MOTION TRACKING AND ML FOR REHABILITATION

WRIST MOTION CLASSIFICATION GAME FOR HAND-PARALYZED PATIENTS

Team Members

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SUBJECT : AIM113 & AIM114

INTRODUCTION

- This project aims to develop an interactive game controlled by wrist movements to help hand-paralyzed patients in rehabilitation.
- A Long short term memory(LSTM) is used to classify wrist movements from an MPU6050 sensor into four categories: up, down, left, and right.
- The classified movements are then used as controls in a MATLAB-based game.
- LSTM is well-suited for motion classification as they can automatically extract features from raw sensor data, improving accuracy and real-time performance.
- This project integrates deep learning with rehabilitation by providing an engaging exercise tool for patients.

LITERATURE REVIEW

S.no	Titles	Years	Methodologies	Key contributions
1	Accuracy and Reliability of a Novel IMU-Based Functional Calibration Algorithm for Clinical 3D Wrist Joint Angle Monitoring	2024	The study used IMUs and optical motion capture to calibrate wrist joint angles with functional movements, assessing accuracy through statistical analysis	The paper presents an IMU-based calibration system for wrist joint monitoring, offering similar accuracy to optical systems without requiring predefined poses.
2	Wrist Movements Estimation Based on Limited Training Dataset	2023	The study uses a single-degree-of-freedom (DOF) training dataset with support vector regression (SVR) to decode multi-DOF wrist movements, optimizing model parameters and evaluating performance using R2.	The paper proposes a novel approach to wrist movement estimation by leveraging limited training data, reducing computational complexity, and alleviating patient burden in neuroprosthetic applications.

S.no	Titles	Years	Methodologies	Key contributions
3	**Design and Performance Analysis of a Bioelectronic Controlled Hybrid Serial-Parallel Wrist Exoskeleton**	2023	**The paper presents a bioelectronic controlled hybrid serial-parallel wrist exoskeleton for rehabilitation, using a 2-DOF parallel configuration and gear set to assist wrist movements.**	**It introduces a novel wrist exoskeleton with enhanced range of motion, adaptable design, and integration of surface electromyography for active rehabilitation, providing significant benefits in clinical rehabilitation.**
4	**Neuro-Musculoskeletal Modeling for Online Estimation of Continuous Wrist Movements from Motor Unit Activities**	2024	**The study utilizes motor unit activities to estimate wrist movements in real-time, combining MU-specific neural excitation with a musculoskeletal model.**	**The research offers a neuro-musculoskeletal model that significantly improves wrist movement estimation from motor unit activities, outperforming previous methods in accuracy.**

S.no	Titles	Years	Methodologies	Key contributions
5	Wrist Angle Estimation Under Different Loads Condition Based on Multi-Layer Perceptron Neural Network and Surface Electromyography Signals	2024	The paper develops a wrist angle prediction system using sEMG signals processed through a multi-layer perceptron neural network, accounting for load variations.	It demonstrates the ability of a neural network model to estimate wrist angles under varying load conditions, with promising applications in rehabilitation and assistive technology.
6	A Robotic Hand for Rehabilitation of Wrist and Fingers	2023	The paper proposes a robotic rehabilitation system for wrist and finger movements, incorporating a five-DOF hand mechanism with actuators for finger and wrist motions.	It presents a comprehensive rehabilitation robot for treating Carpal Tunnel Syndrome with adaptable exercises, providing both wrist and finger rehabilitation and sensor-based progress tracking for clinical use.

S.no	Titles	Years	Methodologies	Key contributions
7	Musculoskeletal Model Predicts Multi-joint Wrist and Hand Movement from Limited EMG Control Signals	2015	The study developed an EMG-driven musculoskeletal model that predicts wrist and metacarpophalangeal (MCP) joint movements using surface EMG signals. Data from two upper limb postures were used to optimize the model's parameters and evaluate its performance across various movement types (fixed and random speed) using a limited number of muscles.	The model successfully predicted multi-joint movements in different postures, showing promise for prosthetic control by utilizing limited EMG signals, offering improved robustness over traditional methods that lack anatomical insights.

PROBLEM STATEMENT

Hand paralysis severely impacts daily activities, and traditional rehabilitation methods often lack engagement, leading to slower recovery. This project proposes an interactive rehabilitation tool using wrist movements for hand-paralyzed patients. An MPU6050 sensor detects wrist movements, which are classified by a Long short term memory(LSTM) into four directions (up, down, left, right). These movements control a MATLAB-based game, providing a more engaging and effective rehabilitation experience. The use of deep learning enhances real-time accuracy and improves patient participation in therapy.

WORKFLOW

1. Data Collection
(MPU6050Sensor → Arduino)

2. Data Preprocessing
(Noise Filtering, Segmentation, Normalization)

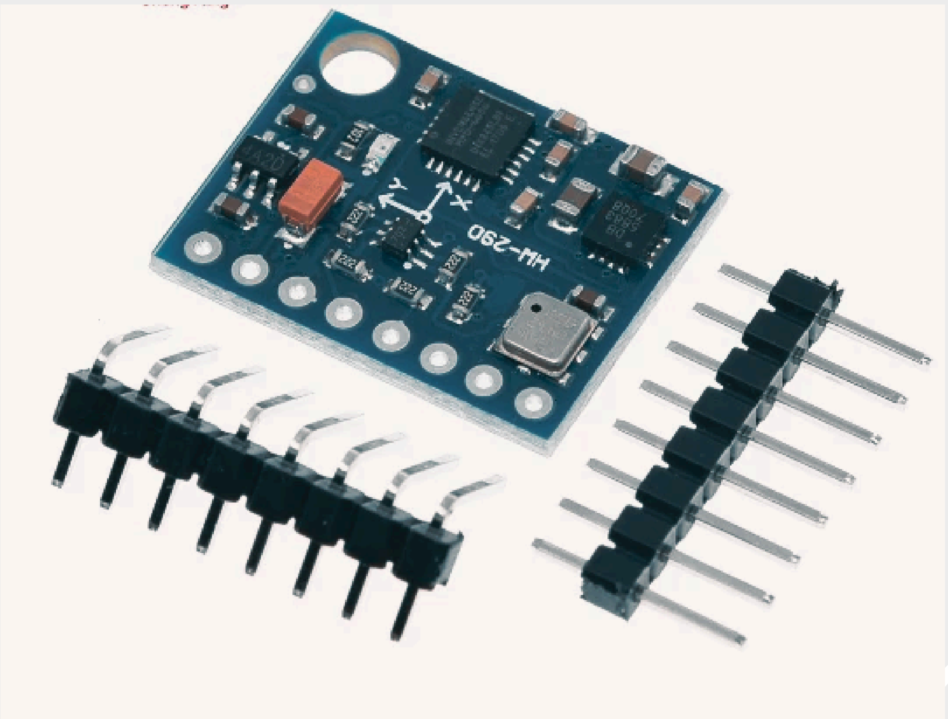
3. LSTM Model Training
(Feature Learning & Classification)

4. Real-Time Prediction
(Live Data → LSTM Model → Movement Class)

5. Game Interaction
(Predicted Motion → Game Actions → Visual Feedback)

HARDWARE IMPLEMENTATION

The sensor used for the project is MPU6050+HMC5883L+BMP180



SENSOR DESCRIPTION

MPU6050

The MPU6050 is a motion-tracking device that combines a 3-axis gyroscope and a 3-axis accelerometer with 6 degrees of freedom.

HMC5883L

It is a multi-chip module designed for low-field magnetic sensing with a digital interface for applications such as low-cost compassing and magnetometry

BMP180

The BMP180 is a barometric pressure sensor that measures air pressure and temperature

SENSOR SPECIFICATIONS

Operating Voltage (VDC)	3 to 5
Gyroscope	Range: ± 250, 500, 1000, 2000
Acceleration (g)	Range: ± 2 ± 4 ± 8 ± 16g
Communication Mode	I^2C protocol
Length (mm)	22
Width (mm)	17
Weight (g)	5

WORKING PRINCIPLE

MPU6050

It measures angular velocity and acceleration, transmitting data via the I2C or SPI interface. The onboard Digital Motion Processor (DMP) can process sensor fusion algorithms for more accurate motion tracking.

HMC5883L

It detects changes in resistance caused by external magnetic fields and converts them into voltage signals. An onboard ADC processes these signals, and data is transmitted via I^2C to a microcontroller. It is commonly used for orientation sensing, navigation, and metal detection applications.

BMP180

It measures atmospheric pressure by detecting changes in a diaphragm's deformation due to air pressure variations. An internal ADC (Analog-to-Digital Converter) converts the analog signal into a digital value, which is then compensated using built-in calibration coefficients.

DATA PREPROCESSING

- Handling missing values: either removing the missing data or filling it with estimates like averages.

- Segmentation: Dividing the data into smaller, meaningful parts to focus on specific features or patterns.

- Normalization: Scaling data to a standard range, to ensure consistency across features.(MinMaxScaler)

IMPORTING THE LIBRARIES

IMPORTING THE DATASET

HANDLING MISSING VALUES

id	xpos	ypos	zpos	xrot	yrot	zrot	target
1	-5.91497	-9.94818	-6.1705	-84.117	118.5505	67.41977	1
2	-4.45206	-2.3624	3.427724	-27.6973	111.468	-110.677	3
3	-1.9862	6.172112	8.406951	-172.942	92.07378	175.1499	3
4	-4.92329	1.08047	0.962015	94.36988	-171.364	62.27528	3
5	-6.52106	3.940774	-6.68902	-112.146	-11.1222	-48.1183	4
6	9.50885	-1.70633	3.769897	86.79268	53.66068	168.126	3
7	-9.46739	-9.98022	2.354217	111.5632	-36.1809	69.99002	4
8	-5.60049	0.455534	-9.4435	-17.034	-32.8224	-123.97	4
9	-7.87895	4.903707	-4.70469	121.2651	71.74903	108.4639	2

LSTM
(Long Short Term Memory)

1. Type of RNN: LSTM is a type of Recurrent Neural Network (RNN) designed to handle sequences of data.
2. Memory Cells: It uses memory cells to store and remember important information over time.
3. Gates: LSTM has three gates:

- **Cell state** : **The "memory" of the network that is passed along and updated.**
- Forget Gate: Decides what to forget.
- Input Gate: Decides what new information to store.
- Output Gate: Decides what to output.
- **Candidate state** : **New information considered for updating the cell state.**

4. Long-Term Dependencies: LSTMs can learn long-term patterns, unlike regular RNNs which struggle with them.
5. Applications: Used in time series prediction, speech recognition, and natural language processing.

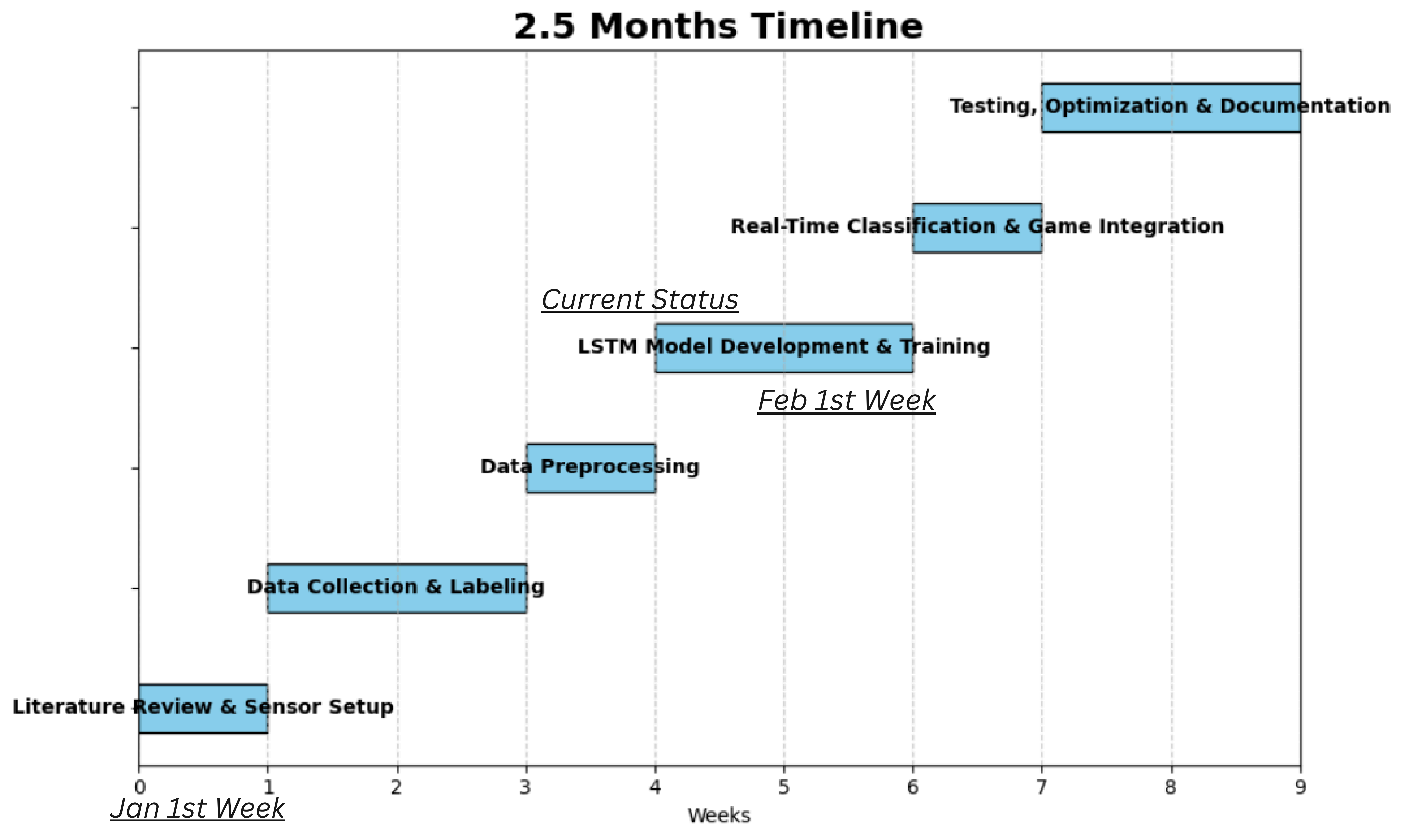
1. **Feature Learning in LSTM:**

- LSTM learns important patterns from sequential data automatically.
- It remembers relevant information over time using memory cells.
- LSTM focuses on important parts of the sequence and ignores irrelevant ones.

2. **Classification with LSTM:**

- After learning features, LSTM can classify data into different categories.
- The output from LSTM is passed through the layers to make predictions.
- A softmax activation is used to predict.

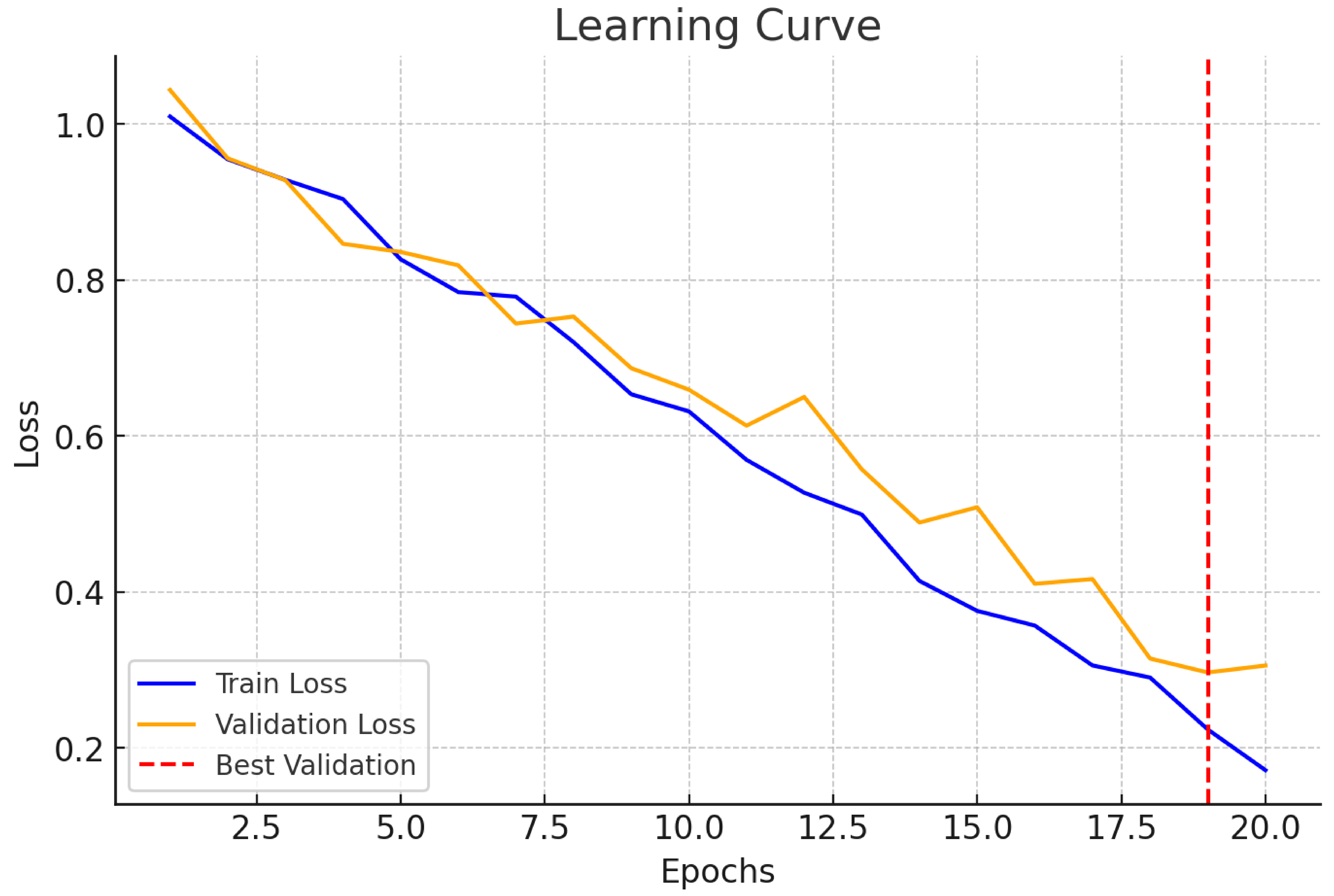
TIME LINE


2.5 Months Timeline
Testing, Optimization & Documentation
Real-Time Classification & Game Integration
Current Status
LSTM Model Development & Training
Feb 1st Week
Data Preprocessing
Data Collection & Labeling
Literature Review & Sensor Setup
0
1
2
3
4
5
6
7
8
9
Jan 1st Week
Weeks

CONCLUSION

This project successfully integrates deep learning with interactive rehabilitation by leveraging a LSTM to classify wrist movements captured by an MPU6050 sensor. The accurate real-time recognition of four distinct movement directions enables effective control of a MATLAB-based game, providing an engaging and motivating platform for hand-paralyzed patients. By transforming conventional rehabilitation exercises into an interactive gaming experience, the system not only enhances patient engagement but also has the potential to accelerate recovery and improve overall treatment outcomes.

THANK YOU


Learning Curve
Loss
Epochs
1.0
0.8
0.6
0.4
0.2
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Train Loss
Validation Loss
Best Validation