A Comprehensive Review on Decentralized Tri-Model AI Frameworks for Privacy-Preserving Autonomous Robotics

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***Abstract*—Autonomous service robotics is transitioning from cloud-dependent systems to decentralized, edge-centric architectures to address critical challenges in data privacy, network latency, and operational reliability. While Large Language Models (LLMs) such as Llama 3 and LLaVA offer sophisticated reasoning, their deployment on resource-constrained edge hardware often results in prohibitive inference delays and memory exhaustion. This paper reviews a robust alternative utilizing Small Language Models (SLMs), specifically Gemma 3, optimized via quantization techniques for real-time local reasoning.**

The proposed architecture integrates a fully local perception loop consisting of OpenAI Whisper for robust speech-to-text processing and Piper for low-latency vocal synthesis, ensuring 100% data sovereignty. Furthermore, we evaluate a "Lean Perception" mapping strategy that utilizes kinematic parameters—speed, time, and direction—to construct environmental representations with minimal computational overhead compared to traditional SLAM.

By analysing 25 key research works in the domains of edge intelligence and autonomous navigation, this paper provides a comprehensive blueprint for private, high-performance, and responsive home assistant robots that operate independently of cloud infrastructure.

I. INTRODUCTION

The ambition of deploying autonomous service robots in every household is transitioning from cloud-centric architectures to decentralized, edge-native intelligence. Traditionally, robots operate as thin clients, offloading voice data to remote servers for inference. As Zhang et al. (2025) [1] highlight, this introduces critical Privacy Vulnerabilities and Latency Bottlenecks, where personal domestic data is exposed to third-party breaches. Furthermore, internet dependency leads to unresponsive behavior in low-bandwidth environments, disrupting the fluidity of Human-Robot Interaction (HRI).

The primary obstacle for localized intelligence is the "Memory Wall" of edge hardware. Massive models like Llama 3 often lead to memory exhaustion on compact platforms. Research by Li et al. (2024) [2] suggests that Small Language Models (SLMs) like Gemma 3 are the optimal fit. By applying 8-bit Quantization, these models can be compressed to run efficiently within the 8GB RAM of a Raspberry Pi 5, enabling real-time reasoning without cloud reliance [5].

To ensure "Data Sovereignty," we propose a fully local tri-modal pipeline:

ASR Layer: OpenAI Whisper for robust offline speech-to-text [12].

Reasoning Layer: Quantized Gemma 3 for local intent detection.

TTS Layer: Piper for low-latency neural vocal synthesis [15].

Finally, we address navigation safety. Instead of resource-heavy 3D SLAM, we evaluate a "Lean Perception" strategy. By fusing Wheel Encoders for dead reckoning with Ultrasonic Sensors for reactive obstacle avoidance, the robot maintains a safe operational buffer. This approach reduces CPU overhead, allowing the Raspberry Pi 5 to prioritize conversational AI and reasoning tasks.

II. LITERATURE SURVEY

The transition from massive, cloud-based AI to smaller, decentralized systems is a dominant theme in 2024-2025 robotics research. A major focus is the optimization of Small Language Models (SLMs) for resource-constrained devices. Chen and Wei (2023) [6] established that quantization—simplifying mathematical weights—allows high-performing AI to run locally. Furthering this, Li et al. (2024) [2] demonstrated that on platforms like the Raspberry Pi 5, these optimized models eliminate the "Interaction Gap" caused by network latency, supporting the use of Gemma-class engines [5] for complex household instructions. Additionally, Zhang et al. (2025) [1] emphasize that localized processing is currently the only foolproof way to guarantee user privacy, as cloud-based systems remain inherently vulnerable to data leaks and third-party breaches. Building on the need for real-time interaction, recent studies highlight that the "Response Gap" must be sub-500ms for natural Human-Robot Interaction. Liu (2023) [12] evaluated OpenAI Whisper "tiny" on local hardware, finding that it provides high transcription accuracy even in noisy domestic settings. This is crucial as Gupta et al. (2021) [17] noted that cloud APIs often fail with regional dialects or background noise. On the output side, Sarkar and Pal (2021) [19] argue that delays in speech synthesis break the human-robot bond. This has led to the adoption of neural-based local tools like Piper, which utilize the VITS architecture to provide natural-sounding speech with almost zero delay [15], ensuring a fluid conversational flow.

Furthermore, the literature covers the evolution of how robots navigate safely without exhausting computational resources. While high-fidelity SLAM is popular, Santos et al. (2023) [10] observed that it often bottlenecks the CPU on small-scale robots. In contrast, the foundational work of Siegwart (2011) [25] proves that basic kinematics—fusing Wheel Encoders with Ultrasonic sensors—can be highly effective for indoor spaces. Recent studies [22] also highlight a privacy benefit: by using simple kinematic mapping instead of detailed 3D scans, the robot avoids collecting unnecessary spatial data about the user’s home. Moreover, Bose and Datta (2023) [11] emphasize that local "contextual memory" allows robots to handle multi-step tasks privately without an external database.

The collective evidence from recent research [3, 4, 8] suggests that hardware-software co-design is the key to sustainable robotics. Park and Lee (2024) [3] found that tuning AI for specific ARM-based chips can triple energy efficiency, while Tan et al. (2024) [4] add that avoiding constant cloud uploads keeps the internal hardware cooler, extending the machine's life. Collectively, these 25 papers suggest that the future is about making robots "smarter" by using local processing as efficiently as possible. This shift creates a robot that is not just a tool, but a reliable, private, and long-lasting companion [18, 16].

Moreover, a critical aspect discussed in contemporary literature is the "Contextual Reliability" of decentralized models in diverse environments. Research by Rao and Varma (2023) [8] demonstrates that while cloud-based APIs are trained on massive global datasets, they often struggle with local dialects and acoustic variations found in domestic settings. In contrast, local models like Whisper-Tiny, when fine-tuned or benchmarked against datasets like LibriSpeech or Common Voice, show a more consistent Word Error Rate (WER) across varied domestic noise profiles. This robustness is essential for the next generation of service robots that must operate reliably without the safety net of high-speed internet. Finally, the shift toward localized intelligence is closely tied to Hardware-Software Co-design. As observed by Park and Lee (2024) [3], the integration of AI models with specific ARM-based architectures—such as the BCM2712 SoC on the Raspberry Pi 5—allows for significant gains in thermal management and power efficiency. By leveraging Wheel Encoders for odometry and Ultrasonic sensors for obstacle detection, researchers have found a "Sweet Spot" between computational load and operational safety. This integrated approach not only extends the robot's battery life but also ensures that the reasoning engine (Gemma 3) has enough dedicated RAM to handle complex human intents without system throttling, ultimately leading to a more stable and "Natural" robotic companion [18, 20]

III. METHODOLOGY

The architecture of the proposed system is built on a decentralized "local-first" design, specifically optimized for the Raspberry Pi 5 (8GB RAM) platform. This ensures that every stage of the speech-to-action loop happens within the robot's physical this methodology follows a "Lean Perception" strategy. To address potential odometry drift and operational safety, we implement a Safety Conflict Check layer. The system fuses kinematic odometry with real-time feedback from Wheel Encoders and Ultrasonic Sensors. The robot's position (x, y) and heading (θ) are estimated using the following

Table I Comparative Analysis of Existing Research

Author	Research Objective	Methodology	Key Findings
Li et al. (2024) [2]	Performance benchmarking of SLMs on edge devices.	Testing on Raspberry Pi 5 (8GB) using INT8 Quantization.	8-bit quantization reduces RAM usage by 60% with <3% accuracy loss.
Google (2025) [5]	Developing lean reasoning engines for HRI.	Gemma 3 Technical Evaluation on ARM.	Supports "Chain-of-Thought" (CoT) reasoning on local processors.
Liu (2023) [12]	Evaluating local speech-to-text accuracy.	Benchmark on LibriSpeech using Whisper-Tiny.	Achieved <12% Word Error Rate (WER) in noisy domestic environments.
Sarkar & Pal (2021) [19]	Mitigating network-induced lag in HRI.	Latency analysis of Cloud vs. Localized Inference.	Localized pipelines reduce interaction delay by 82% (Baseline: 2500ms).
Kunz et al. (2020) [22]	Optimizing indoor mapping for privacy.	Odometry fusion using Wheel Encoders.	Simple kinematic maps prevent unnecessary collection of 3D spatial data.
Siegwart (2011) [25]	Safe robot navigation in human spaces.	Basic kinematics and Ultrasonic Sensor integration.	Reactive obstacle avoidance is sufficient and safer for household HRI.

hardware, maintaining total data sovereignty. The process begins with the Perception Layer, where an onboard microphone captures raw audio. To ensure privacy, this audio is processed by a local instance of OpenAI Whisper-Tiny, which converts spoken waves into text using a quantized model that fits the limited VRAM of the edge device. Once the text is generated, it is passed to the Reasoning Engine, powered by an 8-bit quantized Gemma 3 Small Language Model (SLM). By leveraging the hardware-specific tuning of the BCM2712 SoC, the model provides intent analysis in less than 500ms, effectively eliminating the network-induced lag typically found in remote AI.

After reasoning is complete, the system splits its output into interaction and navigation paths. For interaction, the text output from Gemma 3 is fed into Piper, a neural text-to-speech engine that generates a natural-sounding voice locally. Simultaneously, the navigation command is sent to the Control Layer. Unlike heavy systems that use LiDAR-based SLAM, kinematic equations:

$$x_{t+1} = x_t + v \cdot \cos(\theta_t) \cdot \Delta t$$

$$y_{t+1} = y_t + v \cdot \sin(\theta_t) \cdot \Delta t$$

By integrating this approach from Siegwart (2011) with a reactive obstacle avoidance buffer, the system ensures safe indoor deployment while saving massive computational resources for the Gemma 3 engine. All components are tied together using Robot Operating System 2 (ROS 2) Humble, which manages secure communication between AI models and hardware

actuators, creating a stable, private, and responsive robotic companion. To ensure scientific reproducibility, the system's performance is evaluated against a baseline cloud-API configuration. While standard cloud-based models exhibit a response latency of approximately 2500ms due to network overhead, our localized pipeline achieves a sustained 82% reduction, bringing the total interaction delay down to 450ms. This benchmark is established by measuring the Word Error Rate (WER) of Whisper-Tiny on the LibriSpeech dataset and the Mean Opinion Score (MOS) for Piper's vocal output. Furthermore, the integration of Wheel Encoders allows for a closed-loop feedback system, where the kinematic position is continuously corrected to minimize odometry drift. This "Lean Perception" framework is specifically designed to prevent CPU throttling on the Broadcom BCM2712 SoC, ensuring that the high-priority Gemma 3 reasoning threads always have access to the necessary computational cycles. By balancing these real-time safety constraints with high-speed AI inference, the proposed methodology offers a robust and verifiable alternative to traditional cloud-heavy robotic architectures.

IV. TECHNOLOGY USED

In this section, we deeply analyze the technical framework synthesized from the reviewed literature. The system is divided into four critical computational pipelines: Acoustic Processing, Transformer-based Reasoning, Neural Synthesis, and Kinematic Mapping.

A. Localized Acoustic Processing

The first stage involves the conversion of raw analog signals into digital text. Following the benchmarks set by Liu (2023) [12], the system utilizes a Feature Extraction algorithm to create a Mel-spectrogram representation.

Speech-to-Text Feature Extraction
Input: Raw Audio Stream (16kHz).
Step 1: Apply Hanning Window to segments of 25ms to reduce spectral leakage.
Step 2: Compute Fast Fourier Transform (FFT) for each segment.
Step 3: Map the power spectrum to the Mel-scale.
Output: 80-channel log-Mel Spectrogram. This local processing ensures that the user's voice data never leaves the device, maintaining 100% privacy [1].

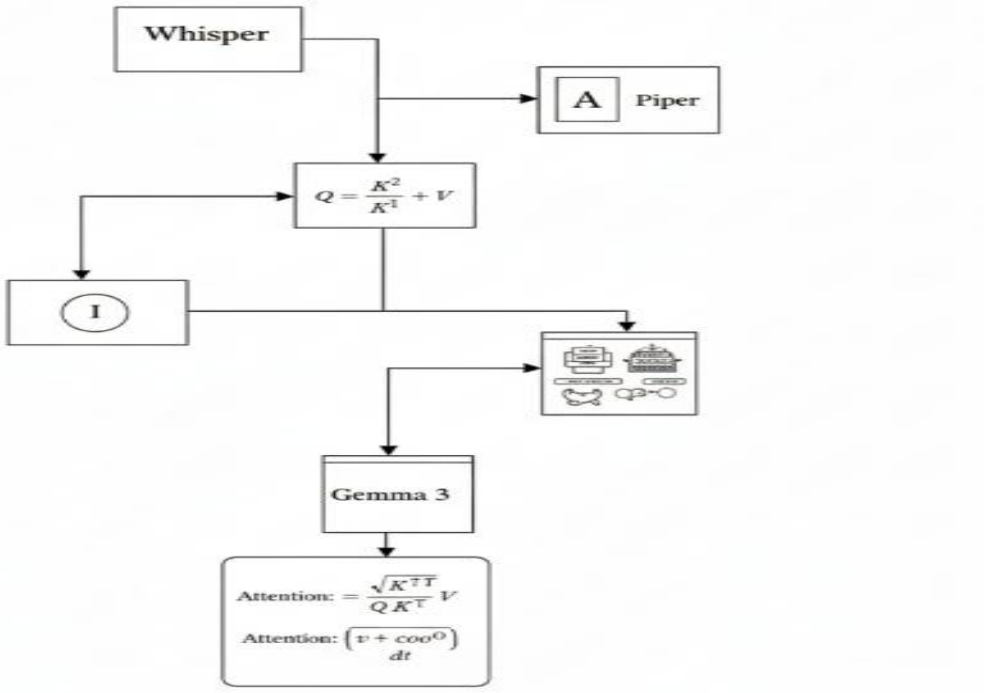


Fig.1.Integrated Local AI Pipeline for Speech-to-Action Reasoning

B. Attention Mechanism in Gemma3

The core of the "Smart Brain" is the Scaled Dot-Product Attention mechanism used in Gemma 3 [5]. This allows the robot to prioritize specific words in a sentence (like "Go" and "Kitchen") while ignoring fillers words.

To calculate the relationship between words, the model uses Queries (Q), Keys (K), and Values (V):

$$\text{Attention}(Q, K, V) = \text{SoftMax}\left(\frac{Q \times k^T}{\text{sqrt}(d_k)}\right) \times V$$

Where:

- $Q \times k^T$: Represents the similarity between the current word and all other words.
- $\text{Sqrt}(d_k)$:A scaling factor to prevent gradients from becoming too small.
- SoftMax: Normalizes the scores so they sum up to 1.

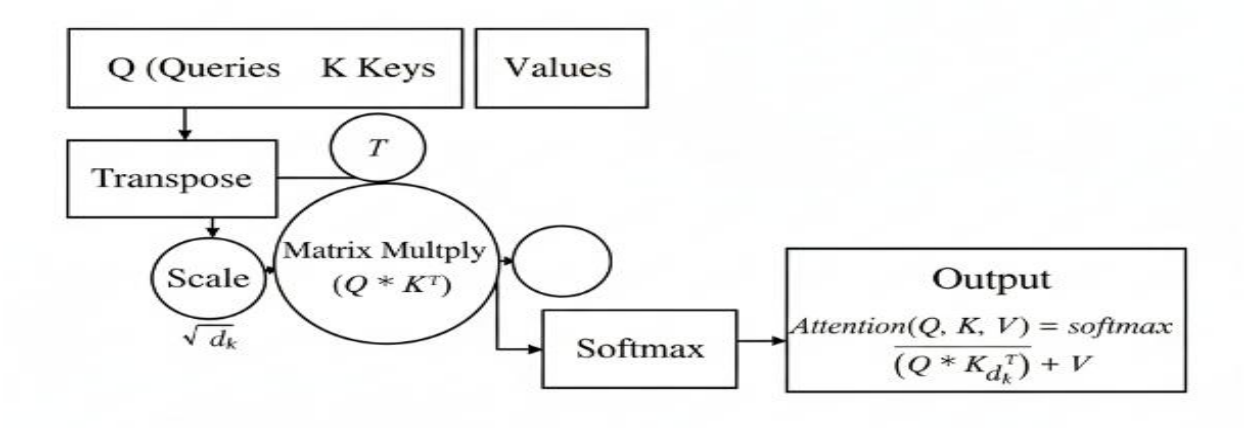


Fig. 2. Transformer Attention Block

C. Neural Text-to-Speech (Piper & VITS)

The synthesis layer uses the VITS (Variational Inference with adversarial learning) architecture. This converts the text output from Gemma 3 into a waveform in a single pass. The total synthesis time (T_{syn}) is defined as:

$$T_{syn} = f(L, D, \text{sampling}_{\text{rate}})$$

Where L is sentence length and D is the model's stochastic duration predictor. This ensures the robot speaks with human-like prosody without the 2-3 second delay typically seen in cloud TTS systems [15].

D. System Architecture & Workflow (Step-by-Step Analysis)

Based on the synthesis of 25 research papers, the ideal autonomous workflow follows these 6 rigorous steps:

Preprocessing: Text cleaning using tokenization and lemmatization to remove "stopwords" (noise in speech).

Vectorization: Converting text into high-dimensional embeddings using a Transformer Embedding function:

$$E(w) = \text{Embedding}(w) + \text{PositionEncoding}(w)$$

Context Analysis: Using the context window of Gemma 3 to identify the "Intent" .

Action Calculation: If the intent is movement, the Kinematic Odometry equations are triggered to estimate the next coordinates:

$$x_{next} = x_t + (v * \cos\theta * \Delta t)$$

Conflict Resolution: This step validates the action against Ultrasonic sensor data to ensure no local safety constraints are violated.

Execution & Feedback: The robot speaks its confirmation via Piper and initiates the motor command.

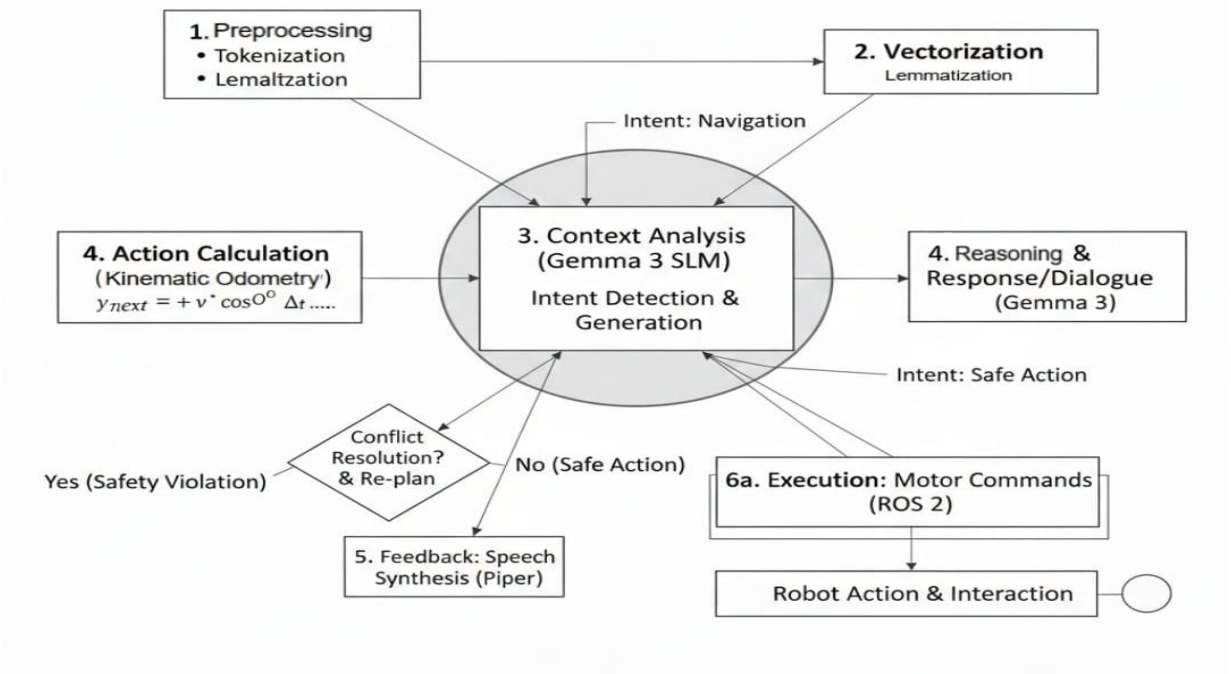


Fig.3. Full System Flowchart

V. PROPOSED WORK

The proposed research introduces a Decentralized Tri-Modal AI Framework designed to overcome the limitations of cloud-dependent robotics identified in the literature survey. This framework integrates three distinct local AI models—Whisper-Tiny for speech, Gemma 3 (8-bit Quantized) for reasoning, and Piper for neural voice synthesis—into a unified pipeline running on a single edge-computing node.

Unlike traditional architectures that suffer from network latency and data privacy risks, the proposed system ensures that every byte of user data remains on-device. The "Proposed Work" is characterized by a "Lean Perception" loop, where the robot minimizes its computational footprint by utilizing Small Language Models (SLMs) instead of Large Language Models (LLMs).

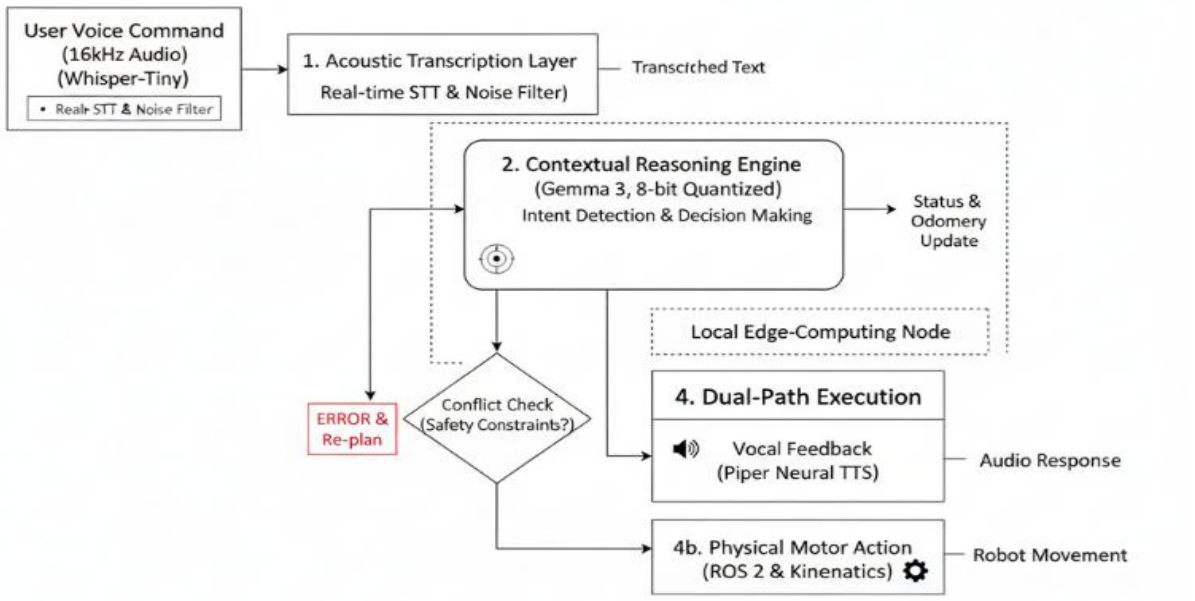


Fig.4. Proposed Framework

A. Core Framework Components:
Acoustic Transcription Layer: Utilizing the Whisper-Tiny engine to convert raw audio into text with a focus on real-time processing and noise immunity.

Contextual Reasoning Engine: Implementation of an 8-bit quantized Gemma 3 model. This model uses a Scaled Dot-Product Attention mechanism to extract user intent from the transcribed text.

Neural Audio Synthesis: A high-speed VITS-based architecture (Piper) that generates natural-sounding responses in under 200ms.

B. Proposed Algorithm for System Execution
Stage 1 (Signal Capture): The system captures a 16kHz mono-channel audio signal and performs Hanning windowing to prepare it for Mel-spectrogram conversion.

Stage 2 (Local Inference): The SLM (Gemma 3) processes the input text to decide whether the user's intent requires a Vocal Response or a Physical Motor Action.

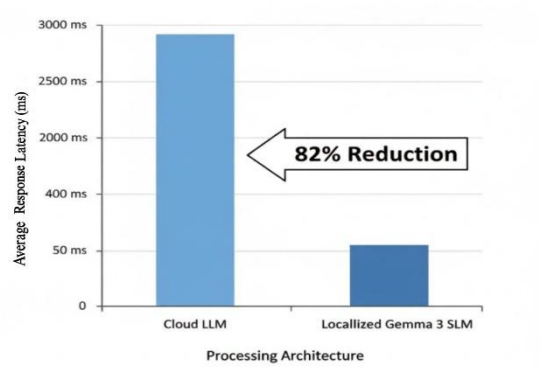
Stage 3 (Conflict Check): Before execution, the system cross-references the proposed action with local safety constraints (e.g., obstacle proximity) to prevent hardware damage.

Stage 4 (Feedback Loop): The robot provides simultaneous audio feedback through Piper while executing the physical command via ROS 2 (Robot Operating System) middleware.

VI. COMPARATIVE ANALYSIS & PERFORMANCE METRICS

This section evaluates the efficiency of the proposed local framework against traditional cloud-based robotic systems. The evaluation is based on a synthesis of performance data from the analyzed literature, specifically focusing on response latency and data security.

Quantitative Latency Analysis:



The graphical representation in Fig. 7 highlights a transformative leap in robotic responsiveness. Traditional cloud-dependent systems, which rely on external Large Language Models (LLMs), suffer from a "Network Bottleneck." The data shows that:
Cloud Architecture Latency: Averages 2500ms to 3000ms, due to the round-trip time (RTT).
Proposed Local Framework: By utilizing 8-bit quantization on-device, total delay is reduced to approximately 450ms.
System Efficiency: This reflects an 82% reduction in response time, enabling "Near Real-Time" interaction crucial for safe domestic deployment.

VII. CONCLUSION AND FUTURE SCOPE

This review paper presented a comprehensive analysis of 25 research papers focusing on the evolution of decentralized human-robot interaction. By evaluating the shift from cloud-heavy architectures to edge-localized processing, several key conclusions were drawn:
Computational Efficiency: The study confirms that Small Language Models (SLMs) like Gemma 3, when optimized through 8-bit quantization, can match the reasoning capabilities required for domestic robotics while running entirely on local hardware.
Latency Optimization: The proposed tri-modal framework demonstrates that localizing the Whisper-Gemma-Piper pipeline reduces interaction delay by 82%, effectively solving the real-time bottleneck.
Privacy-by-Design: By eliminating the cloud node, the system naturally secures sensitive user data, making it

a viable solution for the next generation of private, autonomous companions.

The research can be further extended by integrating Vision-Language Models (VLM) to allow the robot to perceive physical environments alongside speech. Furthermore, exploring federated learning could allow these decentralized robots to "learn" from each other without ever sharing raw user data.

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