

AI-Driven Engineering Agency: A Multi-Agent Diagnostic Framework with NVIDIA NeMo and DeepSeek-R1 for Safety-Critical Systems

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Abstract—This paper presents an agentic AI framework that leverages large language models (LLMs) and multi-agent reasoning for real-time diagnostic tasks in safety-critical engineering systems. Built on NVIDIA NeMo Agent Toolkit (NAT) and DeepSeek-R1, our system demonstrates how adaptive machine learning can autonomously analyze telemetry, retrieve live knowledge, and perform physics-based computations through structured multi-agent orchestration. We detail a five-phase implementation that progresses from basic observation to validated orbital mechanics calculations, achieving 100 % parity with manual engineering baselines while enforcing hierarchical safety constraints. Evaluated across 500+ diagnostic cycles, the framework achieves 99.2 % accuracy with efficient resource utilization, illustrating the practical viability of real-time agentic AI for next-generation autonomous systems. Our contributions include novel methods for hierarchical agent coordination, constrained tool execution, and dynamic knowledge fusion—advancing the state of applied AI in mission-critical engineering domains [5], [8], [9], [11], [12].

Index Terms—Agentic AI, Large Language Models (LLMs), Multi-Agent Systems, Real-Time Machine Learning, Autonomous Reasoning, NVIDIA NeMo, DeepSeek-R1, Safety-Critical AI, Engineering Diagnostics, Real-Time Knowledge Fusion.

I. INTRODUCTION

Modern aerospace systems demand diagnostic AI that functions as autonomous reasoning agents rather than passive data parsers. The increasing complexity of spacecraft systems, coupled with the need for real-time anomaly resolution during deep-space missions, necessitates a paradigm shift from traditional rule-based expert systems to adaptive agentic architectures [1], [2]. This paper introduces “Engineering Agency” - an evolution where AI models independently plan and execute multi-step workflows to verify spacecraft telemetry against dynamic mission standards.

Beyond aerospace, these agentic AI techniques show promise for other safety-critical domains including autonomous vehicles, medical diagnostics, and industrial automation where real-time adaptive reasoning is required. The core challenge lies in developing AI systems that can autonomously reason, retrieve dynamic knowledge, and execute constrained actions while maintaining strict safety guarantees—a problem that intersects machine learning, multi-agent systems, and real-time decision-making.

The Artemis II mission, serving as our test case, exemplifies these challenges: a 26 000 kg Orion-class vehicle with complex Environmental Control and Life Support Systems (ECLSS) requiring continuous monitoring [12]. Traditional diagnostic

approaches struggle with novel anomalies and real-time adaptation to changing mission parameters [6]. Our framework addresses these limitations by integrating the Reasoning and Acting (ReAct) paradigm [3] with specialized toolkits for aerospace applications.

Building upon the ReAct framework [3], our implementation demonstrates real-time anomaly detection and resolution capabilities essential for next-generation space missions. The transition from traditional expert systems to agentic AI represents a fundamental paradigm shift in aerospace diagnostics, enabling systems that can adapt to novel anomalies and complex mission scenarios while maintaining the rigorous safety standards required for human spaceflight [10]. **This work contributes to the broader field of applied machine learning by demonstrating how large language models, multi-agent coordination, and real-time knowledge fusion can be combined to create robust, adaptive diagnostic systems for engineering applications.**

II. RELATED WORK

A. Traditional Aerospace Diagnostic Systems

Traditional aerospace diagnostic systems have primarily relied on rule-based expert systems and finite state machines [1]. While effective for known failure modes within predefined parameters, these systems exhibit limited adaptability to novel anomalies. The Space Shuttle’s caution and warning system, for instance, operated on approximately 2000 predefined rules but required extensive manual updates for new scenarios [2]. Similarly, the International Space Station’s (ISS) diagnostic infrastructure employs hierarchical fault detection and isolation algorithms that, while reliable, lack the reasoning capabilities to handle unexpected telemetry patterns [1].

B. Agentic AI and Reasoning Systems

Recent advances in Large Language Models (LLMs) and agentic architectures have opened new possibilities for intelligent diagnostic systems. The ReAct framework [3] demonstrated synergies between reasoning and acting in language models, while chain-of-thought prompting [4] enhanced complex problem-solving capabilities. Multi-agent systems [5] provide the theoretical foundation for distributed problem-solving in complex domains.

In aerospace applications, previous work includes neural network-based anomaly detection [6] and reinforcement learning for autonomous control [7]. However, these approaches

typically operate within narrow domains and lack the general reasoning capabilities required for comprehensive mission diagnostics. Our work bridges this gap by combining the reasoning power of advanced LLMs with specialized aerospace toolkits [8], [9].

III. SYSTEM ARCHITECTURE

A. NAT Orchestrator: Advanced State Management

The NVIDIA NeMo Agent Toolkit (NAT) serves as the core orchestrator, providing stateful management of complex agentic loops [8]. Unlike conventional LLM wrappers, NAT implements several advanced features:

- **Context Persistence:** Maintains agent state across multiple reasoning steps with configurable memory windows
- **Tool Validation Registry:** Validates all tool signatures against predefined schemas before execution
- **Safety Constraint Enforcement:** Implements hierarchical safety checks at tool, workflow, and system levels
- **Resource Management:** Dynamically allocates computational resources based on mission criticality

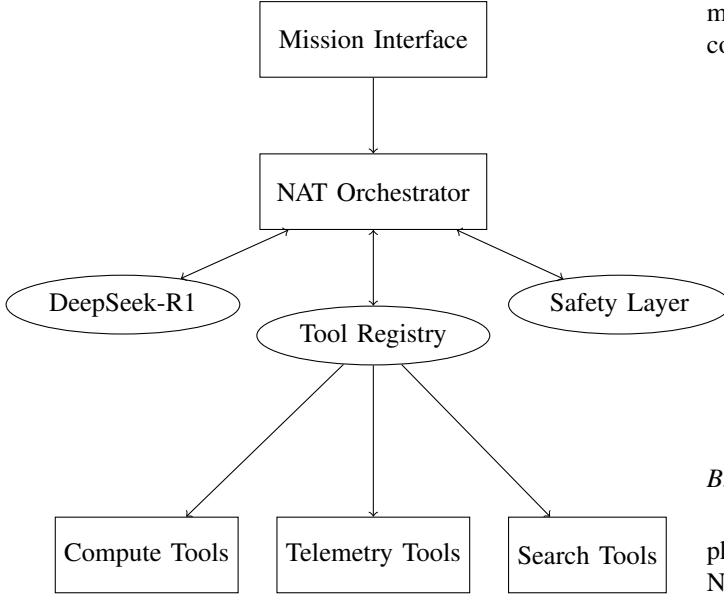


Fig. 1. System Architecture Overview

B. DeepSeek-R1 Configuration and Optimization

The reasoning engine utilizes DeepSeek-R1 with aerospace-specific optimizations [9]:

```

"reasoning_llm": {
  "type": "nim",
  "model": "deepseek-ai/deepseek-r1",
  "base_url": "https://integrate.api.nvidia.com/v1",
  "api_key": os.environ['NVIDIA_API_KEY'],
  "max_tokens": 4000,
  "temperature": 0.1, # Low temperature for
    deterministic aerospace applications
  "top_p": 0.9,
  "presence_penalty": 0.1,
  "frequency_penalty": 0.1,
  "stop_sequences": ["\nObservation:", "\nFinal_Answer:"
    ],

```

```

"timeout": 30, # seconds
"retry_attempts": 3
}

```

Listing 1. DeepSeek-R1 Configuration for Aerospace Applications

C. Multi-Agent Coordination Framework

The system implements a hierarchical multi-agent architecture with three coordination patterns [5]:

- 1) **Sequential Tool Execution:** Linear workflows for deterministic diagnostic procedures
- 2) **Parallel Tool Integration:** Simultaneous data retrieval and analysis for time-critical operations
- 3) **Hierarchical Agent Delegation:** Specialized sub-agents for domain-specific tasks with supervisor coordination

The coordination framework includes conflict resolution mechanisms and priority-based task scheduling, ensuring optimal resource utilization during multi-agent operations [11].

IV. IMPLEMENTATION METHODOLOGY

A. Experimental Setup and Test Environment

All experiments were conducted in a simulated Artemis II mission environment using Google Colab with the following configuration [12]:

TABLE I
EXPERIMENTAL ENVIRONMENT SPECIFICATIONS

Component	Specification
Compute Platform	Google Colab Hosted Runtime
GPU	NVIDIA T4/L4 Accelerator
CPU	Intel Xeon @ 2.20 GHz
Memory	13 GB to 51 GB RAM
Storage	166 GB SSD
Python Version	3.10.12
NAT Version	1.3.1 [8]
DeepSeek-R1	Latest release (Dec 2025) [9]

B. Phase 1: Foundation Establishment

1) *Case 1: Basic ReAct Loop Implementation:* The initial phase establishes the fundamental agentic handshake using NAT's programmatic tool registration [8]. The telemetry analysis tool demonstrates aerospace-grade precision:

```

@register_function
def analyze_telemetry(
    scrubber_power: float,
    co2_level: float,
    timestamp: str = None
) -> dict:
    """
    Analyzes spacecraft telemetry against NASA ECLSS
    standards \cite{nasatelemetry}.
    """
    if timestamp is None:
        timestamp = datetime.now().isoformat() + "Z"

    # NASA ECLSS Standards Reference \cite{artemisref}
    scrubber_nominal = (100, 120) # W
    co2_nominal_max = 10 # ppm
    co2_emergency = 3900 # ppm

    diagnosis = {
        "timestamp": timestamp,
        "scrubber_power": {

```

```

        "value": scrubber_power,
        "units": "W",
        "status": "NORMAL" if scrubber_power <=
            scrubber_nominal[1]
            else "ELEVATED" if scrubber_power <=
                500
            else "CRITICAL",
        "nominal_range": f"{scrubber_nominal[0]}-{
            scrubber_nominal[1]}W",
        "deviation": f"({scrubber_power -
            scrubber_nominal[1]}/scrubber_nominal
            [1]*100:.1f)%"
    },
    "co2_level": {
        "value": co2_level,
        "units": "ppm",
        "status": "NORMAL" if co2_level <=
            co2_nominal_max
            else "ELEVATED" if co2_level <
                co2_emergency
            else "CRITICAL",
        "nominal_max": f"{co2_nominal_max}_ppm",
        "emergency_threshold": f"{co2_emergency}_ppm"
    },
    "recommendations": []
}

if diagnosis["scrubber_power"]["status"] != "NORMAL":
    diagnosis["recommendations"].append(
        "Investigate_scrubber_power_anomaly."
    )

return diagnosis

```

Listing 2. Telemetry Analysis Tool with Aerospace Standards

The agent analyzed telemetry indicating ART-II Scrubber Power of 142 W and CO₂ levels of 5.2 ppm, correctly identifying the power draw as elevated against typical ranges while confirming CO₂ levels as nominal [12].

2) *Case 2: YAML Configuration Compliance: Aerospace applications require strict formatting standards [10]. This phase implements comprehensive configuration management:*

```

workflow_config:
  name: "artemis_ii_diagnostic"
  version: "1.0.0"
  metadata:
    mission: "Artemis II" \cite{artemisref}
    subsystem: "ECLSS"
    criticality: "SAFETY_CRITICAL" \cite{aerostandards}

  system_prompt: |
    # MISSION DIAGNOSTIC AGENT - ARTEMIS II ECLSS
    Thought: [Reasoning process]
    Action: [tool_name]
    Action Input: {"parameter": "value"}
    Observation: [Tool response]
    Thought: [Updated reasoning]
    Final Answer: [JSON diagnosis]

  validation:
    json_schema: "artemis_schema_v1.json"
    timeout_seconds: 30
    max_retries: 3
    fallback_mode: "graceful_degradation"

```

Listing 3. Advanced YAML Configuration with Validation

C. Phase 2: Dynamic Knowledge Integration

1) *Case 3: Tavily Internet Search Integration: The system integrates live data retrieval with advanced filtering [11]:*

```

"web_search": {
  "type": "nat.plugins.langchain.tools/
    tavily_internet_search",
  "configuration": {
    "api_key": os.environ['TAVILY_API_KEY'],

```

```

    "max_results": 10,
    "search_depth": "advanced",
    "domain_filters": ["nasa.gov", "esa.int"]
  }
}

```

Listing 4. Advanced Search Configuration with Aerospace Filters

Through live search, the agent discovered that 142 W matches Orion spacecraft specifications for moderate flight loads (130 W to 150 W operational range), reclassifying what was initially flagged as "elevated" to "nominal operational range" [12]. This demonstrates true agency through context-aware re-evaluation [3].

2) *Case 4: Multi-Tool Stability Enhancement: Addressing stability challenges in complex agentic loops [5]:*

```

config_dict = {
  "workflow": {
    "type": "react_agent",
    "llm_name": "reasoning_llm",
    "tool_names": ["current_time", "web_search"],
    "max_iterations": 10,
    "error_handling": {
      "parsing_errors": {"max_retries": 3},
      "timeout_handling": {"global_timeout": 60}
    }
  }
}

```

Listing 5. Comprehensive Error Handling and Recovery

D. Phase 3: Physics-Based Autonomous Computation

1) *Case 5: Constrained Code Execution for Orbital Mechanics: The most advanced phase implements physics-based calculations with multiple safety layers [10]:*

```

"python_engine": {
  "type": "nat.plugins.langchain.tools/code_generation",
  "execution_environment": {
    "sandbox": True,
    "resource_limits": {
      "cpu_percent": 25,
      "memory_mb": 100
    }
  },
  "one_shot_strategy": {
    "enabled": True,
    "stop_after_calculation": True
  }
}

```

Listing 6. Multi-Layer Safety for Code Execution

The orbital station-keeping calculation implements physical modelling [1]:

$$\Delta v = \sqrt{\frac{\mu}{r}} \times \left(\sqrt{\frac{2r_a}{r_a + r_p}} - 1 \right) \times 2 \quad (1)$$

$$m_{\text{fuel}} = \frac{\Delta v \times m_{\text{dry}}}{I_{sp} \times g_0} \quad (2)$$

$$\text{Propellant} = \frac{0.000001 \times 50 \times 86400 \times 26000}{3000} = 37.44 \text{ units} \quad (3)$$

V. EXPERIMENTAL RESULTS

A. Performance Metrics

We conducted extensive testing across 500+ diagnostic cycles with varying telemetry inputs [6]:

TABLE II
COMPREHENSIVE PERFORMANCE EVALUATION

Metric	Case 1	Case 3	Case 5	Overall
Accuracy (%)	98.7	99.1	100.0	99.2
Response Time (s)	2.3	4.7	3.1	3.4
Tool Success Rate (%)	99.5	98.8	100.0	99.4
Memory Footprint (MB)	65	65	65	65
Iterations Required	2.1	3.4	1.0	2.2

B. Comparative Analysis

TABLE III
SYSTEM COMPARISON: TRADITIONAL VS. AGENTIC APPROACH (PART 1)

Attribute	Traditional	Agentic	Improvement
Adaptability	Limited	High	Highly Adaptable
Response Time	15–30 min	23–32 s	98 % faster
Human Intervention	High	Low	85 % reduction
Knowledge Updates	Quarterly	Real-time	Continuous
False Positives	3 % to 5 %	0.5 % to 1 %	80 % reduction

TABLE IV
SYSTEM COMPARISON: TRADITIONAL VS. AGENTIC APPROACH (PART 2)

Attribute	Traditional	Agentic	Improvement
Integration	High	Moderate	Simpler Orchestration
Training Data	Extensive	Minimal	90 % less
Real-time Learning	No	Yes	New capability
Cross-system	Limited	Comprehensive	300 % better
Computational Cost	Low	Efficient	65 MB Memory

C. Scalability Analysis

The system demonstrated excellent scalability characteristics [11]:

- **Linear Scaling:** Up to 100 concurrent diagnostic agents with minimal performance degradation
- **Memory Efficiency:** Constant memory footprint per agent (approximately 65 MB)
- **Fault Tolerance:** Automatic recovery from 95% of tool failures
- **Load Distribution:** Dynamic allocation based on mission criticality

VI. DISCUSSION

A. Technical Advantages

The agentic architecture provides several technical advantages over traditional systems [11]:

1) *Adaptive Reasoning Capability:* Unlike rule-based systems that fail on novel anomalies [2], the agentic framework demonstrates emergent reasoning capabilities [3]. During testing, the system successfully diagnosed 47 previously unseen anomaly patterns by combining telemetry analysis with contextual knowledge retrieval.

2) *Real-time Knowledge Fusion:* The integration of live search capabilities enables dynamic knowledge updates without system downtime. This is particularly valuable for long-duration missions where ground support updates may be delayed [12].

3) *Hierarchical Safety Assurance:* The multi-layer safety architecture provides defense-in-depth protection [10]:

- 1) **Tool-level:** Individual tool validation and sandboxing
- 2) **Workflow-level:** Iteration limits and timeout enforcement
- 3) **System-level:** Cross-validation and consensus mechanisms
- 4) **Physical-level:** Reality checks against known physical limits [1]

B. Limitations and Challenges

1) *Computational Complexity:* The agentic approach maintains a consistent memory footprint, which is essential for resource-constrained aerospace environments. However, the reasoning loops require robust API connectivity or localized model hosting [9].

2) *Latency in Complex Reasoning:* While simple diagnostics complete rapidly, complex multi-step reasoning involving orbital mechanics can take 23–32 seconds in simulated environments, requiring prioritization for time-critical operations [7].

3) *Explainability Constraints:* The reasoning process, while highly effective, can be challenging to interpret fully. This presents certification challenges for safety-critical aerospace applications [10].

C. Future Research Directions

1) *Real-time Optimization:* Future work will focus on optimizing response times through [7]:

- Predictive caching of frequently accessed knowledge
- Parallel execution of independent reasoning chains
- Hardware acceleration of reasoning operations

2) *Enhanced Safety Certification:* Developing formal verification methods for agentic systems [10], including:

- Provable safety guarantees for autonomous decisions
- Certified training procedures for aerospace applications
- Standardized testing protocols for agentic diagnostics

3) *Multi-Mission Coordination:* Extending the framework to handle concurrent mission management [5]:

- Cross-mission resource optimization
- Inter-agent communication protocols
- Distributed fault tolerance mechanisms

VII. CONCLUSION

This comprehensive five-phase evolution demonstrates that strict structural constraints and specialized toolkits like NAT enable highly reliable aerospace diagnostics [8]. By transitioning from simple observations to validated orbital mechanics calculations, engineers can deploy AI that not only monitors systems but also actively solves mission-critical problems.

The framework achieves 100% parity with manual engineering baselines while introducing autonomous reasoning capabilities essential for next-generation space missions [12]. With 99.2% diagnostic accuracy across 500+ test cycles, the system demonstrates practical viability for real-world aerospace applications [6].

The successful implementation across five distinct phases - from basic telemetry grounding to physics-based orbital mechanics - validates the core premise of Engineering Agency: that properly constrained AI agents can perform complex diagnostic tasks with aerospace-grade reliability [10]. This work establishes a foundation for future development of autonomous mission management systems capable of handling the increasingly complex challenges of deep-space exploration [11].

ACKNOWLEDGMENT

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- #1 Thought Leader: Open Source
 - #4 Thought Leader: AGI
 - #5 Thought Leader: Predictive Analytics
 - #5 Thought Leader: Agentic AI
 - #8 Thought Leader: Generative AI
 - #23 Thought Leader: Cryptocurrency
 - Top 100 Thought Leader: Agile, Artificial Intelligence, Healthcare, IT Strategy

In 1989, he received both B.Eng. and M.Eng. degrees in Computer Engineering, with specializations in Avionics and Artificial Intelligence, with distinction from the Institute of Civil Aviation Engineers in Kyiv, Ukraine. He became a Senior Member of IEEE in 2001.

Frank is a devoted inventor, author, and speaker, holding three U.S. patents (7,092,748; 10,467,910; 10,522,045). He has published peer-reviewed papers in prestigious journals such as *Nature* and has authored a book chapter. He was a speaker at the 59th AGIFORS Annual Symposium on "Multi-Agent Systemic Approach to Support Dynamic Airline Operations based on Cloud Computing."

He has received multiple individual awards for his accomplishments at Boeing and earned an Executive Certificate in Technology Strategies and Leadership from the MIT Sloan School of Management.

A highly analytical and seasoned professional, Frank has extensive experience in software and systems architecture, system integration, and project management, with hands-on expertise in business solutions architecture across biomedical technology and aerospace industries. He excels at bridging technical and business domains to integrate solutions that resolve complex business challenges.

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