provided and handwriting patterns are categorized using machine learning methods.

3.2 Hardware Setup

The hardware setup is the integration of various sensors, to detect the orientation, acceleration, bending angles and the pressure applied for each character to each individual for accurate prediction (Fig 2).

3.2.1 IMU Sensor

The Adafruit BNO055 IMU sensor used in this system is a compact 6 degree-of-freedom sensor consisting of a 3-axis accelerometer and a 3-axis gyroscope. One is placed on the back side of the hand and the other is on the pen holder to capture wrist orientation, angular velocity, and linear acceleration during handwriting. The sensor operates at a 100 Hz sampling frequency and communicates via I²C protocol at 3.3 V. The sensor provides stable, low-latency motion data which is essential for accurate wrist movement tracking and handwriting analysis.

3.2.2 Flex Sensor

Flex sensors are resistive sensors whose electrical resistance varies proportionally with mechanical bending. They are positioned along the index and thumb fingers to quantify flexion during handwriting. Bending of the finger produces a linear change in resistance, which is then converted to an analog voltage signal and processed to estimate joint displacement. The sensors are connected to the microcontroller through an analog input channel, with an operating range of 3.3–5 V.

3.2.3 Pressure Sensor

Pressure sensors are transducers which convert the applied force into electrical signals. In this system, the Force Sensitive Resistor (FSR) sensors are placed on pen holding region and palm region to measure grip strength and pen-tip pressure during handwriting. The sensor values increase with increasing applied pressure.

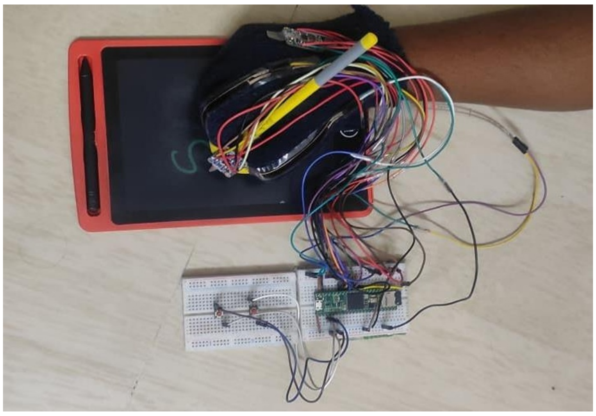

Fig 2. Hardware Setup

3.3 Dataset Collection

The dataset utilized in this work was collected through a custom-designed wearable system integrating tIMU sensors, flex sensors, and pressure sensors. The sensors were interfaced with a microcontroller that continuously recorded all signal streams in real time and stored them in comma-separated value (.csv) format for further processing. The structure of the recorded data is as follows:

- **IMU1_Yaw, IMU1_Pitch, IMU1_Roll**: Euler orientation angles obtained from the first IMU, mounted near the wrist (Fig 3).

- **IMU1_AccX, IMU1_AccY, IMU1_AccZ**: Linear acceleration components along X, Y, and Z axes for IMU1.
- **IMU1_GyrX, IMU1_GyrY, IMU1_GyrZ**: Angular velocity values measured by the gyroscope in IMU1.
- **IMU2_Yaw, IMU2_Pitch, IMU2_Roll**: Euler orientation angles from the second IMU, mounted closer to the fingers for fine-motor tracking (Fig 4).
- **IMU2_AccX, IMU2_AccY, IMU2_AccZ**: Linear acceleration readings from IMU2.
- **IMU2_GyrX, IMU2_GyrY, IMU2_GyrZ**: Angular velocity values from IMU2 sensor.
- **Flex1, Flex2**: Flex sensor values representing finger bending resistance (Fig 4).
- **Press1, Press2**: Pressure sensor outputs measuring the grip force and writing pressure on the surface.

During dataset collection, participants were instructed to write English alphabets (A–Z), each 20 times individually at different speeds and different styles. Each letter strokes were captured as a continuous multivariate time series consisting of orientation, acceleration, angular velocity, flexion, and pressure values. Each letter's data was segmented, labeled, and stored independently in .csv format, to have a neat and clear separation for supervised learning.

The final dataset consists of multiple repetitions of each alphabet from different users of different speed and different styles to contribute for inter-person variations in writing style, stroke patterns, and pressure intensity. This dataset was used to train the Long Short-Term Memory (LSTM) network to learn the temporal dependencies and sequence transitions possessed in human handwriting motion patterns.

Time(ms)	IMU1_Yaw	IMU1_Pitc	IMU1_Roll	IMU1_Acc	IMU1_Acc	IMU1_Acc	IMU1_Gyr	IMU1_Gyr	IMU1_Gyr	IMU2_Yaw
29473	9.19	-1.31	0.25	-0.21	-0.01	9.42	0	0.19	-0.06	0.13
29491	9.19	-1.31	0.25	-0.22	0	9.4	0.06	-0.06	0	0.13
29504	9.19	-1.31	0.25	-0.22	-0.01	9.4	0.13	-0.06	-0.06	0.13
29516	9.19	-1.31	0.25	-0.23	-0.02	9.4	0.06	0.19	0	0.13
29531	9.19	-1.31	0.25	-0.23	-0.02	9.43	-0.06	0.06	0	0.13
29544	9.19	-1.31	0.25	-0.21	0	9.41	0.06	0	-0.13	0.13
29555	9.19	-1.31	0.25	-0.22	0	9.4	0.06	-0.06	0	0.13
29568	9.19	-1.31	0.25	-0.23	-0.01	9.42	-0.06	0.06	-0.06	0.13
29583	9.19	-1.31	0.25	-0.22	0	9.39	-0.06	0	-0.06	0.13
29595	9.19	-1.31	0.25	-0.23	-0.01	9.41	0	-0.06	0	0.13

Fig 3. Data sets (IMU 1)

IMU2_Pitc	IMU2_Roll	IMU2_Acc	IMU2_Acc	IMU2_Acc	IMU2_Gyr	IMU2_Gyr	IMU2_Gyr	Flex1	Flex2	Press1	Press2
-1.25	4.06	-0.23	-0.68	9.34	0	-0.13	0	193	307	44	133
-1.25	4.06	-0.23	-0.69	9.35	-0.06	0.06	-0.06	192	307	42	136
-1.25	4.06	-0.22	-0.67	9.33	0	-0.06	-0.06	215	326	69	158
-1.25	4.06	-0.2	-0.69	9.34	-0.13	0.06	0	192	306	42	147
-1.25	4.06	-0.2	-0.67	9.35	0	-0.13	0	192	304	41	139
-1.25	4.06	-0.22	-0.67	9.3	-0.06	-0.06	0.06	192	303	41	132
-1.25	4.06	-0.22	-0.67	9.35	-0.06	0	0	219	322	72	164
-1.25	4.06	-0.22	-0.67	9.32	-0.06	-0.06	0.19	194	300	41	140
-1.25	4.06	-0.22	-0.67	9.35	-0.06	0	0	195	299	42	140
-1.25	4.06	-0.21	-0.66	9.34	0	-0.19	0.06	194	298	41	143

Fig 4. Data sets (IMU 2, Flex, Pressure)

3.4 Execution Flow

The execution flow of the work assistive glove for handwriting analysis follows a structured sequence from data collection to real-time implementation, also with accurate processing and model evaluation (Fig 5).

1. **Sensor Initialization and Calibration**
   - The IMU, flex, and pressure sensors are first initialized and calibrated to minimize noise, drift, and signal offset.
2. **Dataset Collection**
   - The users are instructed to write English alphabets at different speed and different styles.
   - The IMU sensors captures orientation, acceleration and angular velocity, flex sensors measure finger bending resistance, and pressure sensors measure grip and pen-tip force.
   - The synchronized sensor readings are labelled with their corresponding letters and stored in .csv files for further processing.
3. **Data Transmission and Storage**
   - Sensor data are transmitted to the microcontroller via I²C protocol and analog channels.
   - Datasets are then transferred to a local system or cloud storage for processing.
4. **Preprocessing**
   - Raw signals from each sensors undergo filtering, drift correction, and normalization.
   - Time alignment within the sensors ensures accurate temporal synchronization of the dataset.
5. **Feature Extraction and Segmentation**
   - Handwriting sequences are separated into temporal windows as strokes or individual letters.
   - The necessary motion, flex and pressure-based features are extracted for input fed to the machine learning model.
6. **Model Processing (LSTM Network)**
   - Pre-processed datasets in the form of .csv files are used to train the LSTM network.
   - The LSTM model learns temporal dependencies of sensor data which is then used to classify handwriting patterns and detect irregular motion.
7. **Real-Time Implementation**
   - The trained LSTM model is incorporated on a computer or a microcontroller.
   - Live sensor inputs are processed for real-time prediction and immediate feedback is displayed.
   - The system provides real-time representation of wrist orientation, finger flexion, and pressure variations, helping in handwriting performance evaluation and rehabilitation.
8. **Performance Evaluation**
   - The trained model's performance is examined based on accuracy, loss convergence, and latency.
   - Results are used to test the system's efficiency for both offline analysis and real-time handwriting prediction.

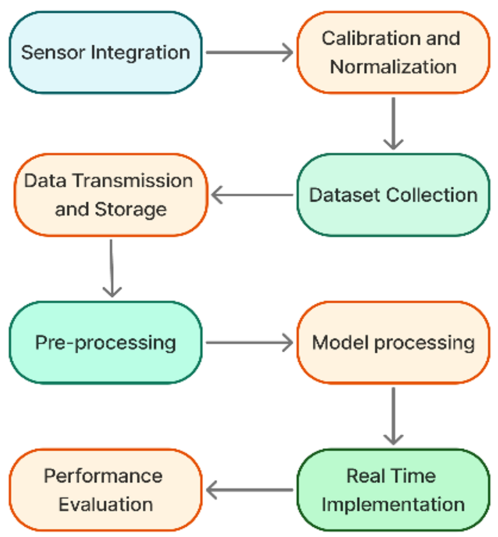

Fig 5. Flow Diagram

3.5 Deep Learning Network

A Long Short-Term Memory (LSTM) network is used to train the temporal sequence variations of handwriting motion data. LSTM, a special type of recurrent neural network (RNN), which effectively captures long-range dependencies within sequential sensor readings, due to which it is suitable for analysing continuous motion patterns. The pre-processed multiple sensor data comprising orientation, acceleration, angular velocity, finger flexion, and pressure signals are given as time-series inputs to the LSTM. The network learns the spatiotemporal relationships between sensor values for differentiating between various handwriting patterns and detecting the variations in stroke formation.

3.5.1 Importance of the Network Utilized (LSTM)

The Long Short-Term Memory (LSTM) network plays an important role in the proposed assistive glove for handwriting analysis system. Its primary importance is, its ability to effectively learn temporal dependencies present in sequential sensor data collected during handwriting motion.

1. **Temporal Sequence Learning:**
   The LSTM network is good at capturing time-dependent relationships between sensor readings. It understands the continuous movement of handwriting strokes, ensuring that the recognition model considers both current and past motion states, which is important in distinguishing between similar alphabet shapes.

2. **Overcoming the Vanishing Gradient Problem:**
   Traditional Recurrent Neural Networks (RNNs) often suffer from gradient vanishing during training. This leads to poor learning over long sequences. The LSTM overcomes this through its gated memory cell mechanism consisting the input, forget, and output gates. These gates control how information is stored, retained, and forgotten.

3. **Robustness to Noise and Variability:**
   In real-world implementation, sensor data can contain noise, drift, and signal fluctuations due to different hand pressure or sensor misalignment. The LSTM network's sequential filtering nature helps in ignoring irrelevant variations while only focusing on consistent temporal motions.

4. **Real-Time Predictive Capability:**
   The LSTM network supports real-time processing, assisting the system to perform live classification of handwriting movements. Once trained, it can predict the alphabet being written from live sensor data, providing immediate prediction result for handwriting recognition and rehabilitation.

5. **High Accuracy and Adaptability:**
   The LSTM-based model achieved over 90% classification accuracy, displaying its ability to learn complex motion patterns. It is flexible in easily adapting to different datasets, writing speeds, and user hand structures. Due to this it is highly used for broader applications in assistive and rehabilitative systems.

3.5.2 Architecture of the Network

The proposed architecture is designed to process multiple sensor data obtained from the assistive glove for real-time letter classification (Fig 6).

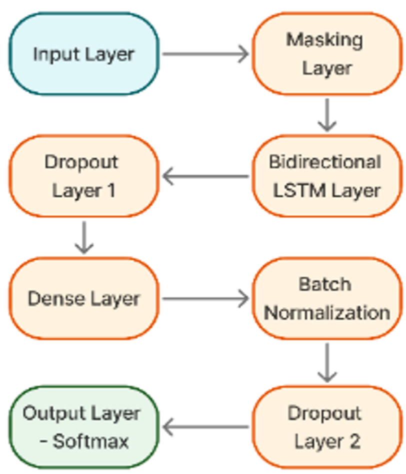

Fig 6. Architecture Diagram

1. **Input Structure**
- Input features: Sensor fusion data from IMU (accelerometer + gyroscope), flex, and pressure sensors.
- Each time step → 23-dimensional vector (depending on sensor count).
- Input sequence length: Varies per gesture, normalized during preprocessing.
- Data normalization: Min–Max scaling to range [0, 1] to ensure uniform sensor response.

2. **Core LSTM Mechanism:**
   Each LSTM cell maintains:

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C_t} \tag{1}$$

$$h_t = o_t * \tanh(C_t) \tag{2}$$

Where:

$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$→ Forget gate
$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$→ Input gate

$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$→ Output gate
$\widetilde{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$→Candidate state

3. **Training Configuration**

- Optimizer: Adam (learning rate = 0.001)
- Loss Function: Categorical cross-entropy
- Epochs: 100
- Evaluation Metrics: Accuracy, Precision, Recall, F1-score

4. **Weight and Bias Updates**

- All gate operations involve separate trainable weights (W_f, W_i, W_o, W_c) and biases (b_f, b_i, b_o, b_c).
- Updated through backpropagation through time (BPTT) using gradient descent.
- Gradients clipped to avoid exploding values.

5. **Output Interpretation**

- The Softmax layer converts the final dense output into a class-probability vector:

$$P(y_i) = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}} \quad (3)$$

- The class with maximum is assigned as the recognized letter.
- The confidence value represents prediction probability for the chosen class.

6. **Model Performance**

- Achieved mean training accuracy: ≈ 81 %
- Achieved Prediction Accuracy: ≈ 93.7 %
- Consistent recognition for most classes; minor confusion observed between similar letter patterns (e.g., Q vs G).
- Confusion matrix visualization aids in class-level error diagnosis and precision tuning.

4 Results

The proposed multi-sensor handwriting analysis system was experimentally validated through both offline training and real-time testing. Data were collected from multiple participants performing English alphabets and structured handwriting patterns. The dataset included time-synchronized samples of wrist orientation, finger bending, and pen pressure, representing the full temporal and spatial dynamics of handwriting motion.

The LSTM network showed strong accuracy in learning temporal dependencies and differentiating between individual alphabet patterns. During model training, the loss function depicted stable convergence with no signs of overfitting, indicating robust performance. The trained model achieved consistently high classification accuracy (Fig 7) across multiple users, confirming its ability to recognize distinct handwriting patterns and motion sequences. The confusion matrix revealed only a small misclassification among similar-shaped letters. The model is trained to achieve high prediction accuracy of 93.7% (Fig 8) for effective real time implementation.

Overall, the integration of IMU, flex, and pressure sensors enabled precise motion tracking, while the LSTM model effectively captured the nonlinear and temporal characteristics of handwriting. The results confirm that the proposed system is highly used for both quantitative handwriting recognition and motor rehabilitation applications. The system demonstrates high scalability, adaptability, and robustness under varying user conditions.

	precision	recall	f1-score	support
A	0.89	0.80	0.84	20
B	0.72	0.54	0.62	24
C	0.96	0.93	0.95	28
D	0.75	0.78	0.77	23
E	0.82	0.56	0.67	25
F	0.62	0.62	0.62	21
G	0.83	0.88	0.86	17
H	0.66	0.70	0.68	27
I	0.80	0.67	0.73	18
J	0.85	1.00	0.92	23
K	0.50	0.75	0.60	16
L	1.00	0.85	0.92	26
M	0.85	0.76	0.80	29
N	0.71	0.83	0.77	12
O	0.79	1.00	0.88	19
P	0.61	0.74	0.67	19
Q	0.93	0.89	0.91	28
R	0.80	0.80	0.80	20
S	0.92	0.88	0.90	25
T	0.93	0.89	0.91	28
U	0.79	0.85	0.81	26
V	0.71	0.71	0.71	17
W	1.00	0.69	0.82	13
X	0.78	0.88	0.82	24
Y	0.85	0.85	0.85	26
Z	0.91	0.97	0.94	31
accuracy			0.81	585
macro avg	0.81	0.80	0.80	585
weighted avg	0.82	0.81	0.81	585

Fig 7. LSTM Results

```
----------------------------------------
✅ Total Files Tested: 4922
✅ Correct Predictions: 4612
🎯 Overall Accuracy on All Folders: 93.70%
----------------------------------------
```

Fig 8. Prediction Accuracy

5 Conclusion

Experimental results demonstrate that the proposed system achieves high recognition accuracy and strong generalization across different subjects and writing conditions. The sensor fusion approach enhances robustness by compensating for individual sensor limitations, while the LSTM model ensures efficient handling of time-dependent variations in writing strokes. Furthermore, the real-time implementation confirms the framework's capability to provide immediate performance feedback with low latency and reliable data transmission.

Overall, the proposed system establishes a technically useful framework for handwriting evaluation and motor rehabilitation. It builds a foundation for future advancements in adaptive assistive technologies, in which personalized feedback and dynamic learning can be integrated to support individuals with motor impairments, also improve fine motor control, and facilitate rehabilitation through intelligent, data-driven analysis.

Future work will focus on expanding the dataset across varied users and implementing adaptive learning for personalized feedback. Further optimization will also be incorporated to achieve real-time, on-device processing and enhanced portability.

Acknowledgement

This research work is funded by Directorate of Technical Education (DoTE), Government of Tamil Nadu under Chief Minister Research Grant (CMRG 2023 - 24), Project ID: CMRG2023AEC02008.

References

1. M. Park, T. Park, S. Park, S.J. Yoon, S.H. Koo, Y.L. Park, Stretchable glove for accurate and robust hand pose reconstruction based on comprehensive motion data. Nature communications, **15**(1), 5821 (2024).
2. Y. Zhu, W. Gong, K. Chu, X. Wang, Z. Hu, Su, H. A novel wearable soft glove for hand rehabilitation and assistive grasping. Sensors, **22**(16), 6294 (2022).
3. C. Wu, K. Wang, Q. Cao, F. Fei, D. Yang, X. Lu, B. Xu, H. Zeng, A. Song, Development of a low-cost wearable data glove for capturing finger joint angles. Micromachines. **12**(7), 771 (2021).
4. A. Filipowska, W. Filipowski, P. Raif, M. Pieniążek, J. Bodak, P. Ferst, K. Pilarski, S. Sieciński, R.J. Doniec, J. Mieszczanin, E. Skwarek, Machine learning-based gesture recognition glove: design and implementation. Sensors (Basel, Switzerland). **24**(18), 6157 (2024).
5. H.D. Bryantono, C.Y. Su, J.K. Huang, T.W. Xin, S.C.Tseng, Soft Gripper Gloves with Mirroring System Design for Hand Rehabilitation. Engineering Proceedings. **103**(1), 29 (2025).
6. Y. Guo, K. Li, W. Yue, N.Y. Kim, Y. Li, G. Shen, J.C. Lee, A rapid adaptation approach for dynamic air-writing recognition using wearable wristbands with self-supervised contrastive learning. Nano-Micro Letters, **17**(1), 41 (2025).
7. D.Y.L. Lim, H.S. Lai, R.C.H. Yeow, A bidirectional fabric-based soft robotic glove for hand function assistance in patients with chronic stroke. Journal of neuroengineering and rehabilitation, **20**(1), 120 (2023).
8. C. Hu, T. Neate, S. Luo, L. Gionfrida, L., MultiClear: Multimodal Soft Exoskeleton Glove for Transparent Object Grasping Assistance. In Annual Conference Towards Autonomous Robotic Systems, pp. 195-209. Cham: Springer Nature Switzerland (2025).
9. T. Ridremont, I. Singh, B. Bruzek, V. Erel, A. Jamieson, Y. Gu, R. Merzouki, M.B. Wijesundara, Soft Robotic Bilateral Rehabilitation System for Hand and Wrist Joints. Machines. **12**(5), 288 (2024).
10. A. Harrison, A. Jester, S. Mouli, A. Fratini, A. A. Jabran, Systematic Evaluation of IMU Sensors for Application in Smart Glove System for Remote Monitoring of Hand Differences. Sensors, **25**(1), 2 (2024).
11. M. Bublin, F. Werner, A. Kerschbaumer, G. Korak, S. Geyer, L. Rettinger, E. Schönthaler, M. Schmid-Kietreiber, Handwriting evaluation using deep learning with SensoGrip. Sensors, **23**(11). 5215 (2023).
12. W. Park, V. Babushkin, S. Tahir, M. Eid, Haptic guidance to support handwriting for children with cognitive and fine motor delays. IEEE Transactions on Haptics, **14**(3), 626-634 (2021).
13. F. Fei, S. Xian, X. Xie, C. Wu, D. Yang, K. Yin, G. Zhang, Development of a wearable glove system with multiple sensors for hand kinematics assessment. Micromachines. **12**(4), 362 (2021).
14. Q. Xia, X. Zhang, H. Wang, L. Yuan, T. Yuan, Wearable Glove with Enhanced Sensitivity Based on Push–Pull Optical Fiber Sensor. Biosensors. **15**(7), 414 (2025).
15. P. Ruppel, J. Zhang, Elastic tactile sensor glove for dexterous teaching by demonstration. Sensors, **24**(6), 1912 (2024).
16. F. Li, J. Chen, G. Ye, S. Dong, Z. Gao, Z. Zhou, Y. Soft robotic glove with sensing and force feedback for rehabilitation in virtual reality. Biomimetics, **8**(1), 83 (2023).
17. A.I. Kottink, C.D. Nikamp, F.P. Bos, C.K.V.D. Sluis, M.V.D. Broek, B. Onneweer, J.M. Stolwijk-Swüste, S.M. Brink, N.B. Voet, J.S. Rietman, G.B. Prange-Lasonder, Therapy effect on hand function after home use of a wearable assistive soft-robotic glove supporting grip strength. Plos one, **19**(7), e0306713 (2024).
18. Y. Zhu, W. Gong, K. Chu, X. Wang, Z. Hu, H. Su, A novel wearable soft glove for hand rehabilitation and assistive grasping. Sensors. **22**(16), 6294 (2022).