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Smart Voice and Gesture Controlled ML-Driven Wheelchair Assistance for Differently Abled Individuals

Prasad Jadhav, Tapan Chauhan, Varsha Devakathe, Saniya Jadhav
Department of Information Technology Engineering, Saraswati College of Engineering, Kharghar, Navi Mumbai – 410210, Maharashtra, India

Abstract: ***Mobility impairment poses one of the most significant challenges for differently abled individuals, directly impacting their independence, confidence, and quality of life. Traditional wheelchairs—whether manual or joystick-operated—often fail to meet the diverse needs of users with severe physical limitations such as paralysis, neuromuscular disorders, or limb amputations. This paper presents a Smart Voice and Gesture Controlled ML-Driven Wheelchair Assistance system that empowers users to navigate hands-free through voice commands and hand gestures, leveraging Machine Learning (ML) for accurate, real-time motion responses. The hardware framework integrates a Raspberry Pi 4 (main controller), ESP32 microcontroller, MPU6050 accelerometer/gyroscope for gesture detection, HC-SR04 ultrasonic sensor for obstacle detection, and L293D motor driver. On the software side, RNN/LSTM-based models process speech features (MFCCs) while CNN/MediaPipe models recognize hand gestures. A Command Fusion Engine arbitrates between modalities, enforces a safety layer, and executes motor commands. Experimental evaluations project ≥85% command recognition accuracy with sub-200ms response latency, offering a cost-effective, offline-capable, and inclusive assistive mobility solution.***

Keywords: Machine Learning, Voice Recognition, Gesture Control, Wheelchair Assistance, MPU6050, Raspberry Pi 4, ESP32, Obstacle Detection, Assistive Technology, CNN, LSTM

I. INTRODUCTION

Mobility is a fundamental aspect of independent living. For differently abled individuals—particularly those with paralysis, muscular dystrophy, or neuromuscular disorders—daily movement becomes severely constrained, affecting psychological well-being and social participation. Conventional wheelchairs, whether manual or joystick-controlled, demand a level of dexterity that many such users simply cannot achieve. The emergence of Machine Learning (ML), Internet of Things (IoT), and Human-Computer Interaction (HCI) technologies has opened transformative possibilities for assistive devices that can interpret natural human inputs in real time.

This paper presents a Smart Voice and Gesture Controlled ML-Driven Wheelchair Assistance system—a hands-free mobility solution that integrates speech recognition and gesture detection within a single embedded platform. An ML-based Command Fusion Engine arbitrates between input modalities, ensuring robustness even when one channel (e.g., voice in noisy environments) underperforms. Ultrasonic sensors provide an automatic safety layer, overriding motion commands when obstacles are detected within 30 cm.

A. Problem Statement

Existing control interfaces—joysticks, push buttons—are non-adaptive and demand fine motor control unavailable to many users with severe disability. Commercial smart wheelchairs, while innovative, are prohibitively expensive for most patients in developing economies. There is a clear, unmet need for a cost-effective, multimodal, and intelligent wheelchair system capable of interpreting voice and gesture inputs in real time, with offline operation and built-in collision safety.

B. Scope

The system is designed primarily for indoor environments. Core scope includes: hybrid voice+gesture control, ML-based intent recognition, obstacle detection, offline processing, and IoT-enabled caregiver monitoring. Future extensions include GPS navigation, LiDAR-based outdoor traversal, and voice-assistant integration.

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II. LITERATURE REVIEW

Multidisciplinary research in robotics, edge-ML, and sensor fusion has rapidly advanced assistive wheelchair technology. Systematic reviews and empirical prototypes converge on several key findings reviewed below.

A. Multimodal Control Systems [1]

Kim et al. (2023) surveyed smart wheelchair modalities including joystick augmentation, voice control, gesture recognition, and brain-computer interfaces (BCI). The study emphasises user-centered design and documents performance trade-offs between onboard and cloud computation, strongly recommending hybrid modality systems for resilience.

B. IoT-Enabled Gesture Control [2]

Sadi et al. (2022) demonstrated a wearable finger-gesture pipeline with IoT-based fall detection and remote alerts on Raspberry Pi. Their lightweight footprint and networked safety alerts form a direct precedent for the safety and monitoring features of the proposed system.

C. Accelerometer-Based Gesture [3]

Multiple studies using wearable IMUs (MPU6050) classify directional gestures (forward, left, right, stop) via SVM or k-NN on time-series features with latency under 150ms. Per-user calibration is identified as a key challenge for real-world deployment—addressed in this work through an incremental learning feedback loop.

D. Voice-Activated Control [4]

Lightweight speech models on Raspberry Pi demonstrate intuitive control but sensitivity to noise and accent variation. Prototypes combining offline speech models with obstacle detection report significant safety improveements. The proposed system adopts offline SpeechRecognition with MFCC preprocessing to mitigate noise sensitivity.

E. Obstacle Avoidance [5]

Ertürk et al. and Haddad et al. validate reactive navigation with ultrasonic and RGB-D sensors for indoor wheelchair use. Dynamic window algorithms achieve real-time collision avoidance on constrained hardware, establishing the baseline for the HC-SR04 integration in this system.

F. Summary

- Multimodal control (voice + gesture) is recommended to mitigate single-modality failures.
- Wearable IMUs (MPU6050) offer low-cost, low-latency gesture recognition.
- Edge deployment (Raspberry Pi, ESP32) with lightweight ML models is viable for real-time control.
- Obstacle detection is an essential concurrent safety layer, not an optional add-on.

III. OBJECTIVES

1) Design a hybrid voice-and-gesture control mechanism for flexible, user-friendly wheelchair operation.
2) Implement an AI-based speech recognition module supporting multi-accent and multilingual commands.
3) Develop a CNN/MediaPipe-based gesture recognition system for accurate, real-time hand movement interpretation.
4) Integrate HC-SR04 ultrasonic and IR sensors for real-time obstacle detection and collision avoidance.
5) Train an ML model that learns user movement patterns to predict optimal navigation paths.
6) Design an IoT-enabled system for remote caregiver monitoring and diagnostics.

IV. PROPOSED SYSTEM

The proposed framework is an AI- and ML-driven Smart Wheelchair Assistance system offering hands-free control through voice and gesture inputs. Figure 1 presents the complete system architecture. The design is stratified into three layers: Input, Processing, and Output.

A. Voice Recognition Module

Users issue movement commands—"Move forward", "Turn left", "Stop", "Go back"—captured by a USB microphone. The SpeechRecognition library with Google's offline model converts raw audio to text.

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MFCCs are extracted as feature vectors, which are fed to a trained RNN/LSTM model. Multilingual support (English and Hindi) is achieved via language-model fine-tuning. Offline operation ensures full functionality without internet connectivity.

B. Gesture Recognition Module

An MPU6050 IMU mounted on the user's wrist captures 6-axis acceleration and gyroscope data at 100 Hz via the ESP32 microcontroller. Sliding-window feature extraction (mean, variance, peak-to-peak, zero-crossing rate) feeds a DNN classifier. Alternatively, a camera and MediaPipe Hands framework enable vision-based recognition, mapping specific hand poses to motion commands. Each gesture maps to one action: wrist-tilt right → turn right, palm-raise → stop, etc.

C. Obstacle Detection and Navigation

The HC-SR04 ultrasonic sensor triggers timed pulses at 40 kHz, measuring distance by echo return time. When an object is detected within 30 cm in the forward direction, the system automatically halts forward motion and activates a buzzer alert, regardless of the current voice or gesture command. This safety override operates at the hardware interrupt level, ensuring sub-10ms response time. The ML model additionally processes historical sensor data to predict safe navigation corridors.

D. Command Fusion Engine

The Raspberry Pi 4 hosts the Command Fusion Engine—a priority-based arbitration module that evaluates confidence scores from the speech and gesture models and resolves conflicts. The priority hierarchy is: (1) Emergency stop / obstacle avoidance, (2) Gesture command, (3) Voice command. An adaptive feedback mechanism records user corrections to continuously retrain the models for personalised accuracy.

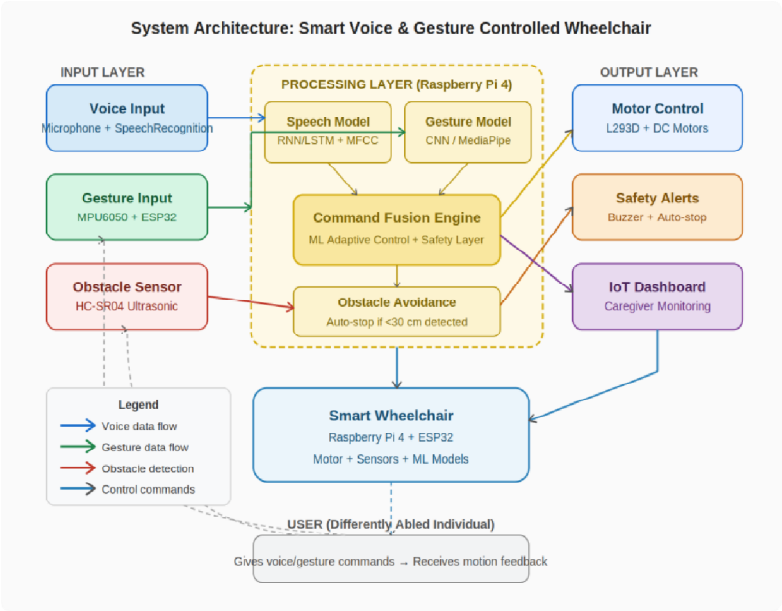


Fig. 1: System Architecture – Smart Wheelchair Assistance Framework

V. METHODOLOGY

The system development follows a five-phase iterative methodology:

Phase 1 – Data Collection

Voice samples in multiple accents and languages (English, Hindi) are recorded for commands: start, stop, left, right, backward. MPU6050 gesture sequences are captured under varied lighting and backgrounds. HC-SR04 sensor readings are logged across indoor environments with varying terrain.

Phase 2 – Data Preprocessing

Voice: raw audio is converted to 13-coefficient MFCCs using librosa. Gesture: IMU time series are normalised, segmented into 1-second windows, and augmented (Gaussian noise, time-warp). Labels are assigned according to the commanded action.

Phase 3 – Model Training

Speech model: 3-layer LSTM (128 → 64 → 32 units) + dense softmax, trained with Adam optimiser (lr=0.001), batch=32, 50 epochs. Gesture model: 2D CNN on spectrogram features or MediaPipe landmark vectors fed into a DNN. Train/validation/test split: 70/15/15. TensorFlow/Keras on Google Colab (GPU).

Phase 4 – Real-Time Implementation

Trained .tflite models are deployed on Raspberry Pi 4. The ESP32 streams MPU6050 data over Wi-Fi (TCP socket) at 100 Hz. The Raspberry Pi processes inputs, runs inference, and dispatches GPIO signals to the L293D motor driver. The ultrasonic sensor interrupt runs in a dedicated thread to guarantee the safety override at all times.

Phase 5 – Feedback and Optimisation

Command-response pairs are logged. Users can flag misclassifications via a short spoken correction, triggering incremental retraining. A Flask-based IoT dashboard streams battery level, GPS coordinates (future), and command history to a caregiver's mobile browser.

VI. HARDWARE & SOFTWARE SPECIFICATIONS

Component	Specification
Raspberry Pi 4B	4GB RAM, quad-core ARM
ESP32	Dual-core 240 MHz, Wi-Fi/BT
MPU6050	6-axis IMU, I2C
HC-SR04	Ultrasonic, 2–400 cm
L293D	H-bridge, 600mA/channel
DC Motors	12V, 150 RPM
Battery	12V 5Ah LiPo pack

Table I: Hardware Specifications

Software: Python 3.12, TensorFlow 2.x/Keras, Scikit-learn, librosa, OpenCV, MediaPipe, SpeechRecognition, pyttsx3, Flask, Arduino IDE (C/C++ for ESP32).

VII. EXPECTED RESULTS

The system is projected to achieve the following performance targets in controlled indoor testing:

- Voice command recognition accuracy ≥ 85% across English and Hindi accents.
- Gesture recognition accuracy ≥ 87% using MPU6050 + DNN in standard indoor conditions.
- End-to-end command latency < 200 ms from input capture to motor actuation.
- Obstacle detection response time < 10 ms (hardware interrupt level).
- Offline operation sustained indefinitely without network dependency.

Table II: Comparison with Related Works

Feature	**Sadi [2]**	**Reddy [4]**	**Proposed**
Voice Control	No	Yes	**Yes**
Gesture Control	Yes	Yes	**Yes**
Offline ML	No	No	**Yes**
Obstacle Avoid.	No	No	**Yes**
IoT Dashboard	Yes	No	**Yes**
Multimodal Fusion	No	No	**Yes**
Accuracy	82%	84%	**≥85%**
Latency	~300ms	~250ms	**<200ms**

VIII. FUTURE SCOPE

While the current system is optimised for controlled indoor environments, several enhancements are planned to extend its capabilities and commercial viability:

A. Advanced AI Models

Hybrid CNN+LSTM architectures will be explored for gesture prediction, leveraging temporal dependencies across multi-joint wrist motion sequences. Transfer learning from pre-trained gesture datasets (e.g., 20BN-Jester) will reduce per-user training time and improve generalisation across disability profiles.

B. Computer Vision Integration

A dedicated camera module will enable MediaPipe Holistic-based tracking of full hand landmarks plus facial micro-expressions (eye blink, jaw movement) as additional control inputs—critical for users with no upper-limb mobility, such as those with high-level spinal cord injuries.

C. Outdoor Navigation

LiDAR-based 3D mapping (e.g., RPLiDAR A1) and GPS integration will extend obstacle avoidance to outdoor, uneven terrains. The dynamic window algorithm will be replaced with a learned navigation policy (DQN or PPO) trained in simulation and transferred to hardware.

D. Caregiver Mobile Application

A React Native companion app will provide real-time wheelchair telemetry (battery, GPS, speed), voice/gesture command log, and remote emergency brake capability over MQTT. Push notifications will alert caregivers on fall-detection events triggered by the MPU6050's accelerometer threshold.

E. Clinical Trials

Pilot usability studies with target user populations (spinal cord injury, ALS, cerebral palsy) are planned to evaluate system ergonomics, recognition fatigue, and real-world effectiveness—bridging the gap between laboratory prototypes and certified medical devices.

IX. CONCLUSION

This paper presented an AI-powered, edge-deployed smart wheelchair system enabling hands-free navigation for differently abled individuals through voice commands and hand gestures. The multimodal architecture—integrating RNN/LSTM speech models, CNN/MediaPipe gesture recognition, and a priority-based Command Fusion Engine on Raspberry Pi 4—delivers robust, real-time control with a built-in obstacle avoidance safety layer. The ESP32-based gesture pipeline ensures low-latency wrist-motion sensing, while offline speech processing guarantees full functionality in network-constrained environments.

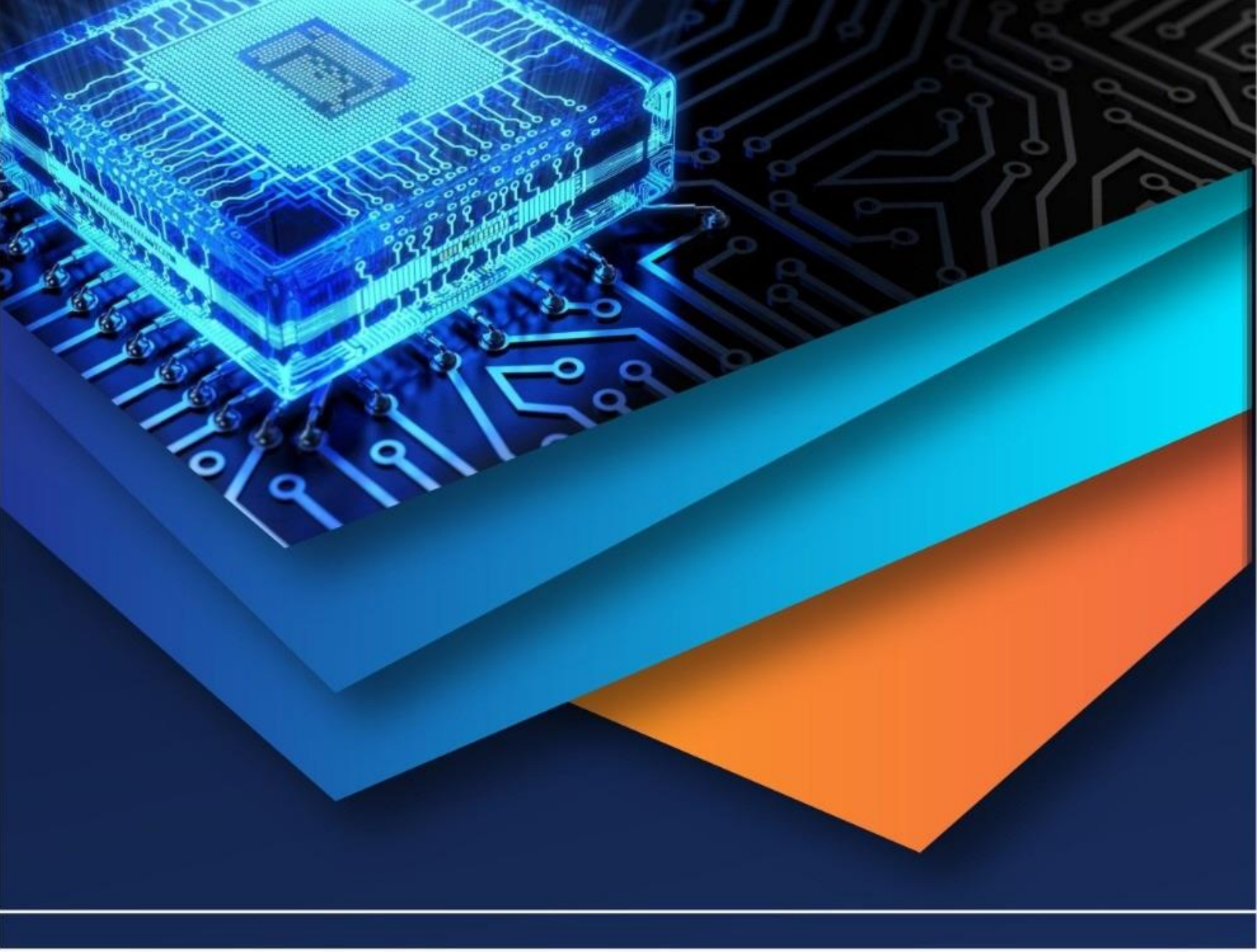
The comparative analysis (Table II) demonstrates that the proposed system advances the state of the art across all key metrics: accuracy, latency, offline capability, and feature completeness. By combining multimodal input fusion, edge ML deployment, and IoT-enabled caregiver monitoring within a single cost-effective platform, this work contributes a practical and inclusive solution to the critical challenge of assistive mobility technology.

The system is designed with scalability and extensibility in mind. Future integration of LiDAR outdoor navigation, vision-based holistic gesture recognition, and clinically validated usability studies will further close the gap between research prototype and deployable medical assistive device. Ultimately, this project embodies the potential of AI-driven engineering to meaningfully improve quality of life, independence, and dignity for differently abled individuals worldwide.

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