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MACHINE LEARNING BASED SYSTEM FOR PREDICTING FINGER MOVEMENT OF THE ROBOTIC HAND USING SMART GLOVE

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Abstract
In robot-assisted surgeries, robots are familiar with performing many complicated surgeries with minimal invasiveness and flexibility. This research paper aims to propose a machine learning (ML)-based method for predicting finger movement of the robotic hand. The method utilizes Smart gloves with Light Dependent Resistor (LDR)-based sensors to control Robotic hand-finger movements. The ESP-WROOM-32 microcontroller, connected via Arduino IDE and Jupyter software, records real-time finger movements, including flexion and extension, refined by the microcontroller before real-time integration between the Smart glove and robotic hand. The data generated corresponds to different movements of different fingers involved in multi-learning problems, which deal with scenarios requiring the synchronous prediction or analysis of multiple outputs, such as in multi-output regression. To address this problem, we used the ML algorithm (K-nearest neighbors regressor). This regressor has the inherent property of handling the multiple output regression problem. The regressor used was estimated to predict finger movements concerning Root Mean Square Prediction Error (RMSPE). After implementing this algorithm in real-time integration of the Smart glove and robotic hand, our robotic hand has successfully moved the finger toward the smart glove. The proposed method improves control precision, reduces latency, and improves the user experience, potentially revolutionizing artificial limb control and remote robot operation.

1. INTRODUCTION

The first robotic prosthetic hand, developed in 1986, uses Resolved Inter-Finger Decoupling Solver (RIFDS) and Resolved Inter-Joint Decoupling Solver (RIJDS) processes for flexible gripping on geometric objects, focusing on noise reduction, lightness, and human sensitivity [1]. Substitute electronic devices are becoming more complex, with 60% having 1-4 degrees of flexibility, 30% 5-10 degrees, and 10% more than 10 degrees [2]. ML uses past data to identify patterns, predict future events, and enhance Internet of things (IoT) networks' predictive capabilities for various use cases and automation possibilities [3]. Robotic surgery has significantly impacted the medical field, allowing surgeons to perform complex procedures with greater precision and flexibility, increasing the percentage of general surgery operations using robot assistance [4]. Research is ongoing to capture hand movements and respond to robotic hand control, enabling natural and intuitive control of tele-robots remotely [5].

In the context of the research scope, we are introducing two pivotal elements: the robotic hand [6], "Using 3D

Printing Technology to Develop Electromyography Signals Based Prosthetic Arm" and the smart glove. The robotic hand, designed to be controlled by Smart gloves, eliminates electromyography (EMG) usage and serves as the visible endpoint of the project. These two technological components are at the core of our undertaking, each contributing distinct capabilities to the broad system we aim to create.

ML is a multidisciplinary field that involves creating algorithms that enable computers to learn, encompassing various disciplines such as information technology, statistics, artificial intelligence, psychology, and neurobiology [7]. There are different types of ML (supervised, unsupervised, semi-supervised, and reinforcement learning) [8][9]. Data Pre-processing includes data cleaning, normalization, transformation, feature extraction, selection, etc. It decreases the dimensionality of the data collected from the Smart glove, allowing learning algorithms to function more quickly and effectively [10][11]. A model fitted to a dataset containing several related problems is known as Multitask Learning (a type of Supervised learning). The objective is to create a model that can be trained on diverse tasks so that training across multiple tasks improves model performance over training on a single task. A multitasking learning case or supervised learning problem often enlists the same input pattern for many outputs. In this arrangement, each output can be predicted by a separate portion of the model, allowing the model's core to generalize across tasks with the same inputs [12]. K-Nearest Neighbors (KNN) is a machine learning technique used for classification and regression tasks, assuming similar data points and using the complete training dataset as a reference. For KNN classification, we utilized accuracy to measure how closely our predictions matched the actual labels. Since our predictions rarely match the effective response variable values, we cannot manage to apply the same metric in the regression context. Therefore, we instead used RMSPE in the context of KNN regression [13].

$$RMSPE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (1)$$

Where:

- η is the number of observations,
- y_i is the observed value for the i^{th} observation,
- $\hat{y}_i$is the forecasted/predicted value for the i^{th} observation.

This research aims to develop an innovative robot control method using Smart gloves and advanced ML techniques. The gloves, equipped with sensors, allow robots to accurately emulate human hand movements, simplifying control in areas like healthcare and production while decreasing material costs. The objectives of this research are to design a wearable, sensor-based glove that records finger movements, collect data for each finger corresponding to angle values, develop an ML model using the KNN algorithm based on Python (Jupyter Notebook), and integrate a Smart glove and Robotic hand on Jupyter.

2. Proposed Work

The schematic figure for the suggested method is demonstrated in Fig. 1.

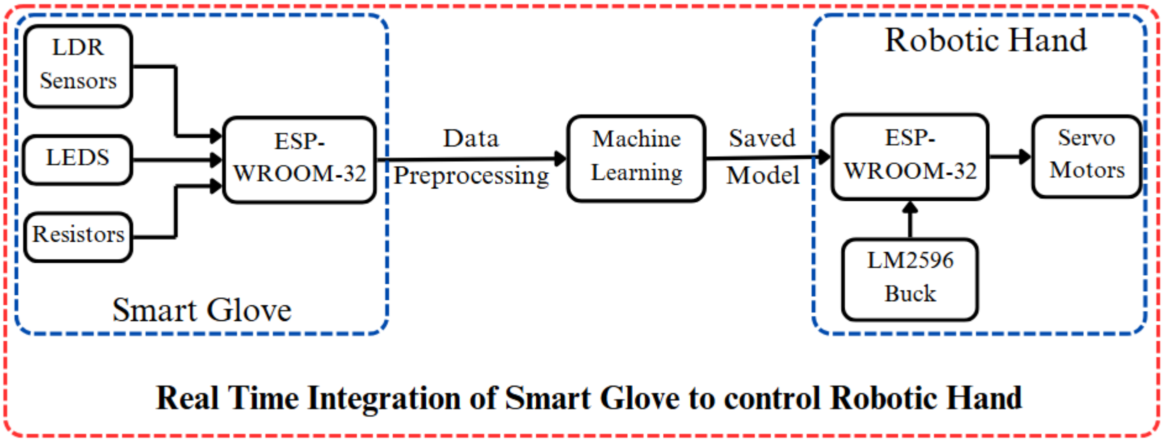

Fig.1. Schematic Representation of Real-Time integration of smart glove and Robotic hand

2.1 Smart Glove Interface

While constructing a Smart glove to operate a robotic hand includes many essential steps. The Smart glove's preliminary steps include integrating a LDR sensor and an light emitting diode (LED) to capture sophisticated hand motions. An ESP32 microcontroller installed within the smart glove see Fig. 2, subsequently process this sensory data in real-time.

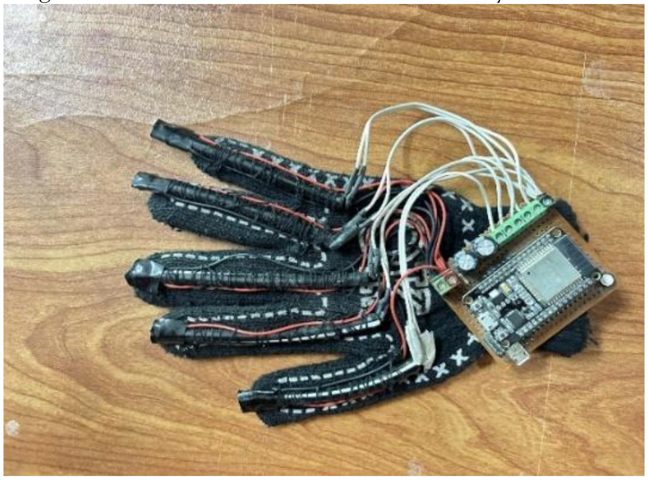

Fig. 2. Smart Glove Prototype

2.1 Robotic Hand Prototype

The robotic hand is furnished with servo motors, as shown in Fig. 3. It facilitates the synchronization of complex finger motions. The robotic hand's design incorporates an LM2596 Buck to control the power delivered to the servo motors, ensuring the stability and effectiveness of these movements.

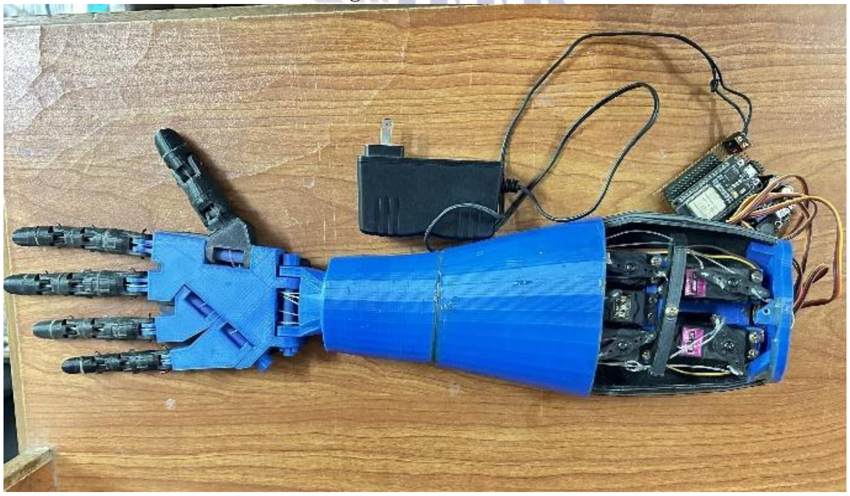

Fig. 3. Robotic Hand Prototype

3. Workflow

Controlling robotic hand finger movements with a smart glove typically falls under the category of a closed feedback system. In a closed feedback system, there is a continuous loop where the system receives feedback from sensors (the smart glove), processes the information, and adjusts the output accordingly to achieve the desired result (controlling the robotic hand).

This research has successfully integrated a robotic hand with a smart glove, with a strong emphasis on mapping finger movements to equivalent actions on the robotic hand. The wearable prototype (Smart Glove) consists of LDR sensors that provide voltage and angle values regarding finger movements. The voltage and angle value of separate fingers are sent to the microcontroller through the Arduspreadsheet. Serial values are then sent to the trained model and used to generate predictions. After predictions, evaluate the model and save it in the Joblib library. Collect the real-time data from the Smart glove through Arduino and send it to Jupyter. Jupyter reads data from the glove, predicts the angle of each finger, and then sends it to a robotic hand. The final working process of the prototype is represented in Fig. 4.

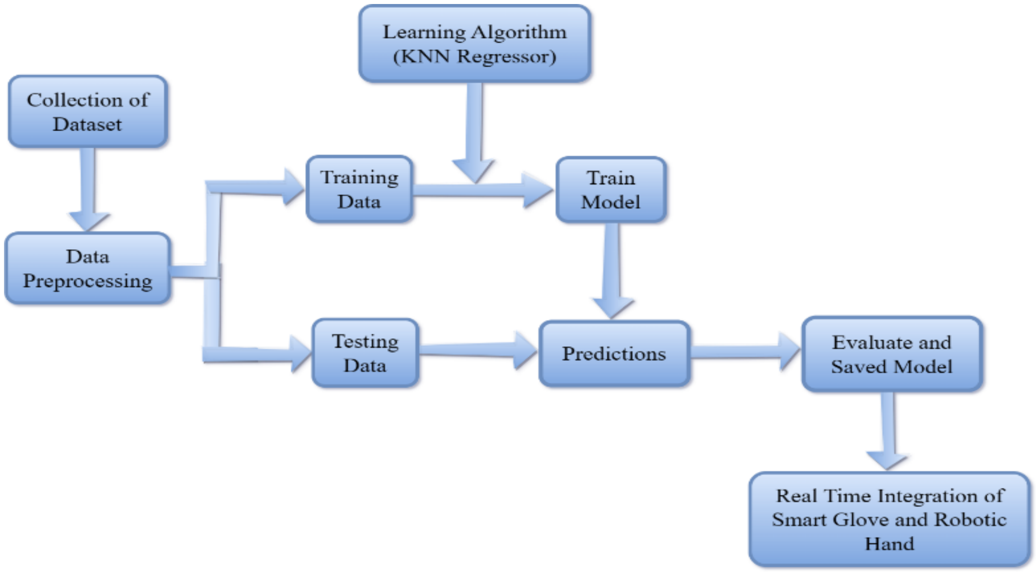

Fig. 4. Working of the Developed model of Prototype

3.1 Data Collection

As shown in Fig 2, the developed prototype (Smart Glove) was used to collect the raw data. For data collection, the ESP-WROOM-32 and LDR sensors were employed. Five LDR sensors must be used in the setup, and they must be linked to the ESP-WROOM-32 board and associated pins. The system that receives the generated data is connected to the ESP-WROOM-32 board. Collection of datasets in form of voltage and angle as shown in below **Table 1:**

Table 1
Voltage and Angle Dataset

Voltage (volt, V)	Angle (degrees, θ)
0.192	10
0.356	19
0.543	29
0.646	35
0.817	44
1.039	56
1.224	66
1.371	74
1.627	88
1.667	90
2.471	134
2.823	154
3.041	165

3.211	175
3.3	180

The steps followed to collect the dataset using the developed wearable hand glove (Prototype) are shown in Fig

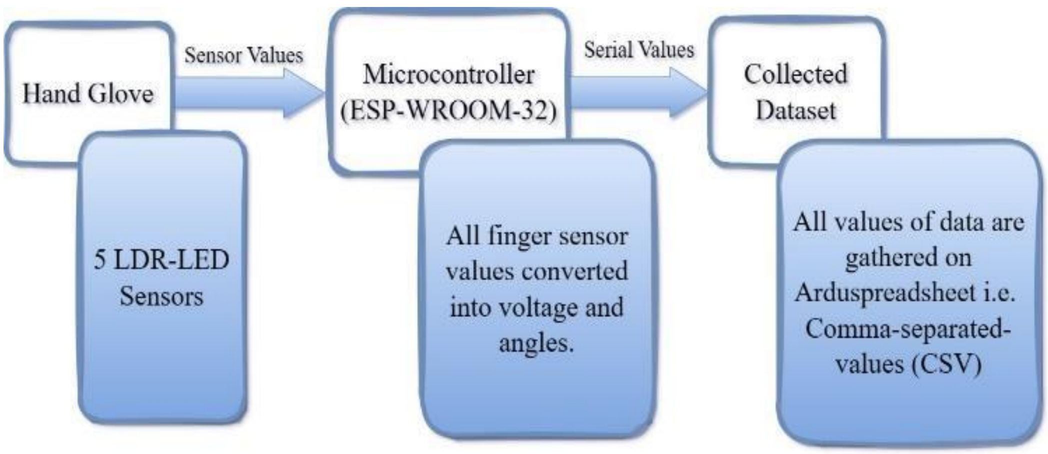

Fig. 5. Block diagram of Dataset Collection

Collect data in seven different scenarios, including individual finger movement and no movement of the finger. Each dataset was saved in a Comma Separated Value (CSV) file using Arduspreadsheet. As a result, there are seven types of data instances:
1) THUMB M (Movement of Thumb Finger)
2) INDEX M (Movement of Index Finger)
3) MIDDLE M (Movement of Middle Finger)
4) RING M (Movement of Ring Finger)
5) LITTLE M (Movement of Little Finger)
6) WM1 (Without Movement Flat Fingers)
7) WM2 (Without Movement Bend Fingers)

3.2 Data preprocessing

We utilized numpy, pandas, scikit-learn, and Matplolib libraries for data preprocessing, uploading datasets via Pandas Library, and integrating into one file for samples, selecting features as voltage and targets as angles as shown in Table 2.

Table 2
Features and Targets

Fingers	Features	Target
Thumb	Volatge_1	Angle_1
Index Finger	Volatge_2	Angle_2
Middle Finger	Volatge_3	Angle_3
Ring Finger	Volatge_4	Angle_4
Little Finger	Volatge_5	Angle_5

3.3 Training and Testing Data

The developed prototype was trained using a KNN ML algorithm on a dataset divided into input (X) and output (Y) sets, with the dataset split into 80% and 20% for training and testing, as illustrated in Fig. 6.

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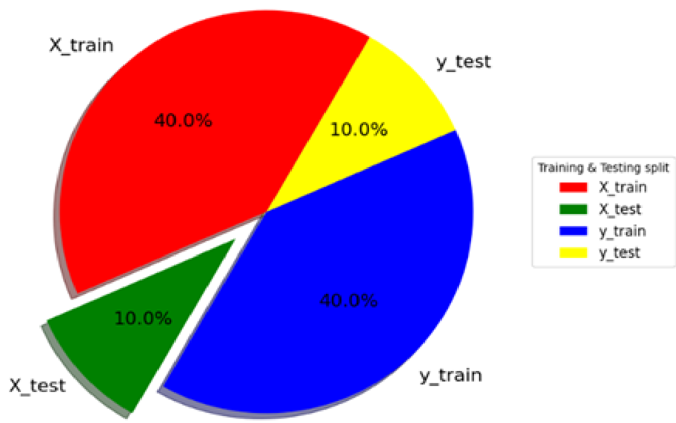


Fig. 6. Training and Testing split data

3.4 Learning Algorithm (K-Nearest Neighbors)

The model uses libraries sklearn.neighbors and sklearn.multioutput to create a multi-output regression model. Multioutput Regressor applies a base regressor to each target variable independently, with multioutput regression support added to any regressor as shown in Fig. 7. The KNN algorithm considers the five nearest neighbors for predictions. The model is trained using training data and utilized for predictions, with expected values stored in a variable containing the model's predictions for target variables based on the X_test input data.

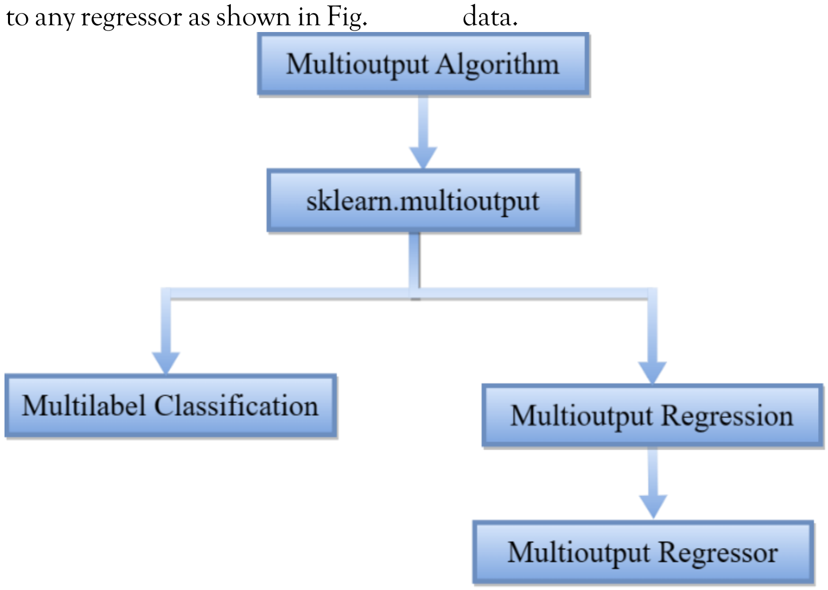


Fig. 7. Multioutput Regressor

3.5 Real-time integration of Smart Glove to control Robotic Hand

Communication using two serial ports, one linked to a glove and the other to a robotic hand, allows for real-time integration of a Smart glove to operate a robotic hand as shown in Fig. 8. The glove serially sends data from five-fingers voltage and angle sensors, which are read and analyzed. The code estimates the angles of the fingers based on the received voltage data from the glove using a pre-trained KNN model fetched from a file. These angles are predicted and shifted as orders to the robotic hand's corresponding fingers via the other serial connection. The code repeats indefinitely to collect data from the glove, forecast finger angles, and send orders to control the robotic hand depending on the predicted angles.

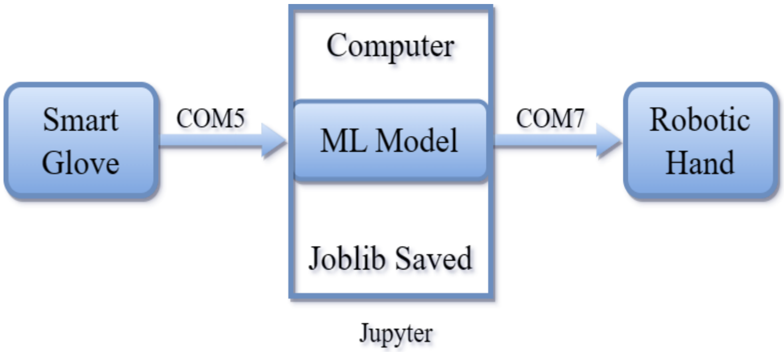
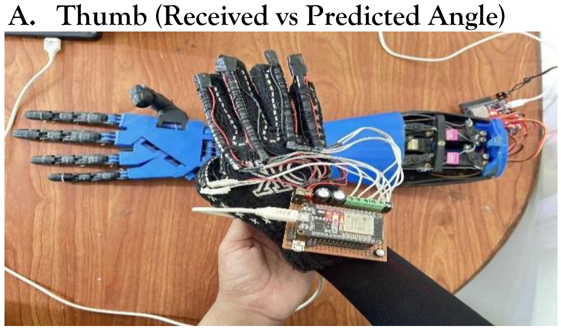


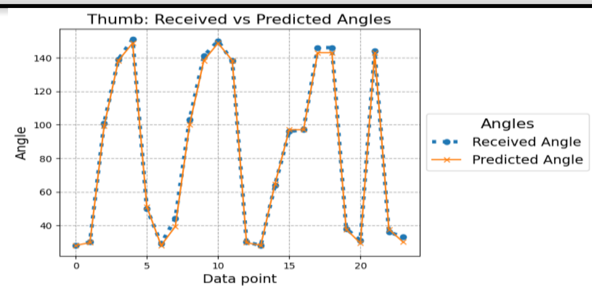
Fig. 8. Smart Glove and Robotic Hand Integration

4. Experiments

The wearable hand glove prototype uses LDR sensors to capture voltage and angle values of finger movements, transmitting them to a microcontroller via Arduspreadsheet. The data is prepared by a trained model for prediction, evaluated, and saved using the Joblib library. Real-time integration with Arduino and Jupyter enables precise finger movement replication in a robotic hand. The received and predicted angles for each finger (thumb, index, middle, ring, and little) are retained in a CSV file, with physical and graphical representations presented.

A. Thumb (Received vs Predicted Angle)

(a) 

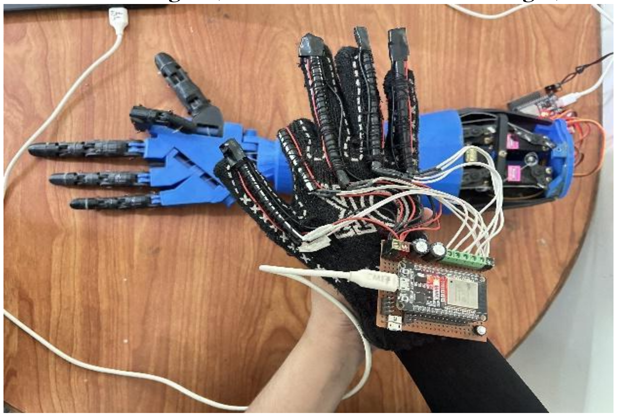


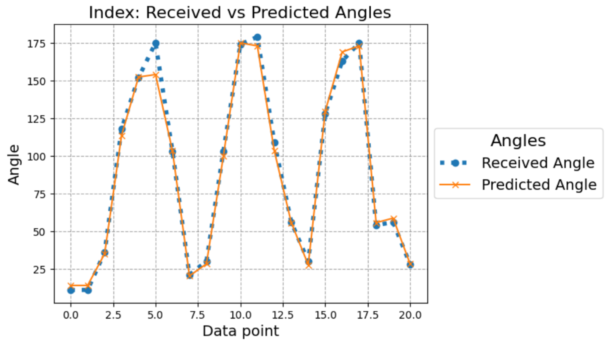
(b)

Fig. 9. Comparison of Received & Predicted angle for the Thumb (a) Physical Representation (b) Graphical Representation

B. Index Finger (Received vs Predicted Angle)

(a)

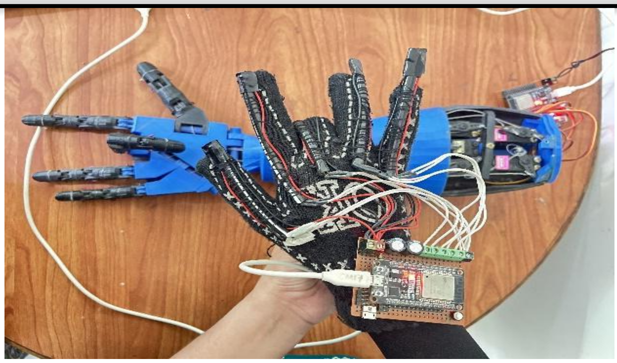




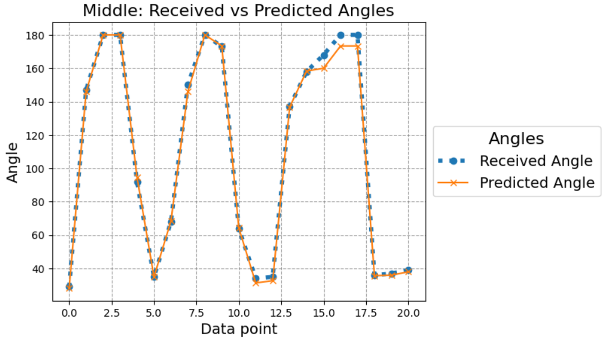
(b)

Fig. 10. Comparison of Received & Predicted angle for the Index Finger (a) Physical Representation (b) Graphical Representation

C. Middle Finger (Received vs Predicted Angle)



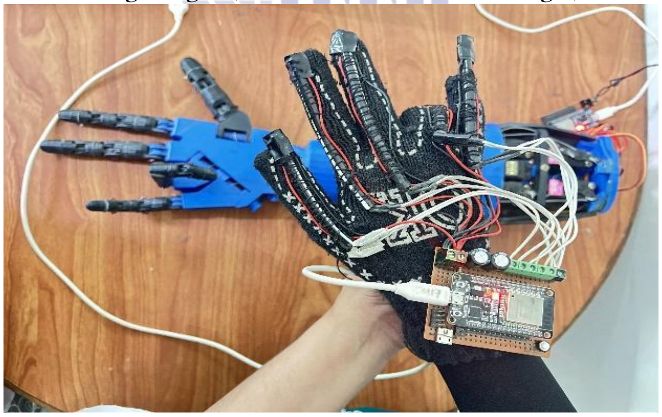
(a)



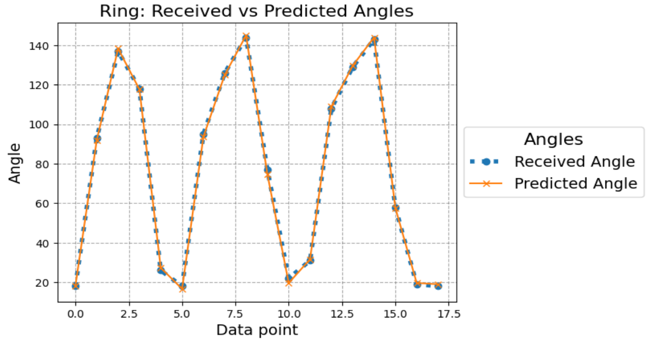
(b)

Fig. 11. Comparison of Received & Predicted angle for the Middle Finger (a) Physical Representation (b) Graphical Representation

D. Ring Finger (Received vs Predicted Angle)



(a)



(b)

Fig. 12. Comparison of Received & Predicted angle for the Ring Finger (a) Physical Representation (b) Graphical Representation

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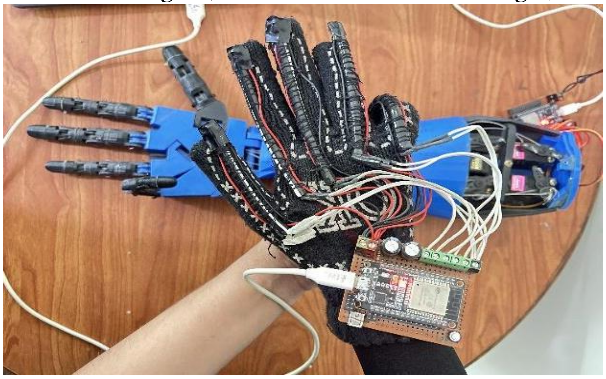
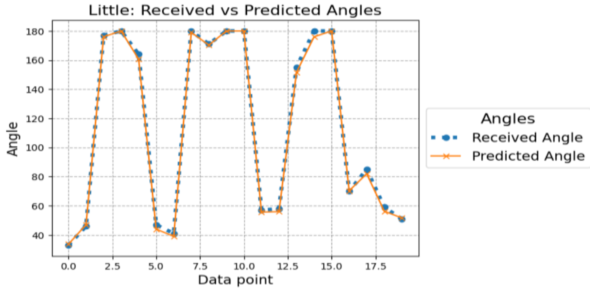
E. Little Finger (Received vs Predicted Angle)



(a)



(b)

Fig. 13. Comparison of Received & Predicted angle for the Little Finger (a) Physical Representation (b) Graphical Representation

The RMSPE values represent the model's prediction accuracy for each finger when considering their respective measurements or predictions. The RMSPE for the KNN regression model as shown in Table 3.

Table 3
Root Mean Square Prediction Error (RMSPE)

S.NO	Fingers	RMSPE
1.	Thumb	2.807673
2.	Index	3.106020
3.	Middle	2.966750
4.	Ring	2.596089
5.	Little	2.461616

Lower RMSPE values indicate better prediction accuracy, with less variance between predicted and actual values. The results suggest that the model predicts the little finger has the lowest average prediction error, followed by the Ring finger. In contrast, the Index finger has the highest average prediction error among the fingers analyzed. These insights help refine the model for improved accuracy in real-time applications.

5. Conclusion

At last, our research study effectively created a revolutionary Smart glove interface method for commanding a robotic hand. Servo motors in the robotic hand integrated into the Smart glove allowed for accurate and natural control of individual fingers. By properly converting hand angles into the equivalent movement of the robotic hand, the KNN ML technique was implemented, significantly improving the user experience. This study provides a basis for future advancements and uses of technology as it develops. The seamless integration of sensors, actuators, and machine learning algorithms opens the door to more sophisticated and adaptable robotic systems, improving the quality of life for people with disabilities or in need of precise remote manipulation capabilities while also advancing human-robot collaboration.

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