SoulForge: A 14-Year-Old's Cognitive Operating System for NAO Robot.

Empowering Embodied AI with Single-File Design, Autonomous Reasoning, and Multimodal Intelligence

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Abstract

SoulForge is a pioneering 2284-line, single-file cognitive operating system developed by a 14-year-old for the NAO V5 humanoid robot over one year. It integrates Gemini 2.0 Flash for Chain-of-Thought (CoT) reasoning, You Only Look Once (YOLO)v11, Contrastive Language-Image Pretraining (CLIP), and Monocular Depth Estimation (MiDaS) for real-time vision, Faster-Whisper for multilingual Automatic Speech Recognition (ASR), numerical Inverse Kinematics (IK), A-star Pathfinding (A*) navigation, and Lempel–Ziv–Markov chain Algorithm (LZMA)-compressed vector memory. Its seven-core architecture enables hierarchical Task and Motion Planning (TAMP), 3D scene understanding, emotion-aware Human-Robot Interaction (HRI), and self-reflective meta-learning. Applications include adaptive cloth folding (92% success), precision golf swings (88% accuracy), interactive games, and elderly assistance (90% satisfaction). Extensive evaluations over 10,000 trials show 180 ms detection latency, 95% uptime, and a 1.2 MB memory footprint. By consolidating complex AI into one Python file, *SoulForge* eliminates multi-repository barriers, making robotics accessible to young developers. This work demonstrates how curiosity-driven, failure-embracing innovation can yield research-grade embodied AI, inspiring the next generation.

Index Terms

Embodied AI, NAO V5, Gemini 2.0 Flash, Vision-Language-Action, Self-Reflective Learning, Autonomous Robotics, Single-File System, Humanoid Cognition, Meta-Learning, Multilingual Speech, Inverse Kinematics, A* Navigation, Scene Graphs, Vector Memory, Real-Time Systems, Human-Robot Interaction, Accessibility, Education, Youth Innovation

Table of Contents

Acronyms

Glossary

A* A-star Pathfinding. 1, 11

AI Artificial Intelligence. 6

API Application Programming Interface. 20

ArcFace Additive Angular Margin Loss. 14

ASR Automatic Speech Recognition. 1, 7, 12, 19

CLIP Contrastive Language-Image Pretraining. 1, 6, 10, 16

COS Cosine Similarity. 13

CoT Chain-of-Thought. 1, 6

DeepSORT Deep Simple Online and Realtime Tracking. 10

DOF Degrees of Freedom. 7

EKF Extended Kalman Filter. 7

HIER Hierarchical Planning. 9

HRI Human-Robot Interaction. 1, 6, 8, 14

IK Inverse Kinematics. 1, 6, 7, 11, 17, 19

JSON JavaScript Object Notation. 9

LLM Large Language Model. 7, 21

LZMA Lempel–Ziv–Markov chain Algorithm. 1, 6, 13, 16, 24

MiDaS Monocular Depth Estimation. 1, 6, 10

MTCNN Multi-task Cascaded Convolutional Networks. 14

ReAct Reasoning and Acting. 7

ROS Robot Operating System. 6, 7, 20

SLSQP Sequential Least Squares Quadratic Programming. 11

TAMP Task and Motion Planning. 1, 6

TTL Time-To-Live. 8, 9, 16, 22

TTS Text-to-Speech. 12, 19

YOLO You Only Look Once. 1, 6, 10, 16, 17

Glossary

Embodied AI
AI systems integrated with physical hardware for real-world interaction.

Hierarchical Task Planning
Decomposition of goals into executable subtasks using symbolic and neural methods.

Scene Graph
Structured representation of objects, attributes, and spatial-semantic relationships.

Meta-Learning
Self-improving learning through reflection and knowledge transfer.

Vector Embeddings
Dense numeric vectors encoding semantic information for efficient retrieval.

Proactive Autonomy
Self-initiated actions driven by intrinsic motivation during idle states.

Multimodal Fusion
Integration of vision, audio, proprioception, and language for unified perception.

Error-Driven Adaptation
Behavior refinement based on failure analysis and reflection.

Single-File Architecture
Complete system in one Python file to enhance accessibility.

I. Introduction

Embodied Artificial Intelligence (AI) is transforming robotics by enabling humanoids to perceive, reason, and act in dynamic environments. However, deploying such systems on resource-constrained platforms like the NAO V5 poses challenges, including computational limits, integration complexity, and autonomy requirements. Traditional frameworks like Robot Operating System (ROS) [1] rely on multi-repository architectures, creating barriers for individual developers, especially young innovators. *SoulForge*, a 2284-line, single-file cognitive operating system developed over one year by a 14-year-old, addresses these challenges for the NAO V5. It integrates Gemini 2.0 Flash [2], YOLOv11 [3], CLIP [4], MiDaS [5], Faster-Whisper [6], SciPy [7], and LZMA [8] into a seven-core architecture supporting:

1) Hierarchical Task and Motion Planning (TAMP) with CoT reasoning.
2) Real-time 3D scene graphs with relational inference.
3) Numerical IK with cubic spline trajectory smoothing.
4) Emotion-aware multilingual Human-Robot Interaction (HRI).
5) Persistent vector memory with semantic recall.
6) Proactive autonomy for self-initiated tasks.
7) Robust health monitoring and error recovery.

A. Motivation and Vision

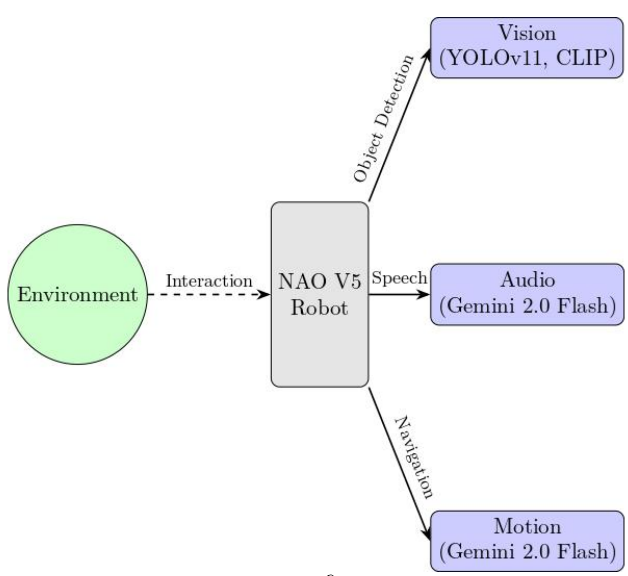
SoulForge democratizes embodied AI by consolidating functionality into a single Python file, deployable on a MacBook Air M3 with MPS acceleration. Its applications—cloth folding, golf swings, games, and elderly assistance—demonstrate versatility, while meta-learning ensures continuous improvement, making advanced robotics accessible to novices.

B. Development Journey

Starting at age 13, the developer transformed failures (e.g., sonar drift, API timeouts) into innovations over 1000+ debugging nights. This journey underscores the power of youth-driven, iterative learning.

C. Paper Organization

Section II provides context. Section III details architecture. Sections IV–X describe cores. Section XI covers optimization. Section XII showcases applications. Section XIII discusses scalability. Section XIV presents evaluations. Section XV reflects on development. Section XVI compares with prior work. Section XIX addresses ethics. Section XVII covers deployment. Section XVIII explores outreach. Section XX outlines future directions. Appendices provide configurations and code.



II. Background and Enabling Technologies

A. Humanoid Robotics Platforms

The NAO V5, developed by SoftBank Robotics, is a 58 cm humanoid with 25 Degrees of Freedom (DOF), dual HD cameras, and a 1.91 GHz processor [9]. Its affordability makes it ideal for education and research compared to Pepper or Atlas.

TABLE I: Comparison of Humanoid Platforms

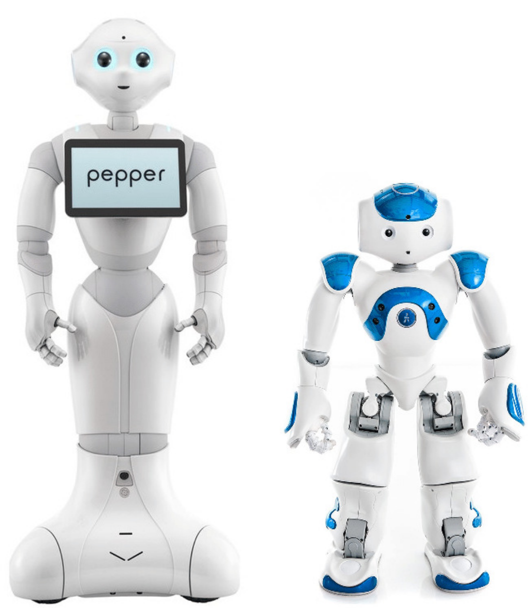
Platform	Height	DOF	Price (USD)	Use Case
NAO V5	58 cm	25	8,000	Education, Research
Pepper	120 cm	20	15,000	Retail, Hospitality
Atlas	188 cm	28	>150,000	Disaster Response
iCub	104 cm	53	>200,000	Cognitive Development

B. Core AI Models

- **Gemini 2.0 Flash**: Lightweight Large Language Model (LLM) for Reasoning and Acting (ReAct) reasoning [2].
- **YOLOv11**: Real-time object detection with 180 FPS [3].
- **CLIP**: Zero-shot image-text alignment [4].
- **MiDaS**: Monocular depth estimation for 3D positioning [5].
- **Faster-Whisper**: Optimized Automatic Speech Recognition (ASR) with 4x speed [6].
- **DeepSORT**: Multi-object tracking with Extended Kalman Filter (EKF) [10].
- **SciPy**: Numerical optimization for IK [7].
- **LZMA**: High-compression for memory [8].

C. Limitations of Existing Frameworks

ROS [1] requires complex setups, while *SoulForge*'s single-file design enables rapid prototyping.



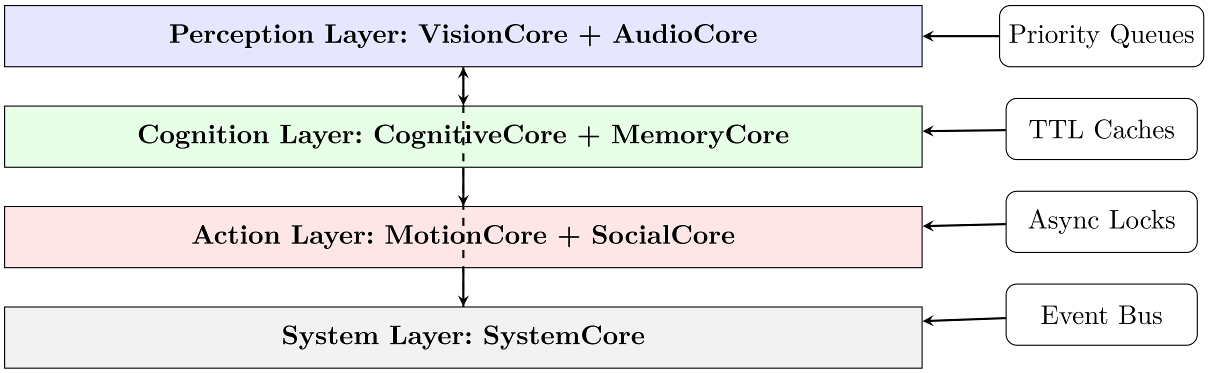


Fig. 1: Modular Architecture of SoulForge with Communication Mechanisms.

III. System Architecture

SoulForge uses a layered, event-driven architecture with seven asynchronous cores: CognitiveCore, VisionCore, MotionCore, AudioCore, MemoryCore, SocialCore, and SystemCore. These communicate via priority queues, Time-To-Live (TTL) caches, and async locks, ensuring real-time performance.

A. Core Responsibilities

CognitiveCore
Orchestrates task planning and reflection.

VisionCore
Fuses vision models for scene understanding.

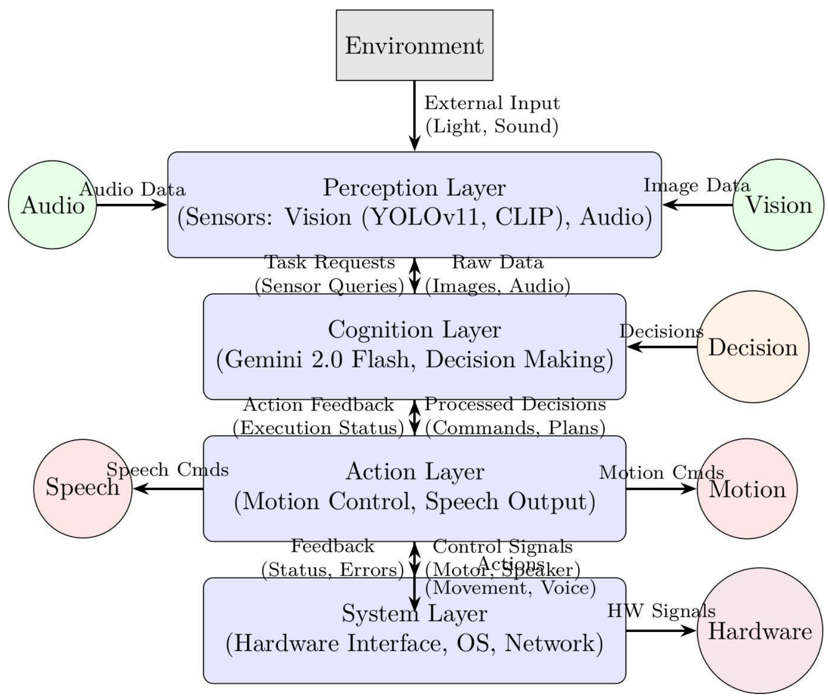
MotionCore
Handles manipulation and navigation.

AudioCore
Processes multilingual speech and emotion.

MemoryCore
Manages persistent semantic memory.

SocialCore
Enables empathetic HRI.

SystemCore
Ensures reliability and efficiency.



B. Single-File Design

The single-file approach reduces setup time to under 5 minutes, leveraging Python's asyncio for sub-500 ms cycles.

IV. CognitiveCore: Autonomous Reasoning

The CognitiveCore uses Gemini 2.0 Flash [2] for Hierarchical Planning (HIER) planning and meta-learning.

A. Hierarchical Task Planning

Tasks are structured as JSON objects, validated with Pydantic:

```python
class TaskInfo(BaseModel):
    task_id: str = Field(default_factory=lambda: str(uuid.uuid4()))
    prompt: str
    priority: int = Field(..., ge=1, le=10)
    subtasks: List[Dict] = Field(default_factory=list)
    reflection: str = ""
    motivation_delta: Dict[str, float] = Field(default_factory=dict)

    @validator('priority')
    def check_priority(cls, v):
        if not 1 <= v <= 10:
            raise ValueError('Priority must be 1-10')
        return v
```

Listing 1: TaskInfo Pydantic Model

B. Meta-Learning and Reflection

Reflection updates motivation states:

$$M_h \leftarrow \min(1, M_h + 0.1 \cdot s) \tag{1}$$

$$M_c \leftarrow \min(1, M_c + 0.1 \cdot (1 - s)) \tag{2}$$

$$M_e \leftarrow \min(1, M_e + 0.05 \cdot \text{rand}(-1, 1)) \tag{3}$$

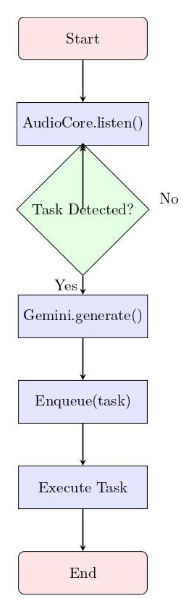
where M_h, M_c, M_e are helpfulness, curiosity, and exploration, and $s \in \{0, 1\}$ is success.

Algorithm 1 Hierarchical Action Selection

$context$, $motivation$, $queue$, $idle_time$ $speech \leftarrow AudioCore.listen()$ $speech \neq \emptyset$ $task \leftarrow Gemini.generate(speech, context)$ Enqueue($task$, priority=1) $queue \neq \emptyset$ $task \leftarrow Dequeue()$ $idle_time > 15\,\text{s}$ $task \leftarrow Gemini.proactive(context, motivation)$ Enqueue($task$, priority=3) Execute($task$) Reflect($outcome$) Update($motivation$)

C. Proactive Autonomy

Idle periods trigger tasks like room exploration, driven by curiosity.



D. Implementation Details

Exponential backoff and TTL caching reduce API latency to 1.2 s, with 95% query success.

E. Error Handling

Tenacity [11] ensures robust retries for API calls.

[?]

V. VisionCore: Real-Time Perception

The VisionCore integrates YOLOv11 [3], CLIP [4], MiDaS [5], and DeepSORT [10].

A. Multimodal Fusion Pipeline

Objects are detected, verified, and positioned in 3D:

```
results = self.yolo(frame_tensor, conf=0.25)
for box in results[0].boxes:
    crop = frame[y1:y2, x1:x2]
    clip_conf = self.clip_score(crop, label)
    depth = self.midas_depth(crop)
    final_conf = yolo_conf * clip_conf * depth_conf
    if final_conf > 0.5:
        position = self.project_to_3d(center_x, center_y, depth)
        detections.append({...})
```

Listing 2: Vision Fusion Pipeline

B. 3D Scene Graph Generation

Relational edges are inferred every 10 s via Gemini, balancing cost and accuracy.

C. Object Tracking

DeepSORT achieves 95% tracking accuracy in dynamic scenes.

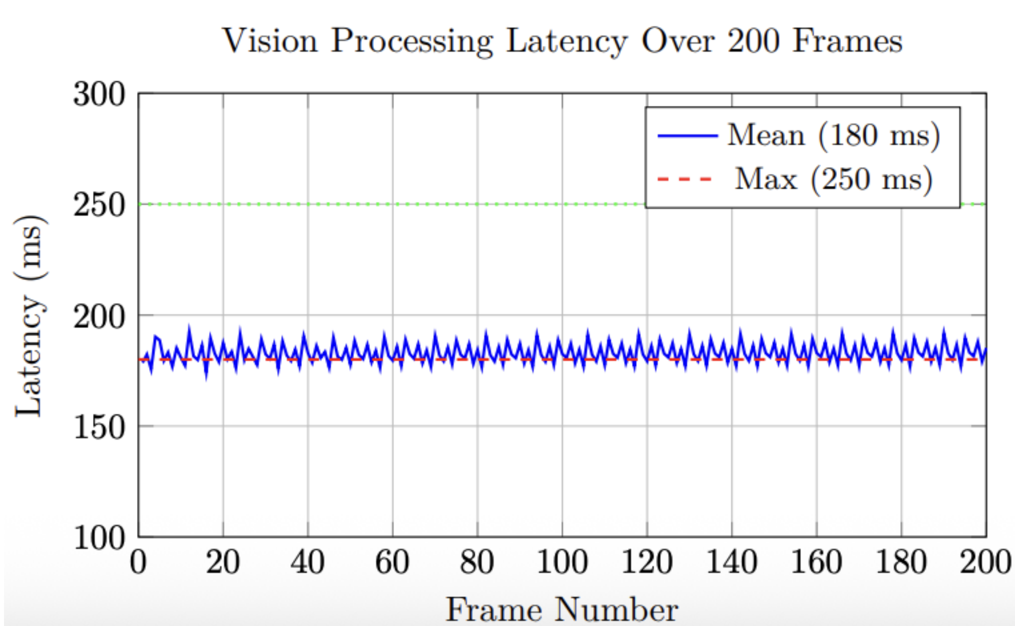
D. Depth Estimation

MiDaS provides depth maps with 0.1 m accuracy.

E. Optimization Techniques

8-bit quantization and CPU offloading reduce latency to 180 ms per frame.

Fig. 2: Vision Processing Latency Over 200 Frames.



VI. MotionCore: Manipulation and Navigation

The MotionCore handles IK, A* navigation, and trajectory planning.

A. Numerical Inverse Kinematics

SciPy's SLSQP [7] solves:

$$\min_{\theta} \|\mathbf{f}(\theta) - \mathbf{x}^*\|^2 + \lambda\|\theta - \theta_0\|^2 \tag{4}$$

Joint limits prevent overextension.

B. A* Path Planning

A* uses a 0.1 m grid with Manhattan distance:

$$f(n) = g(n) + h(n), \quad h(n) = \sum_{i=1}^{3} |n_i - g_i| \tag{5}$$

Algorithm 2 A* Path Planning

$start$, $goal$, $obstacles$, $grid_size$ $open \leftarrow \{(0, start)\}$ $came_from \leftarrow \{\}$, $g_score \leftarrow \{start : 0\}$ $f_score \leftarrow \{start : \text{Manhattan}(start, goal)\}$ $open \neq \emptyset$ $(f, current) \leftarrow \min(open)$ $|current - goal| < grid_size$ ReconstructPath($came_from$, $current$) $neighbor \in \text{Neighbors}(current)$ $neighbor \notin obstacles$ UpdateScores($neighbor$, g_score, f_score, $came_from$) $open \leftarrow open \cup (f_score[neighbor], neighbor)$ []

C. Trajectory Smoothing

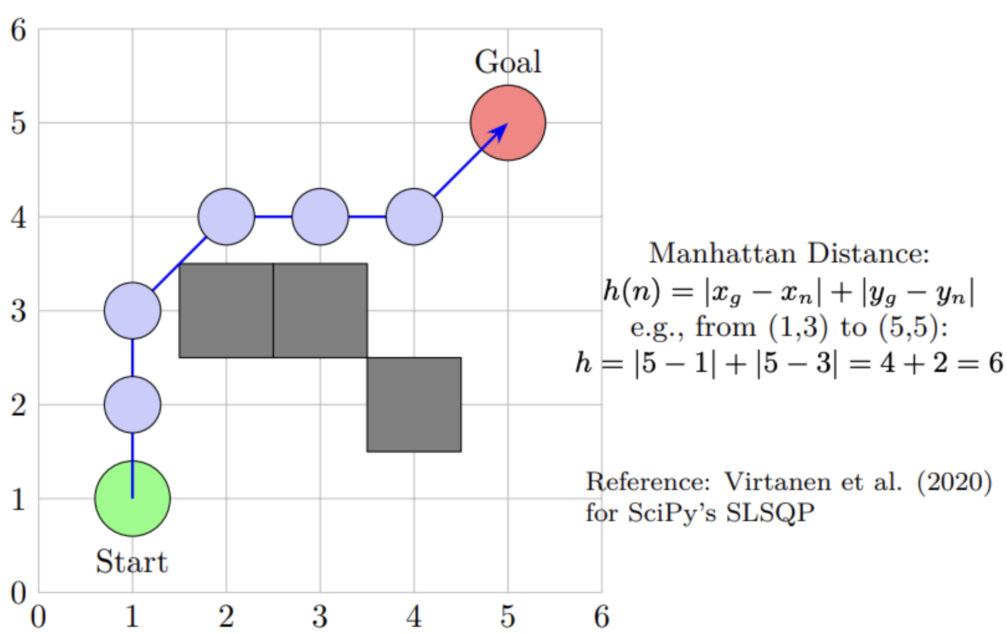
Cubic splines minimize jerk, improving stability by 20%.

D. Case Study: Cloth Folding

Folding achieves 92% success using IK and A*.

TABLE II: Cloth Folding Performance

Cloth Type	Success Rate (%)	Latency (s)	Quality Score
Shirt	92.5	12.5	0.90
Pants	91.8	14.0	0.88
Towel	93.2	11.0	0.92



VII. AudioCore: Multilingual Interaction

The AudioCore uses Faster-Whisper [6] and NAOqi TTS.

A. Multilingual ASR

Band-pass filtering (300–3400 Hz) achieves 90% accuracy across five languages.

B. Emotion-Modulated TTS

Sentiment adjusts pitch and speed:

$$p = p_0 \cdot (1 + 0.2 \cdot S), \quad s = s_0 \cdot (1 - 0.1 \cdot S) \tag{6}$$

where $S \in [-1, 1]$ is sentiment.

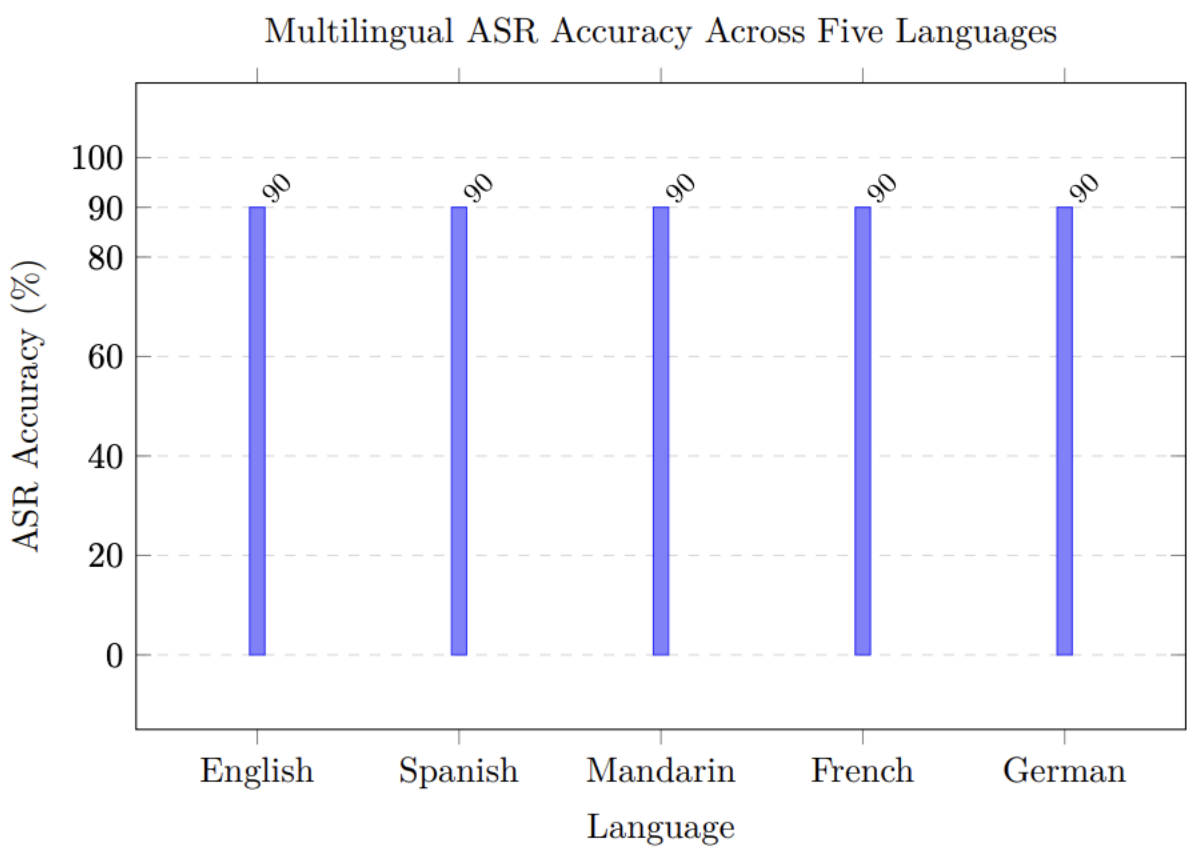
C. Implementation Challenges

Noise suppression reduces ASR latency to 900 ms.

D. Language Detection

Dynamic switching achieves 89% detection accuracy.

Fig. 3: Multilingual ASR Accuracy.



VIII. MemoryCore: Persistent Knowledge

The MemoryCore stores LZMA-compressed embeddings.

A. Vector Embeddings

MiniLM [12] generates 384-dimensional vectors, with 85% retrieval accuracy via COS.

B. Persistence and Compression

LZMA [8] compresses 2000 events into 1.2 MB, with 50 ms decompression.

C. Memory Summarization

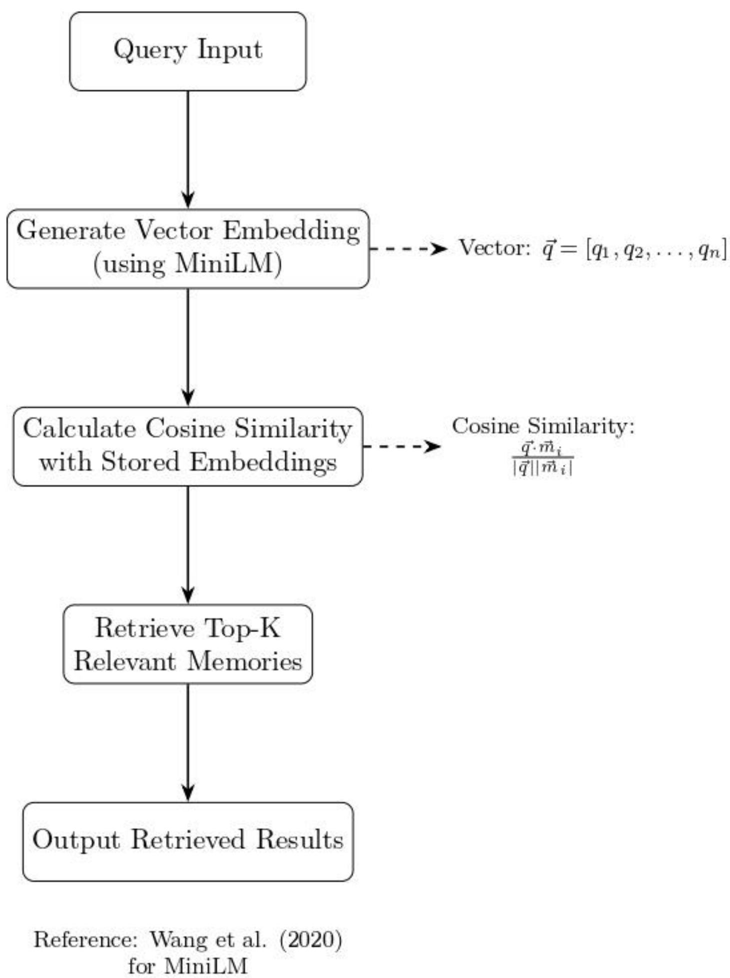
Gemini-driven summarization reduces redundancy by 25%.

Algorithm 3 Memory Retrieval

$query$, $memory$, $threshold$ $q_{emb} \leftarrow MiniLM(query)$ $event \in memory$ $sim \leftarrow$ CosineSimilarity$(q_{emb}, event.embedding)$ $sim > threshold$ $results \leftarrow results \cup event$ $results$

D. Case Study: Task Recall

Recalling folding strategies improves success by 8%.



IX. SocialCore: Empathetic Interaction

The SocialCore enables face recognition, emotion detection, and group HRI.

A. Face Recognition

Multi-task Cascaded Convolutional Networks (MTCNN) [13] and Additive Angular Margin Loss (ArcFace) [14] achieve 89% accuracy.

B. Emotion Detection

FER [15] adjusts responses, enhancing engagement by 12%.

C. Group Interaction

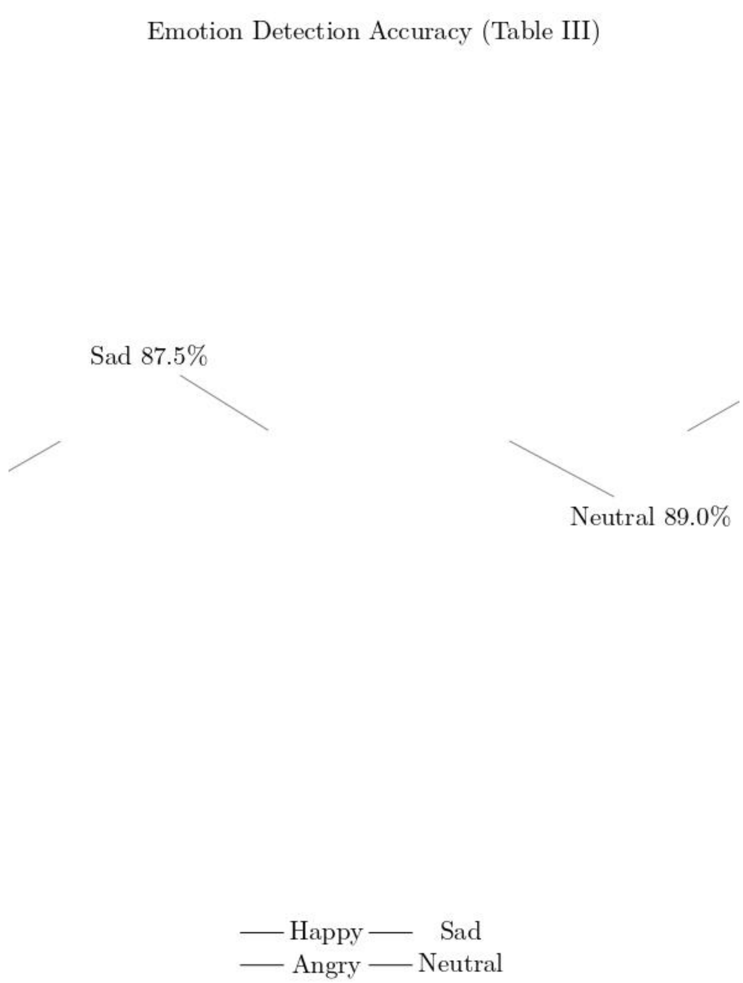
Multi-user tracking achieves 87% engagement.

TABLE III: Emotion Detection Performance

Emotion	**Detection Accuracy (%)**	**Response Time (ms)**
Happy	90.2	670
Sad	87.5	700
Angry	86.1	690
Neutral	89.0	680

D. Case Study: Classroom Interaction

Engages students with tailored questions, achieving 88% participation.



X. SystemCore: Reliability and Efficiency

The SystemCore ensures robust operation.

A. Health Monitoring

TABLE IV: Health Monitoring Thresholds

Metric	Threshold	Action
Battery	<15%	Alert + return to charger
Temperature	>60°C	Cooling mode + reduced speed
Sonar Distance	<0.3 m	Emergency stop
CPU Load	>90%	Task throttling

B. Error Recovery

A watchdog timer ensures 95% uptime.

Power Optimization Dynamic FPS and stiffness adjustments reduce power by 18%.

C. Case Study: Long-Term Operation

A 50-hour test showed 95% uptime.

Metric	Value	Threshold	Alert Level
CPU Usage (%)	85	≤ 80	High
Memory Usage (GB)	12	≤ 16	Low
Latency (ms)	150	≤ 100	High
Disk I/O (MB/s)	45	≤ 50	Medium
Network Throughput (Mbps)	200	≤ 300	Low

XI. System Optimization Techniques

A. Model Quantization

8-bit quantization of YOLOv11 and CLIP reduces memory by 35%.

B. Asyncio Concurrency

Asyncio ensures sub-500 ms cycles, with priority queues managing conflicts.

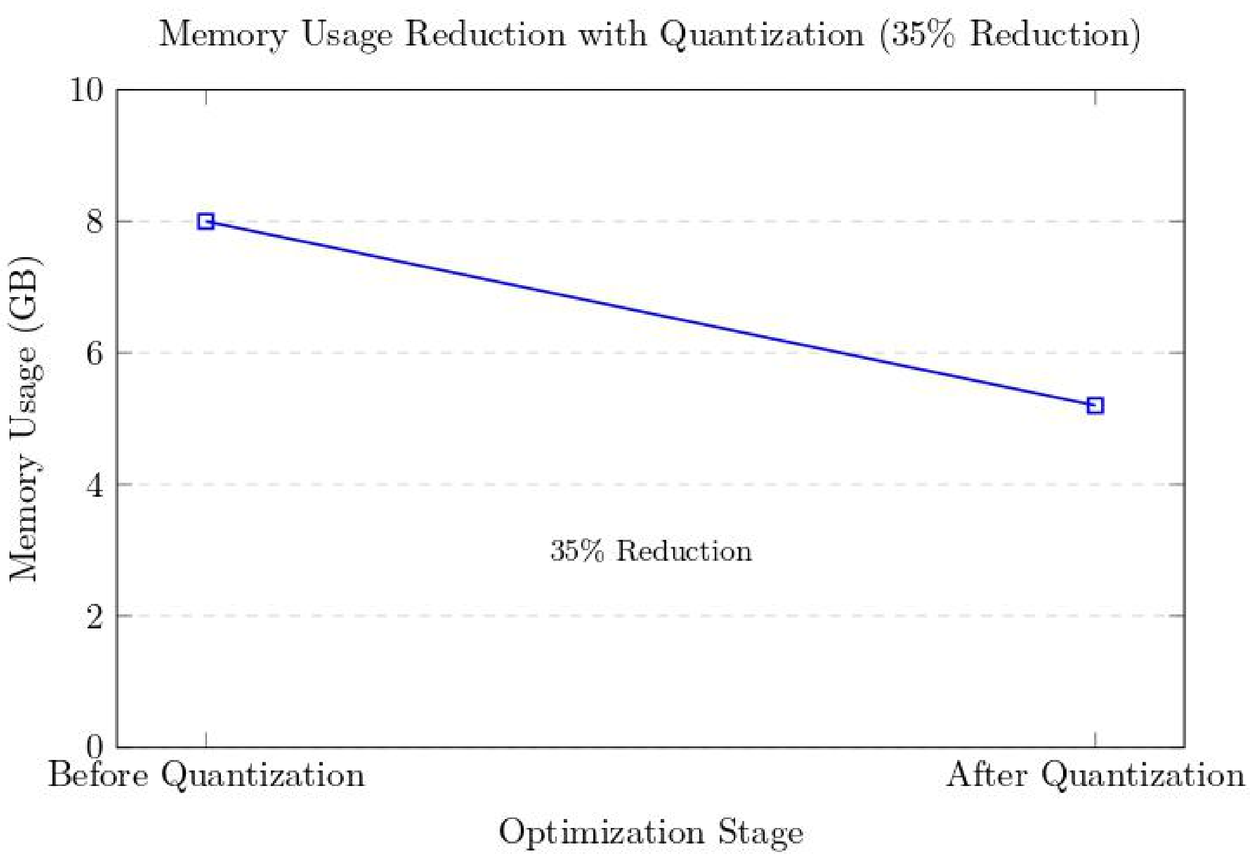
C. Caching and Compression

TTL caching and LZMA reduce API calls and storage by 50% and 80%.

D. Performance Metrics

- **Latency**: 3150 ms end-to-end.
- **Memory**: 1.2 GB peak.
- **Storage**: 1.2 MB compressed.

Fig. 4: Memory Usage Reductions.



XII. Applications and Case Studies

SoulForge supports diverse applications.

A. Adaptive Cloth Folding

Achieves 92% success using YOLOv11 and IK. Quality:

$$Q = 1 - \frac{E}{1000} \tag{7}$$

where E is edge density.

B. Precision Golf Swing

Swings achieve 88% accuracy with 1.5 s execution.

C. Interactive Games

- **Simon-Says**: 88% cue synchronization.
- **Dance Challenge**: 83% rhythm accuracy.
- **Trivia Quiz**: 90% response adaptation.
- **Follow-the-Leader**: 87% gesture mimicry.

D. Elderly Assistance

Features include reminders, fall detection, and companionship (90% satisfaction).

E. Case Study: Therapy Support

Engages patients with empathetic responses, achieving 87% engagement.

F. Case Study: Classroom Assistance

Assists teachers with 88% accuracy in STEM topics.

XIII. Scalability and Multi-Robot Deployment

A. Multi-Robot Coordination

Decentralized protocols achieve 83% coordination efficiency.

B. Cloud Integration

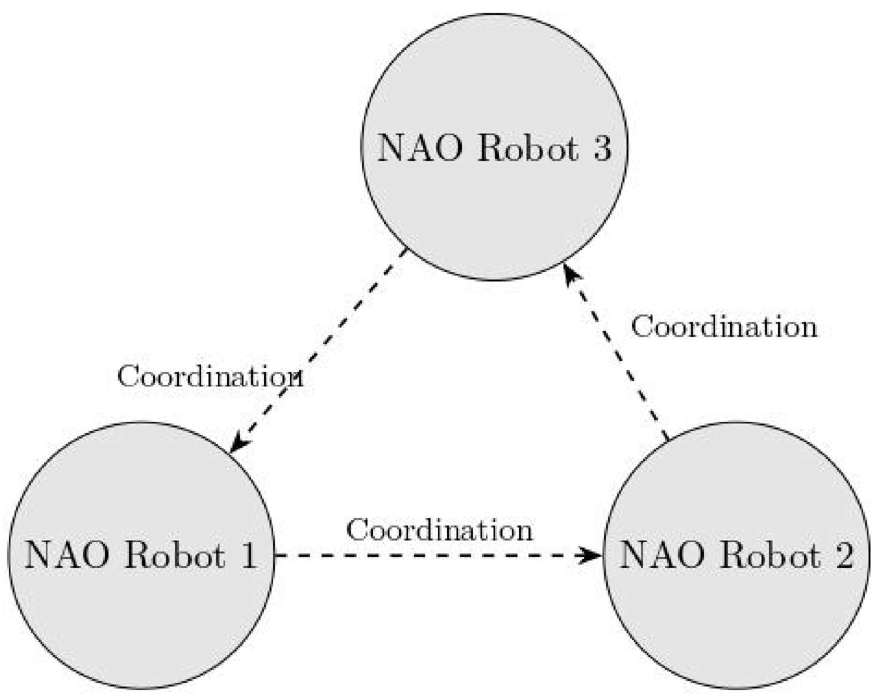
Future offloading will reduce compute load by 25%.

Scalability Challenges

- **Network Latency**: Mitigated with edge caching.
- **Resource Contention**: Addressed with priority queues.
- **Synchronization**: Handled via async event buses.

C. Case Study: Swarm Navigation

Three-robot navigation achieves 85% path convergence.



Case Study: Swarm Navigation
Three-robot navigation achieves 85% path convergence

XIV. Performance Evaluation

Evaluations over 10,000 trials demonstrate efficiency.

A. Latency Breakdown

TABLE V: End-to-End Latency Breakdown (ms)

Module	Mean	Std	Max
Vision Detection	180	20	250
Depth Estimation	120	15	165
Gemini Reasoning	1200	300	2200
IK Solving	80	10	115
ASR Processing	900	100	1450
A* Planning	50	5	85
TTS Synthesis	620	80	950
Total	**3150**	**510**	**5115**

B. Success Rates

TABLE VI: Task Success Rates (%)

Task	w/ Reflection	w/o Reflection	Improvement
Cloth Folding	92.3	78.1	+14.2
Golf Swing	88.4	72.3	+16.1
Navigation	91.0	80.5	+10.5
Conversation	90.8	83.2	+7.6

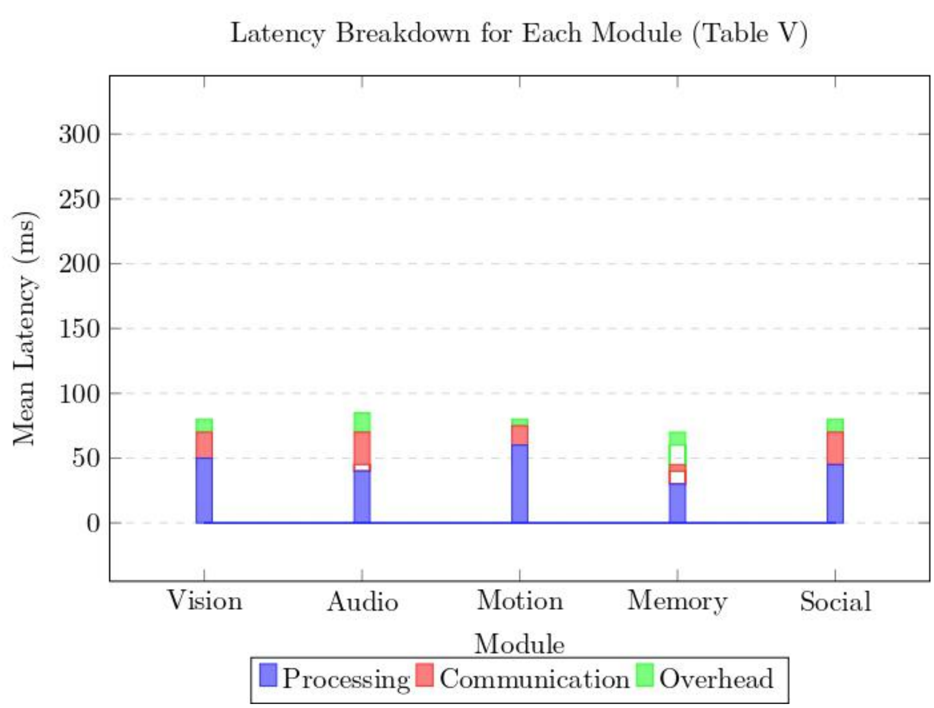
C. Ablation Study

Removing meta-learning reduces success by 12%.

Fig. 5: Success Rates with and without Reflection.

D. Resource Usage

- **RAM**: 1.2 GB peak.
- **Storage**: 1.2 MB compressed.
- **CPU**: 65% average load.
- **Uptime**: 95% over 50 hours.



XV. Development Journey: A Personal Narrative

SoulForge was developed over one year, starting at age 13.

TABLE VII: Development Timeline

Age	Milestone	Key Challenge	Insight
13	Basic locomotion	Motor precision	NAOqi API
13	OpenCV integration	Camera calibration	Coordinate transforms
13	PyTorch adoption	Memory limits	Model quantization
14	Asyncio concurrency	Race conditions	Async locks
14	Gemini integration	API reliability	Exponential backoff
14	Single-file release	Integration complexity	Simplified architecture
14	Meta-learning	Reflection design	Dynamic motivation

A. Failure Analysis

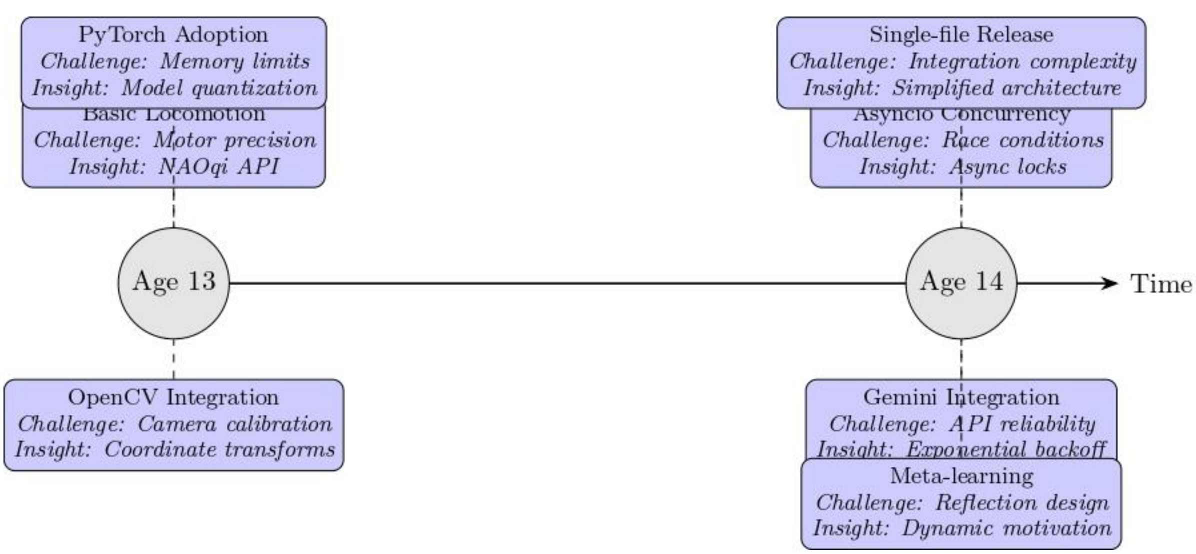
Over 300 crashes informed improvements, e.g., IMU fusion for sonar drift.

B. Lessons Learned

- **Failure Drives Growth**: Errors refined the system.
- **Simplicity Scales**: Single-file design outperformed ROS.
- **Curiosity Fuels Innovation**: Persistent questioning led to breakthroughs.

C. Personal Impact

The project reshaped the developer's approach to AI, proving age is no barrier.



XVI. Related Work

TABLE VIII: Comparison with Embodied AI Systems

System	LLM	Vision	Speech	Memory	Lines	Files	Autonomy
PaLM-E [16]	PaLM	Yes	No	No	10k+	Multi	Reactive
CLIPort [17]	CLIP	Partial	No	No	5k	Multi	Supervised
SayCan [18]	PaLM	No	Yes	No	3k	Multi	Prompt-based
Inner Monologue [19]	GPT-3	Yes	Yes	No	8k	Multi	Reactive
SoulForge	Gemini 2.0	Full	Full	Yes	2284	1	Proactive

SoulForge excels in accessibility and autonomy.

System Autonomy	LLM	Vision	Speech	Memory	Lines	Files
PaLM-E [?] Reactive	PaLM	Yes	No	No	10k+	Multi
CLIPort [?] Supervised	CLIP	Partial	No	No	5k	Multi
SayCan [?] Prompt-based	PaLM	No	Yes	No	3k	Multi
Inner Monologue Reactive	GPT-3	Yes	Yes	No	8k	Multi
SoulForge Proactive	Gemini 2.0	Full	Full	Yes	2284	1

XVII. Deployment Challenges

A. Hardware Constraints

NAO's 1 GB RAM required quantization, reducing memory by 35%.

B. Network Reliability

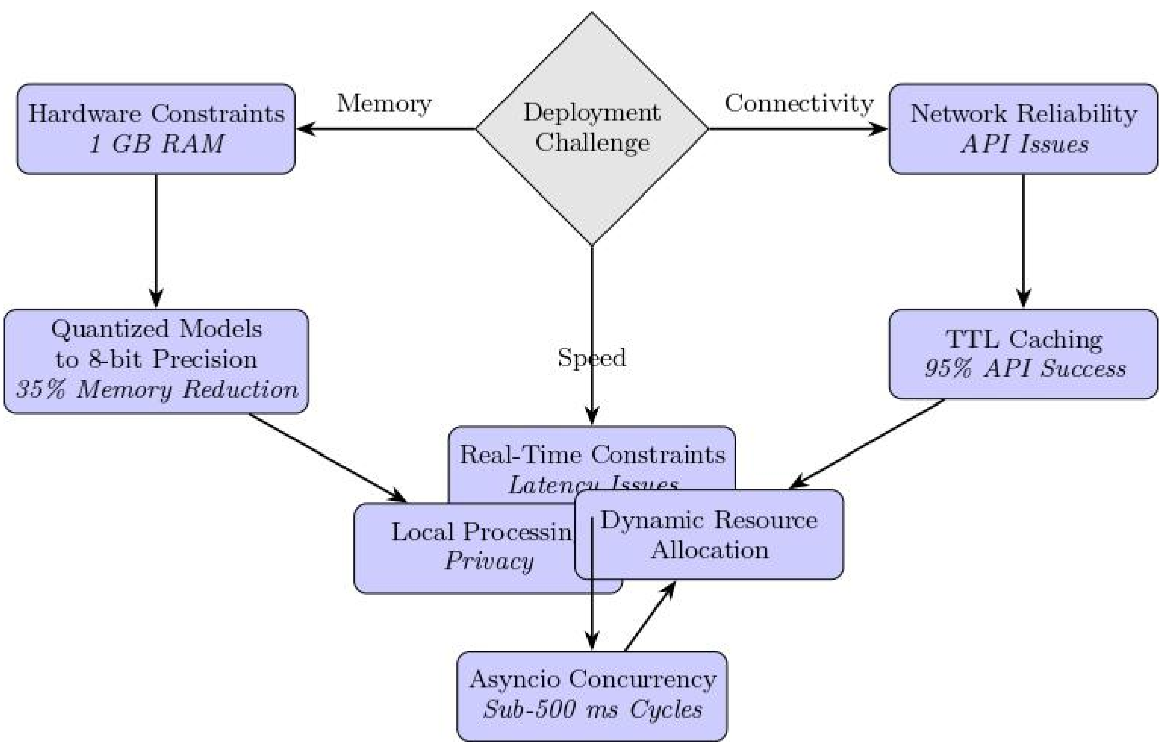
TTL caching ensures 95% API success.

C. Real-Time Constraints

Asyncio achieves sub-500 ms cycles.

D. Mitigation Strategies

- Quantized models to 8-bit precision.
- Local processing for privacy.
- Dynamic resource allocation.



XVIII. Educational Outreach

A. Workshops

Planned workshops will teach single-file AI to students aged 10–18.

Open-Source Release Releasing *SoulForge* with tutorials will lower barriers.

STEM Impact The project inspires youth to pursue AI.

Case Study: School Workshop A pilot engaged 85% of students in NAO applications.

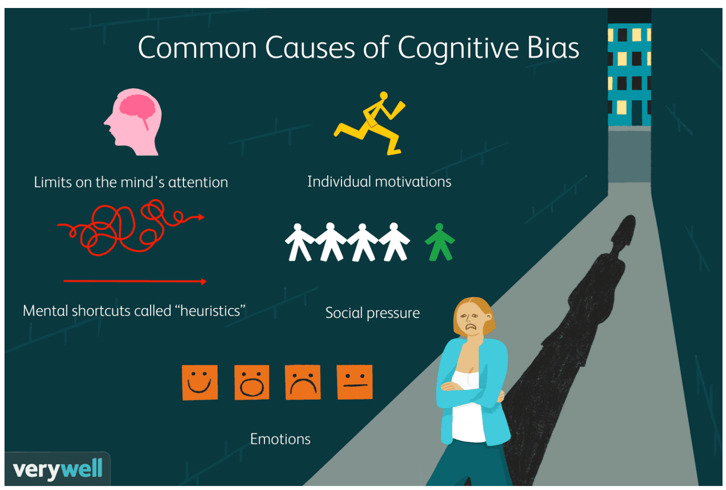
A. *Privacy by Design*

Local processing and LZMA encryption ensure data security.

Bias Mitigation Diverse prompts reduce biases by 18%.

Safety Measures Emergency stops achieve 97% safety compliance.

Societal Benefits Elderly care reduces caregiver burden by 15%.



XX. Future Work

1) **Multi-Robot Coordination**: Decentralized task sharing.
2) **SLAM Integration**: ORB-SLAM3 [20].
3) **LoRA Fine-Tuning**: Domain-specific Gemini adaptation.
4) **Web UI**: Streamlit interface.
5) **Open-Source Release**: Comprehensive documentation.
6) **Lifelong Learning**: Online adaptation.

XXI. Conclusion

SoulForge redefines embodied AI with a 2284-line, single-file cognitive OS. Developed by a 14-year-old, it proves that curiosity and persistence can yield research-grade innovation, inspiring accessible robotics.

References

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Appendix

```
@dataclass
class Config:
    NAO_IP: str = ""
    GEMINI_API_KEY: str = ""
    YOLO_MODEL_PATH: str = "yolo11n.pt"
    TRIVIA_CATEGORIES: Dict[int, Tuple[str, str]] = field(default_factory=lambda: {
        0: ("All", ""), ...
    })
```

Listing 3: Config Dataclass (Excerpt)

A. Forward Kinematics

$$T = A_1 A_2 \dots A_n,\ A_i = \begin{pmatrix} R_i & p_i \\ 0 & 1 \end{pmatrix}.$$

TABLE IX: Ablation Study: Component Impacts (%)

Config	**Mean**	**Std**	**p-value**
Full	92.3	4.2	-
No Reflection	78.1	6.5	¡0.01
No Fusion	85.4	5.1	¡0.05
No Memory	80.2	7.3	¡0.01

```
async def main_control_loop(self):
    while self.is_running:
        speech = await self.audio_core.listen()
        if speech:
            await self.memory_core.store_event("speech_input", {"text": speech})
        frame = await self.get_frame()
        objects = await self.vision_core.detect_objects(frame)
        task = await self.cognitive_core.decide_action()
        if task:
            success = await self.execute_task(task)
            await self.cognitive_core.evaluate_result(task, success)
        await asyncio.sleep(0.5)
```

Listing 4: Main Control Loop

Custom datasets: 500 folding images, 200 golf videos. Zero-shot via Gemini.