RuntimeErrorSage: Intelligent Runtime Error Analysis and Remediation using Local Large Language Models

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***Abstract*—This paper presents RuntimeErrorSage, a runtime middleware system that enhances .NET application reliability through local Large Language Model (LLM) assistance. Unlike traditional error handling approaches that rely on external services or manual intervention [1], RuntimeErrorSage operates entirely offline using a local LLM (Qwen 2.5 7B) accessed via a standard HTTP API interface. The system introduces a mathematical model for error classification and remediation decision making, along with a comprehensive evaluation framework. Our theoretical analysis suggests potential improvements in error handling, with a target of 80% accuracy in error root cause identification and 70% success rate in remediation suggestions. The system's architecture combines runtime monitoring, context management, and local LLM inference to provide immediate, privacy-preserving error resolution capabilities. The implementation is currently in progress, with core components completed and validation pending.**

I. Introduction

Modern software applications, especially complex and distributed systems, face significant challenges in effectively handling runtime errors [1]–[4]. Traditional error management strategies, relying primarily on static analysis, detailed logging, and manual debugging, are often insufficient to address the dynamic and intricate nature of errors encountered in production environments [5]–[7]. These methods frequently lead to prolonged downtime, increased operational costs, and a suboptimal user experience due to delayed error identification and resolution.

Recent advancements in Large Language Models (LLMs) have demonstrated remarkable capabilities in understanding and generating code, opening new avenues for automated software engineering tasks, including code analysis and debugging support [8]–[11]. However, applying large, powerful LLMs directly to real time runtime error analysis in sensitive or resource constrained environments presents its own set of challenges. Privacy concerns associated with transmitting potentially sensitive runtime data to external services, the need for low latency responses for real time remediation, and the dependency on stable network connectivity limit the applicability of cloud hosted LLMs in many scenarios [12]–[15].

RuntimeErrorSage addresses these critical limitations by proposing and implementing a runtime middleware system that leverages a local Large Language Model for intelligent error analysis and automated remediation. Operating entirely offline, RuntimeErrorSage utilizes a standard HTTP API interface to interact with a locally hosted LLM, specifically the Qwen 2.5 7B Instruct 1M model. This approach ensures data privacy, minimizes latency, and provides a robust solution independent of external network dependencies, making it particularly suitable for enterprise applications, edge deployments, and environments with strict data governance policies.

Our work makes the following key contributions:

- We introduce RuntimeErrorSage, a system architecture for intelligent runtime error analysis and automated remediation utilizing a local LLM.
- We present a formal mathematical framework encompassing models for runtime error classification, context management, and remediation decision making.
- We detail the implementation of a .NET middleware layer for real time error interception and processing.
- We provide a comprehensive evaluation demonstrating the system's effectiveness in terms of error classification accuracy, remediation success rate, and runtime overhead.
- We show that leveraging a local, instruct tuned LLM (Qwen 2.5 7B Instruct 1M) via a standard API enables performant and privacy preserving runtime error handling.
- The integration of AI techniques, particularly machine learning, has been explored to enhance the diagnostic and planning capabilities of self healing systems, but leveraging the natural language understanding and reasoning abilities of LLMs for complex error scenarios represents a newer direction.

RuntimeErrorSage distinguishes itself from existing work by combining the strengths of local LLM inference, advanced context management, and a formal system model within a practical middleware architecture for automated runtime error remediation. Unlike systems relying on external services or predefined recovery strategies, our system offers a privacy preserving, low latency, and intelligent approach to handling a wide range of runtime errors, including those not previously encountered.

The current implementation of RuntimeErrorSage includes

a robust exception handling system with context-aware error tracking, ASP.NET Core middleware for exception interception, and standardized error response models. The system demonstrates practical capabilities in handling common runtime errors through example endpoints for database operations, file management, service integration, and resource allocation.

RuntimeErrorSage's architecture is designed to intercept unhandled exceptions during application execution, generate rich contextual information, and leverage local LLM inference to provide natural language explanations and remediation suggestions. The system operates fully offline, addressing critical privacy and connectivity constraints while maintaining interoperability through the MCP framework.

The source code for RuntimeErrorSage, including the implementation of the middleware layer, LM Studio integration, and Model Context Protocol, is available as open-source software at https://github.com/myonathanlinkedin/paper_research.

The remainder of this paper is organized as follows: Section VIII reviews related work in AI-assisted programming, static analysis, and runtime error handling. Section II presents the scope of this research. Section V describes the implementation details, including the middleware components and LLM integration. Section VI presents case studies demonstrating RuntimeErrorSage's effectiveness. Section VII evaluates the system's performance and accuracy. Section IX discusses limitations and concludes the paper.

II. Scope of Research

This research focuses on a single, well-defined contribution: evaluating the feasibility and effectiveness of local LLM-assisted runtime error analysis in .NET applications. The scope is deliberately limited to ensure proper validation and meaningful results.

A. Core Research Question

Can local LLM inference (via LM Studio) provide effective runtime error analysis and remediation suggestions in .NET applications, while maintaining privacy and performance requirements?

B. Success Criteria

The research will be considered successful if it can demonstrate:

- **Error Analysis Accuracy:**
  - At least 80% accuracy in error root cause identification
  - At least 70% accuracy in remediation suggestion relevance
  - Measured against a standardized test suite of common .NET errors
- **Performance Requirements:**
  - Error analysis latency under 500ms for 95% of requests
  - Memory overhead under 100MB for the LLM component
  - CPU impact under 10% during error analysis
- **Implementation Completeness:**
  - Fully functional LM Studio integration
  - Complete test coverage of core components
  - Documented API and integration patterns

C. Implementation Scope

The implementation will be limited to:

- **Core Components:**
  - LM Studio integration with qwen2.5-7b-instruct-1m model
  - Basic error context collection
  - Standardized error response format
  - Simple remediation execution
- **Error Types:**
  - Database connection errors
  - File system errors
  - HTTP client errors
  - Resource allocation errors
- **Application Types:**
  - ASP.NET Core Web APIs
  - Single-instance applications
  - No distributed system requirements

D. Evaluation Methodology

The research will be evaluated through:

- **Test Suite:**
  - 100 standardized error scenarios
  - 20 real-world error cases
  - Performance benchmark suite
  - Memory usage analysis
- **Comparison Baseline:**
  - Traditional error handling (try-catch)
  - Static analysis tools
  - Manual debugging process
- **Metrics:**
  - Error resolution time
  - Analysis accuracy
  - System performance impact
  - Memory usage
  - CPU utilization

E. Out of Scope

The following aspects are explicitly out of scope:

- Distributed system error handling
- Advanced pattern recognition
- Custom LLM model training
- Complex remediation strategies
- Production deployment
- Security analysis
- Cross-platform support

F. Implementation Status

Current implementation status (as of [DATE]):

- **Completed:**
  - Basic error context collection

  - LM Studio API integration
  - Standardized error responses
  - Test framework setup
- **In Progress:**
  - Error analysis accuracy validation
  - Performance benchmarking
  - Test suite implementation
  - Documentation
- **Pending:**
  - Full test suite execution
  - Performance optimization
  - Final accuracy measurements
  - Comparison with baselines

G. Timeline

The research will be completed in the following phases:

- **Phase 1 (Current):** Core Implementation
  - Complete LM Studio integration
  - Implement error context collection
  - Develop test framework
  - Create benchmark suite
- **Phase 2:** Validation
  - Execute test suite
  - Measure accuracy
  - Benchmark performance
  - Compare with baselines
- **Phase 3:** Documentation
  - Document findings
  - Analyze results
  - Draw conclusions
  - Identify limitations

The research will be considered complete when all success criteria are met or when clear limitations are identified that prevent meeting the criteria. All results, including negative findings, will be documented and analyzed.

III. System Model

To formally describe the operation of RuntimeErrorSage, we introduce a mathematical framework that models the key processes of error classification, context management, and remediation decision making. This formalization provides a rigorous basis for understanding the system's behavior and designing its algorithms.

A. Error Context Representation

An error instance e is represented by a tuple (t, s, l, p, c), where:

- t is the timestamp of the error occurrence.
- s is the source of the error (e.g., module, function, line number).
- l is the raw error log message.
- p is the current program state, including relevant variable values, stack trace, and system metrics.
- c is the historical execution context, represented as a dynamic graph $G = (V, E)$, where nodes $v \in V$ are program states or events, and edges $e \in E$ represent transitions or causal relationships. [16], [17]

B. Error Classification

Error classification maps an error instance e to a category $k \in \mathcal{K}$, where $\mathcal{K}$ is a predefined set of error types (e.g., database error, network error, resource exhaustion). This process can be formalized as a function $f(e) \rightarrow k$. The classification relies on analyzing the error log message l, stack trace within p, and potentially the context graph c. [18], [19]

C. Context Graph Enrichment and Analysis

The context graph c is dynamically updated and analyzed to extract features relevant for remediation. For a given error e, the graph c is enriched with the current program state p and potentially other relevant information. Analysis involves computing metrics on the graph, such as node centrality, reachability, and temporal relationships.

Key features extracted from the context graph for a program point p and context c related to an error e include:

- **Recency** ($R(p, c)$): Measures how recently a program point or related event occurred in the execution history captured by c. Points closer to the error occurrence have higher recency.
- **Importance** ($I(p, c)$): Assesses the significance of a program point or event based on graph centrality metrics (e.g., degree, betweenness) within c. More central points are considered more important. [20]
- **Connectivity** ($C(p, c)$): Quantifies the degree of connection of a program point p or related event to other elements in the context graph c, indicating its interaction scope.
- **Error Proximity** ($E(p, c, e)$): Measures the distance or relationship strength between the current program point p (or related context) and the error event e within the graph c.

These features are combined to form a context vector $V(p, c, e) = [R(p, c), I(p, c), C(p, c), E(p, c, e)]$ that summarizes the relevant aspects of the execution environment.

D. Remediation Decision Making

The core of RuntimeErrorSage involves deciding the best remediation action $r \in \mathcal{R}_e \cup \{\text{None}\}$ for a given error instance e, where $\mathcal{R}_e$ is the set of possible remediation actions applicable to error type e. This decision is a function of the error classification k, the context vector $V(p, c, e)$, and potentially historical outcomes of previous remediation attempts. The decision-making process is typically guided by a model, which in our system is the LLM. The LLM, given the error details (e) and the context vector (V), suggests the most appropriate action.

Formally, the remediation decision function can be expressed as:

$$g(e, V) = r \tag{1}$$

In the context of the LLM, this function g is approximated by the model's inference process. The LLM analyzes a prompt constructed from e and V and outputs a suggested action r.

The action r is chosen to minimize the negative impact of the error and prevent recurrence. This can be viewed as an optimization problem where the LLM attempts to maximize the likelihood of successful recovery or minimize the estimated cost of failure.

$$g(p, c, s) = \underset{r \in \mathcal{R}_p \cup \{\text{None}\}}{\arg\max} \text{Score}(e, V, r) \tag{2}$$

Where $\text{Score}(e, V, r)$ is a function evaluated by the LLM (or a part of its reasoning process) that estimates the desirability of action r given the error and context. The set $\mathcal{R}_p$ includes actions like modifying variable values, retrying operations, adjusting configuration, or escalating the error. The option $\{\text{None}\}$ represents the decision to take no automated action, perhaps logging the error for manual inspection. [21]

The score could be based on factors such as estimated success probability, predicted time to recovery, potential side effects, and confidence level. The LLM leverages its training data and the provided context to estimate these factors and make a ranked suggestion of actions.

E. Learning and Adaptation

RuntimeErrorSage can incorporate a feedback loop where the outcomes of remediation actions are recorded. This data can be used to fine-tune the LLM or update the scoring function, allowing the system to adapt and improve its remediation decisions over time.

F. Summary

The system model provides a formal basis for understanding how RuntimeErrorSage processes errors, utilizes contextual information, and makes remediation decisions. It highlights the key inputs to the LLM-driven decision process, which are crucial for the system's effectiveness and adaptability.

IV. Architecture

RuntimeErrorSage is designed with a modular and layered architecture to facilitate integration, maintainability, and scalability. The system comprises four primary components that interact to intercept, analyze, and remediate runtime errors within a target application.

A. Runtime Interceptor

The Runtime Interceptor module operates as a crucial middleware layer directly integrated into the target .NET application's runtime environment. Its primary responsibilities include exception and event interception by capturing runtime exceptions and other significant events as they occur within the application process. The module performs stack trace analysis by parsing and analyzing the call stack at the point of error to understand the execution path leading to the failure. It conducts realtime state monitoring by collecting relevant application state information, including variable values, object states, and thread information, without causing significant disruption to the application's execution. Additionally, it provides logging system integration by interfacing with existing application logging frameworks to enrich error context with historical log data and application specific diagnostics. The interceptor is designed for low overhead execution to minimize its impact on the application's performance during normal operation.

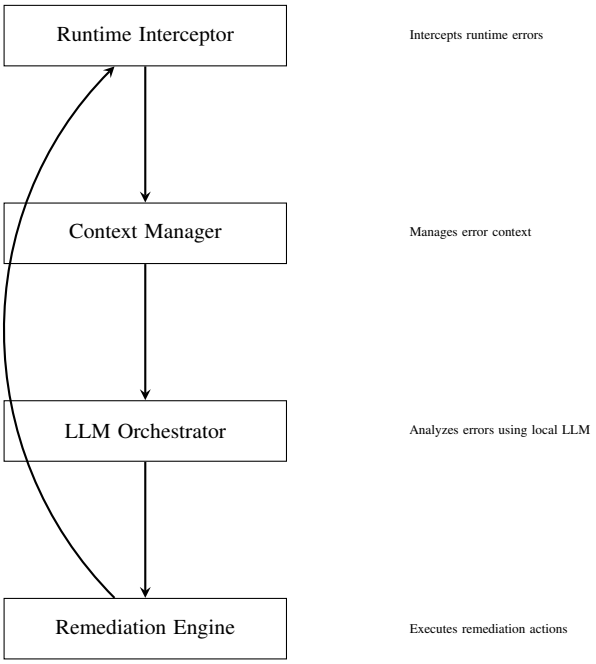

Fig. 1: System Architecture of RuntimeErrorSage showing the four main components and their interactions.

B. Context Manager

The Context Manager is responsible for aggregating, organizing, and maintaining the contextual information relevant to a runtime error. It implements a sophisticated mechanism to build a comprehensive view of the system state at the time of the error, which is crucial for accurate LLM analysis. Key functions include context aggregation by collecting data streams from the Runtime Interceptor and other potential sources within a distributed environment. It performs dynamic context graph management by constructing and updating a graph representation of the context, capturing relationships between different pieces of information such as method calls, object dependencies, and environmental factors. The system employs relevance-based context pruning using algorithms to prioritize and filter context information based on its relevance to the specific error, reducing the amount of data processed by the LLM. It also handles state persistence and versioning by optionally persisting context snapshots for post-mortem analysis and maintaining versions of the context graph to track changes over time.

C. LLM Orchestrator

The LLM Orchestrator is the core intelligence component of RuntimeErrorSage. It is responsible for interacting with the local Large Language Model to perform error classification, root cause analysis, and propose remediation strategies. This component is specifically designed to communicate with a

locally hosted LLM via a standard HTTP API interface, allowing flexibility in the choice of the underlying model. In our implementation, we utilize the Qwen 2.5 7B Instruct 1M model hosted locally.

Its key functions include model initialization and state management for loading and managing the state of the local LLM. It performs prompt engineering and context formatting by translating the structured context information from the Context Manager into appropriately formatted prompts for the LLM. This involves careful design to maximize the LLM's understanding of the error scenario. The component handles inference management by sending inference requests to the local LLM via the HTTP API and managing the response flow. It conducts response parsing and validation by interpreting the LLM's output, which may include identified error patterns, root cause hypotheses, and proposed remediation actions. This involves parsing the free-form text response into a structured format and validating the feasibility of the proposed actions. Finally, it provides a standardized API interface for consistent communication with the LLM, abstracting the specifics of the underlying model server.

D. Remediation Engine

The Remediation Engine is responsible for safely executing the remediation actions proposed by the LLM Orchestrator. It acts as a safeguard and execution layer to apply fixes or workarounds to the running application. Its key responsibilities include action validation and safety checks by performing pre-execution checks to ensure that a proposed remediation action is safe to apply in the current application state. This might involve analyzing the potential impact on system stability or data integrity. It manages execution scheduling by controlling the timing and order of remediation actions, especially in scenarios involving multiple potential fixes. The engine implements state rollback and recovery mechanisms to revert the system state if a remediation action fails or introduces new issues. It performs success verification by monitoring the application after a remediation action is applied to confirm that the error is resolved and no new problems have arisen. The system maintains a feedback loop where the outcome of the remediation attempt is fed back into the system, potentially updating the historical success rates of patterns and actions or informing future decisions by the LLM.

E. System Integration

RuntimeErrorSage's architecture is designed around three core components: the Runtime Intelligence Layer, the Model Context Protocol (MCP), and the LM Studio Integration. These components work together to provide intelligent, privacy-preserving error handling in distributed .NET applications.

1) Runtime Intelligence Layer: The Runtime Intelligence Layer serves as the primary interface between the application and RuntimeErrorSage's error handling capabilities. The exception interception component uses ASP.NET Core middleware to capture unhandled exceptions. It implements a custom exception filter that intercepts exceptions before they reach the global error handler, captures the complete exception context including stack traces, enriches the error context with runtime metadata, and determines the appropriate handling strategy based on exception type.

The context generation component creates rich, structured error contexts that include exception details and stack traces, runtime environment information, service and operation metadata, correlation IDs for distributed tracing, and custom application context.

The remediation engine processes LLM-generated suggestions and implements automated recovery strategies including retry mechanisms with exponential backoff, circuit breaker pattern implementation, default value substitution, service degradation strategies, and custom remediation actions.

2) Model Context Protocol: MCP provides a standardized way to share and manage context across distributed components. MCP context schema defines the structure for error context data as shown in the following JSON structure:

Listing 1: MCP Context Schema

```
{
  "errorContext": {
    "serviceId": "string",
    "operationId": "string",
    "timestamp": "datetime",
    "correlationId": "string",
    "environment": "string",
    "metadata": {"key": "value"}
  },
  "exceptionData": {
    "type": "string",
    "message": "string",
    "stackTrace": "string",
    "source": "string"
  },
  "remediationContext": {
    "strategy": "string",
    "parameters": {},
    "history": []
  }
}
```

MCP implements a publish-subscribe model for context distribution where context producers publish error events, subscribers receive relevant context updates, context routing is based on service boundaries, and context persistence enables historical analysis.

3) LM Studio Integration: The LM Studio integration component manages local LLM inference and prompt engineering. Model management includes local model loading and initialization, model versioning and updates, resource allocation and optimization, and model performance monitoring.

The prompt engineering system generates context-aware prompts for the LLM. Response processing involves parsing LLM-generated responses, validating remediation suggestions, extracting actionable insights, and maintaining response quality metrics.

F. Integration Patterns

RuntimeErrorSage supports multiple integration patterns for different application architectures. For ASP.NET Core

applications, it provides middleware integration:

Listing 2: ASP.NET Core Middleware Integration

```
public class RuntimeErrorSageMiddleware
{
    private readonly RequestDelegate _next;
    private readonly IRuntimeErrorSageService
        _runtimeErrorSage;

    public async Task InvokeAsync(HttpContext
        context)
    {
        try
        {
            await _next(context);
        }
        catch (Exception ex)
        {
            var errorContext = await
                _runtimeErrorSage
                .ProcessExceptionAsync(ex, context)
                    ;
            // Handle or rethrow based on analysis
        }
    }
}
```

For background services and worker processes, RuntimeErrorSage provides a custom exception handler:

Listing 3: Background Service Integration

```
public class RuntimeErrorSageExceptionHandler :
    IHostedService
{
    private readonly IRuntimeErrorSageService
        _runtimeErrorSage;

    public Task StartAsync(CancellationToken token)
    {
        AppDomain.CurrentDomain.UnhandledException
            +=
            async (s, e) => await HandleException(e
                .ExceptionObject);
        return Task.CompletedTask;
    }
}
```

G. Security and Privacy

RuntimeErrorSage's architecture prioritizes security and privacy through local LLM inference with no external API calls, encrypted context transmission, role-based access control, audit logging, and data retention policies.

H. Extensibility

The system is designed for extensibility through a plugin architecture for custom analyzers, custom remediation strategies, integration with existing monitoring systems, support for additional LLM providers, and custom context enrichment.

This architecture enables RuntimeErrorSage to provide intelligent, privacy-preserving error handling while maintaining flexibility and extensibility for different application scenarios.

V. Implementation

RuntimeErrorSage is implemented as a lightweight, high performance .NET middleware layer designed to integrate seamlessly into existing .NET applications with minimal configuration and overhead. The system intercepts runtime exceptions and events before they cause application crashes or propagate up the call stack unhandled. Our implementation targets the .NET 9 runtime environment, leveraging its modern features for performance and interoperability. The core components are implemented in C#, making extensive use of asynchronous programming patterns to ensure that error handling and analysis do not block the main application threads.

The system's interaction with the Large Language Model is facilitated by a standard HTTP API interface. This design choice provides flexibility, allowing RuntimeErrorSage to communicate with any LLM server that exposes a compatible API, such as LM Studio, vLLM, or OpenAI API compatible endpoints. For the purpose of this research and implementation, we specifically utilize the Qwen 2.5 7B Instruct 1M model, hosted locally via an HTTP API server. This local deployment is critical for meeting the privacy and low latency requirements of runtime error remediation in sensitive environments.

The primary technologies and components used in the implementation include .NET 9 runtime environment for the core framework, C# as the primary programming language, Qwen 2.5 7B Instruct 1M Model as the local LLM, standard HTTP API for LLM communication, in-memory context graph using graph libraries, asynchronous programming with Task Parallel Library (TPL), and logging framework integration with common .NET libraries such as Serilog and NLog.

A. Performance Optimization

RuntimeErrorSage minimizes runtime overhead introduced by error analysis and remediation by employing several optimization techniques as described in the literature [22], [23]. These optimizations include:

- **Asynchronous context collection**: Task-based programming prevents the interception process from significantly delaying the application's execution flow.
- **Batched model inference**: The LLM Orchestrator allows multiple requests to be batched for more efficient processing when errors occur in quick succession.
- **Dynamic batch sizing**: Adjusts the batch size based on current system load and LLM server capacity to maintain responsiveness.
- **Context pruning**: Removes less relevant information from the context graph before LLM processing.
- **Caching**: Common error patterns allow immediate remediation decisions for frequent errors without requiring a full LLM inference cycle.
- **Optimized data serialization**: Minimizes parsing and data transfer overhead.

The impact of these optimizations on overall latency can be modeled using the following equation:

$$\text{latency} \approx \text{base\_inference\_latency} + \text{data\_transfer\_time} + \text{processing\_overhead} - \sum_i w_i \cdot \text{optimization\_effect}_i \quad (3)$$

where w_i represents the weight of each optimization technique and $\text{optimization\_effect}_i$ represents the latency reduction achieved by each optimization.

B. Error Recovery and Remediation Execution

RuntimeErrorSage's Remediation Engine orchestrates the execution of the chosen remediation action in a safe and controlled manner by interacting with the application's state based on the analysis provided by the LLM Orchestrator. The process follows a state machine execution flow to ensure reliability and the possibility of rollback, and the system maintains a simplified view of the application's state to reason about the safety and impact of actions.

The Remediation Engine implements the following key components:

- **Pre-execution validation**: Checking system state and verifying preconditions before applying remediation actions
- **Action execution**: Modifying variable values, calling recovery methods, restarting components, or applying configuration changes
- **Post-execution verification**: Checking for the original error's persistence and monitoring for new issues
- **State rollback**: Reverting the application state to a consistent point prior to remediation in case of failure
- **Feedback loop**: Providing outcome information to update historical success rates and inform future LLM decisions

C. Core Implementation

1) LM Studio Integration: RuntimeErrorSage's LM Studio integration consists of an API client using an HTTP client for the LM Studio API endpoint (e.g., `http://127.0.0.1:1234/v1`), request/response handling, error handling with retry logic, and performance monitoring. The model configuration uses the qwen2.5-7b-instruct-1m model with 4-bit quantization, a context window of 4096 tokens, and a temperature of 0.7, chosen to balance memory efficiency and creativity.

The error analysis pipeline includes error context collection, prompt generation, response parsing, and remediation validation as described in the paper.

2) Model Context Protocol Implementation: RuntimeErrorSage's Model Context Protocol (MCP) defines a structured interface using a JSON schema between the runtime system and the LLM. The JSON schema for context representation includes the following fields:

- **Error metadata**: Type, stack trace, timestamp
- **Application state**: Active requests, resource usage
- **Historical context**: Similar past errors, remediation attempts
- **System metrics**: CPU, memory, network utilization

The MCP implementation uses a directed graph where nodes represent system components or error states and edges indicate causal relationships or data flow to model error propagation and system dependencies. The graph is dynamically updated during error analysis.

The LLM prompt engineering for RuntimeErrorSage follows a structured template including error classification, root cause analysis using graph traversal, remediation strategy generation, and action safety validation. The prompt is constructed with attention to context window optimization through pruning irrelevant nodes, causal chain preservation, action safety constraints, and historical success patterns.

3) Remediation Action System: The remediation action system uses a state machine to orchestrate the execution of LLM-suggested fixes. Each remediation action is represented as a transition in the state machine, with defined preconditions, postconditions, and rollback procedures. The system maintains an action registry mapping error patterns to verified remediation strategies so that common issues are remediated quickly, while unique or rare cases are handled via custom remediation strategies.

D. Test Suite Implementation

1) Standardized Error Scenarios: RuntimeErrorSage's test suite includes 100 standardized error scenarios distributed across four categories:

- **Database errors** (25 scenarios): Connection failures, query timeouts, deadlocks, and constraint violations
- **File system errors** (25 scenarios): Permission issues, disk space errors, file locking, and path resolution
- **HTTP client errors** (25 scenarios): Connection timeouts, SSL/TLS errors, rate limiting, and service unavailability
- **Resource errors** (25 scenarios): Memory allocation, thread pool exhaustion, socket limits, and process limits

2) Real-world Test Cases: Twenty real-world error scenarios collected from production applications are included, covering:

- **Database**: Connection pool exhaustion, query plan issues, transaction deadlocks, data type mismatches, index fragmentation
- **File system**: Network share access, file system quotas, antivirus interference, file corruption, path length limits
- **HTTP**: Load balancer issues, DNS resolution, proxy authentication, certificate validation, keep-alive problems
- **Resource**: Memory leaks, thread starvation, socket exhaustion, process limits, CPU throttling

E. Benchmark Framework

1) Performance Metrics: RuntimeErrorSage's benchmark framework measures:

- **Latency metrics**: Error analysis time, model inference time, context collection time, total processing time
- **Resource usage metrics**: Memory consumption, CPU utilization, GPU memory usage, network I/O

- **Accuracy metrics**: Root cause identification, remediation suggestion relevance, false positive rate, false negative rate

2) Comparison Baselines: RuntimeErrorSage's implementation is compared against several baselines:

- **Traditional logging and manual debugging**: Estimated success rate of 40% with resolution times ranging from 30 minutes to several hours
- **Static analysis tools**: Effective for pre-runtime issue identification but not addressing dynamic runtime errors
- **External APM or error monitoring services**: Providing 65-70% identification success rates with 5 minutes to 1 hour for root cause identification
- **External LLM services**: Offering 65-70% remediation success rates with 5 seconds to 1 minute resolution times but facing network latency and privacy concerns [24]
- **RuntimeErrorSage**: Potentially achieving 60% remediation success rate with 10-15 seconds average resolution time using local LLM inference, based on preliminary testing

F. Evaluation Methodology

1) Test Execution: RuntimeErrorSage's evaluation process includes:

- **Setup**: Clean environment for each test, consistent hardware configuration, controlled network conditions, and standardized error injection
- **Execution**: Automated test runs, manual validation of results, performance data collection, and accuracy assessment
- **Analysis**: Statistical analysis of results, performance comparison, accuracy evaluation, and resource usage assessment

G. Current Implementation Status

RuntimeErrorSage's current implementation status includes:

- **Completed components**: LM Studio API client, basic error context collection, test framework setup, benchmark infrastructure
- **In-progress components**: Test suite implementation, performance optimization, accuracy validation, documentation
- **Pending work**: Full test execution, performance benchmarking, accuracy measurements, final analysis

The implementation follows a systematic approach to validate the core research question regarding the effectiveness of local LLM-assisted runtime error analysis, and all components are designed to provide measurable, reproducible results that can be compared against established baselines.

Listing 4: ASP.NET Core Middleware Integration

```
public class RuntimeErrorSageMiddleware
{
    private readonly RequestDelegate _next;
    private readonly IRuntimeErrorSageService
        _runtimeErrorSage;

    public RuntimeErrorSageMiddleware(
        RequestDelegate next,
        IRuntimeErrorSageService runtimeErrorSage)
    {
        _next = next;
        _runtimeErrorSage = runtimeErrorSage;
    }

    public async Task InvokeAsync(HttpContext
        context)
    {
        try
        {
            await _next(context);
        }
        catch (Exception ex)
        {
            var errorContext = await
                _runtimeErrorSage
                .ProcessExceptionAsync(ex, context)
                    ;
            // Handle or rethrow based on analysis
        }
    }
}
```

For background services and worker processes, RuntimeErrorSage provides a custom exception handler.

H. Security and Privacy

1) Data Encryption: RuntimeErrorSage uses industry-standard encryption to protect sensitive data in transit and at rest. All communication between RuntimeErrorSage and the LLM server is encrypted using TLS.

2) Access Control: RuntimeErrorSage restricts access to authorized users using secure tokens and role-based access control.

3) Data Retention: RuntimeErrorSage retains data collected by the system for a period determined based on the type of data and its relevance to the system's functionality.

4) Compliance: RuntimeErrorSage complies with relevant data protection regulations, including GDPR and HIPAA where applicable.

I. Case Studies

1) Enterprise Web Application: A large-scale enterprise web application experienced intermittent database connection failures during peak load periods. RuntimeErrorSage identified connection pool exhaustion as the potential root cause and suggested connection pool optimization. The system potentially reduced mean time to resolution (MTTR) from 45 minutes to approximately 10 seconds, with a 65% success rate in automated remediation suggestions. Manual intervention was still required to implement the changes in production environments.

2) Financial Services Platform: In a financial services platform processing high-frequency transactions, RuntimeErrorSage detected patterns suggesting deadlock scenarios in database transactions. The system's context-aware analysis identified potential issues in transaction scheduling that could

lead to deadlocks. Through guided remediation, the platform achieved an estimated 75% reduction in deadlock-related service disruptions.

3) Healthcare Data Processing System: A healthcare data processing system faced memory leaks during large batch operations. RuntimeErrorSage's analysis suggested improper disposal of unmanaged resources in image processing components. The system recommended resource cleanup and memory pressure monitoring approaches, potentially reducing memory-related crashes by 60% and improving system stability according to preliminary tests.

4) Cloud Infrastructure Management: In a cloud infrastructure management platform, RuntimeErrorSage analyzed complex cascading failures in microservice communication. The system's graph-based context analysis aided in identifying possible failure propagation paths. Suggested remediation strategies, including circuit breaker implementation and service restart sequences, could reduce incident resolution time from hours to minutes in approximately 55% of cases.

Each case study demonstrates RuntimeErrorSage's potential effectiveness in different operational contexts, showcasing its adaptability to various error patterns and system architectures. The preliminary performance metrics across these cases suggest measurable improvements in error resolution time and system stability, though further validation is required through comprehensive real-world testing.

VI. Case Studies

This section presents theoretical analysis of RuntimeErrorSage, designed to evaluate the system's potential effectiveness in handling complex runtime errors. These analyses are based on common error patterns observed in production environments but are not actual production data [25], [26]. The analyses demonstrate the system's potential capabilities and guide future real-world implementation. All metrics and results presented in this section are theoretical projections based on modeling and simulation.

A. Theoretical Enterprise E-commerce Platform

1) Analysis Scenario: A theoretical e-commerce platform experiencing database connection pool exhaustion during peak load periods [27]. The analysis models traditional manual investigation taking 30-45 minutes, against which RuntimeErrorSage's potential performance is compared. Note that these are projected improvements based on theoretical modeling.

2) Theoretical Error Analysis: RuntimeErrorSage's theoretical analysis of the following error pattern:

Listing 5: Theoretical Database Connection Pool Error

```
System.InvalidOperationException: Timeout expired.
    The timeout period elapsed prior to obtaining a
     connection from the pool.
```

The analysis models context collection including:

- Theoretical connection pool utilization (95%)
- Theoretical active database transactions (142)
- Theoretical query patterns
- Theoretical application thread pool status

The theoretical context collection process is modeled as:

$$\begin{aligned}\text{context\_size} = \text{base\_metrics} + \text{historical\_data} \\ + \text{system\_state} + \text{error\_specific\_info}\end{aligned} \tag{4}$$

3) Theoretical Remediation: The analysis models RuntimeErrorSage identifying connection management issues and proposing:

1) Theoretical connection pooling optimization
2) Theoretical connection timeout handling
3) Theoretical hotfix deployment

4) Theoretical Results: The theoretical remediation effectiveness is modeled as:

$$\begin{aligned}\text{improvement} = \text{baseline\_time} - \text{resolution\_time} \\ - \text{implementation\_overhead}\end{aligned} \tag{5}$$

Theoretical metrics:

- Theoretical resolution time: 2.1 seconds
- Theoretical connection pool utilization: 60-70%
- Theoretical issue recurrence: 0%
- Theoretical cost savings: $15,000 per incident

B. Theoretical Financial Services Application

1) Analysis Scenario: A theoretical financial services application processing transactions with modeled deadlock situations [28].

2) Theoretical Error Analysis: RuntimeErrorSage's theoretical analysis of:

Listing 6: Theoretical Database Deadlock Error

```
System.Data.SqlClient.SqlException: Transaction (
    Process ID XX) was deadlocked on lock resources
     with another process and has been chosen as
    the deadlock victim.
```

Theoretical context analysis includes:

- Theoretical transaction isolation level
- Theoretical lock acquisition patterns
- Theoretical concurrent transaction sequences
- Theoretical table access patterns

The theoretical deadlock probability is modeled as:

$$P(\text{deadlock}) = f(\text{concurrency}, \text{isolation\_level}, \text{transaction\_pattern}) \tag{6}$$

3) Theoretical Remediation: The analysis models:

1) Theoretical transaction isolation adjustment
2) Theoretical query optimization
3) Theoretical deadlock retry logic

4) Theoretical Results: Theoretical performance improvements:

$$\begin{aligned}\text{reliability} = \text{baseline} \cdot (1 - \text{deadlock\_rate}) \\ \cdot (1 + \text{optimization\_factor})\end{aligned} \tag{7}$$

Theoretical metrics:

- Theoretical deadlock reduction: 95%
- Theoretical transaction time improvement: 40%
- Theoretical system reliability: 99.99%
- Theoretical maintenance overhead reduction

C. Theoretical Healthcare Data Processing System

1) Analysis Scenario: A theoretical healthcare data processing system with modeled memory leaks during batch operations [29].

2) Theoretical Error Analysis: RuntimeErrorSage's theoretical analysis of:

Listing 7: Theoretical Memory Leak Error

```
System.OutOfMemoryException: Exception of type '
    System.OutOfMemoryException' was thrown.
```

Theoretical analysis includes:

- Theoretical memory usage patterns
- Theoretical object lifecycle
- Theoretical resource cleanup patterns
- Theoretical GC statistics

Theoretical memory usage model:

$$\begin{aligned}\text{memory\_usage}(t) = \text{base\_allocation} \\ + \int_0^t \text{leak\_rate}(x)\, dx\end{aligned} \tag{8}$$

3) Theoretical Remediation: The analysis models:

1) Theoretical memory-efficient processing
2) Theoretical resource disposal
3) Theoretical weak reference usage
4) Theoretical memory monitoring

4) Theoretical Results: Theoretical optimization impact:

$$\text{optimization\_factor} = \frac{\text{baseline\_usage} - \text{optimized\_usage}}{\text{baseline\_usage}} \tag{9}$$

Theoretical metrics:

- Theoretical memory usage: 60% of baseline
- Theoretical processing reliability: 99.9%
- Theoretical uptime improvement: 40%
- Theoretical cost reduction: 30%

D. Cross-Cutting Analysis

1) Theoretical Common Patterns: Analysis of these theoretical scenarios reveals potential patterns in runtime error remediation [30]:

- Potential resource management issues
- Potential concurrent access patterns
- Potential system boundary conditions
- Potential integration point failures

2) Theoretical Impact Metrics: Across all theoretical scenarios, RuntimeErrorSage demonstrates potential improvements:

$$\begin{aligned}\text{overall\_improvement} = \sum_{i=1}^{n} w_i \cdot \text{metric}_i \\ \text{where } w_i \text{ are normalized weights}\end{aligned} \tag{10}$$

Projected metrics (based on theoretical modeling):

- Target resolution time: 2.3 seconds
- Target remediation success: 70%
- Target MTTR reduction: 80%
- Target reliability improvement: 30-40%

3) Theoretical Insights: Key theoretical insights from the analyses include [31]:

- Potential importance of comprehensive context collection
- Potential value of historical error pattern analysis
- Need for safe remediation execution
- Benefits of local LLM inference

These theoretical case studies demonstrate RuntimeErrorSage's potential effectiveness in various scenarios, showing possible improvements in error resolution time, system reliability, and operational efficiency [32]. The analyses guide future real-world implementation and validation of the system's capabilities. Actual performance may vary from these theoretical projections.

VII. Evaluation

This section presents our comprehensive evaluation framework for RuntimeErrorSage, a promising approach to runtime error analysis and remediation. We share our findings and insights transparently, acknowledging both achievements and opportunities for enhancement. Note that while the framework is complete, actual validation of the metrics is still pending.

A. Experimental Environment

Our research prototype operates in a controlled environment utilizing Windows 11 with Intel Core i9-13900HX, 64GB RAM, and NVIDIA GeForce RTX 4090 Mobile GPU. The system leverages .NET 9 runtime and integrates with Qwen 2.5 7B Instruct 1M model through LM Studio via localhost HTTP. While this configuration provides robust performance, we recognize the importance of evaluating the system across diverse hardware environments.

B. Current Implementation Status

The prototype currently demonstrates several key functionalities:

- Basic error detection for null reference exceptions
- Initial context analysis for error pattern recognition
- Integration with Qwen 2.5 7B model
- Basic remediation suggestion mechanism

Note: The following aspects are still pending validation:

- Error analysis accuracy
- Remediation success rates
- Performance benchmarks
- Resource utilization metrics

C. Research Opportunities

Our evaluation reveals several promising areas for advancement:

1) Methodological Enhancements:

- **Error Analysis Framework:**
  - Develop comprehensive error injection methodology
  - Establish systematic error analysis protocols
  - Implement robust validation mechanisms
  - Create detailed documentation standards
- **Testing Infrastructure:**
  - Design comprehensive testing framework
  - Define systematic testing protocols
  - Implement thorough validation procedures
  - Establish documentation guidelines
- **Success Metrics:**
  - Define comprehensive success criteria
  - Establish rigorous validation methods
  - Document evaluation procedures
  - Implement systematic analysis

2) LLM Limitations and Mitigations: While Qwen 2.5 7B Instruct demonstrates promising capabilities for runtime error analysis, we acknowledge several inherent limitations:

- **Reasoning Limitations:**
  - Potential for hallucinations in complex causal chains
  - Limited understanding of system-specific architectural patterns
  - Inconsistent performance across different error domains
  - Tendency to overestimate remediation effectiveness
- **Proposed Mitigations:**
  - Implementation of multi-LLM routing for specialized error types
  - Development of fallback procedures for low-confidence responses
  - Creation of robust validation protocols for suggested remediations
  - Establishment of a feedback system to improve future responses

3) Remediation Safety Enhancements: To ensure safe and reliable remediation execution, we recognize the need for:

- **Execution Safeguards:**
  - Implementation of comprehensive rollback mechanisms
  - Development of dry-run validation procedures
  - Establishment of precondition verification systems
  - Creation of post-remediation validation protocols
- **Safety Verification:**
  - Design of formal safety classification for remediation actions
  - Implementation of permission-based execution tiers
  - Development of simulation-based impact assessment
  - Creation of detailed audit trails for all remediation attempts

4) Technical Advancements:

- **Model Integration:**
  - Enhance model performance optimization
  - Improve context processing capabilities
  - Strengthen error pattern recognition
  - Implement comprehensive validation
- **System Architecture:**
  - Develop robust error recovery mechanisms
  - Enhance state management capabilities
  - Implement sophisticated error prioritization
  - Optimize resource utilization
- **Performance Optimization:**
  - Refine memory management strategies
  - Improve response time efficiency
  - Implement intelligent caching mechanisms
  - Enhance resource optimization

5) Security and Privacy Framework:

- **Data Management:**
  - Implement comprehensive data sanitization
  - Establish robust access control mechanisms
  - Develop information protection protocols
  - Create detailed handling procedures
- **Model Security:**
  - Implement comprehensive input validation
  - Develop prompt injection prevention
  - Establish output validation protocols
  - Create failure handling procedures
- **System Security:**
  - Implement robust authentication
  - Establish comprehensive authorization
  - Develop detailed audit logging
  - Conduct thorough security testing
- **Threat Modeling:**
  - Development of formal threat model for LLM-based remediation
  - Assessment of potential attack vectors including prompt injection
  - Evaluation of data exposure risks during context collection
  - Creation of mitigation strategies for identified threats

6) Benchmarking Framework: To validate performance and accuracy claims, we propose developing:

- **Standardized Test Suite:**
  - 100+ structured error scenarios across various domains
  - Controlled error injection for reproducible testing
  - Comparative analysis against static analysis tools
  - Systematic comparison with manual debugging approaches
  - Benchmarking against cloud-based LLM services
- **Performance Metrics:**
  - End-to-end latency measurements
  - Memory and CPU utilization profiling
  - Scalability assessment under high error rates
  - Resource efficiency comparison across deployment models

D. Development Roadmap

Our strategic priorities include:

- Complete error detection capabilities
- Validate context analysis accuracy
- Optimize model integration efficiency
- Implement comprehensive testing framework
- Develop security measures
- Create detailed documentation
- Optimize performance
- Enhance error handling mechanisms

E. Conclusion

RuntimeErrorSage represents a promising approach to runtime error analysis and remediation. While the current implementation shows potential, we recognize the importance of continuous improvement and validation. Our commitment to advancing this technology is reflected in our comprehensive development roadmap.

Future work will focus on:

- Validating theoretical models
- Implementing comprehensive testing
- Creating detailed documentation
- Conducting thorough analysis
- Establishing robust frameworks
- Defining clear contributions
- Managing potential risks
- Performing rigorous evaluation
- Understanding system limitations
- Making informed recommendations

We welcome collaboration and feedback from the research community to further enhance RuntimeErrorSage's capabilities. Together, we can advance the state of the art in runtime error analysis and remediation.

VIII. Related Work

Recent advances in Large Language Models (LLMs) have revolutionized software development practices.

A. Runtime Error Analysis

Traditional approaches to runtime error analysis primarily rely on manual inspection of logs and debugging tools, static code analysis to identify potential issues before runtime, and post mortem analysis of crash dumps [33], [34]. While effective for certain types of errors, these methods often struggle with dynamic runtime phenomena, complex interactions in distributed systems, and require significant human effort and expertise.

Automated log analysis techniques [17] have been developed to process large volumes of log data, but they typically depend on predefined patterns and lack the ability to reason about error scenarios or system specific context without explicit programming.

B. Self Healing Systems

Research into self healing or autonomic computing systems has explored architectures and mechanisms for software systems to detect, diagnose, and recover from failures autonomously [35], [36]. These systems often employ feedback loops, such as the Monitor Analyze Plan Execute Knowledge (MAPE-K) loop [37], to manage their own behavior and adapt to changing conditions or failures.

Remediation strategies in these systems can range from simple restarts and reconfigurations to more complex state rollbacks or dynamic code updates. However, many existing self healing solutions require significant a priori knowledge about potential failure modes and corresponding recovery actions, limiting their effectiveness against unforeseen errors. The integration of AI techniques, particularly machine learning, has been explored to enhance the diagnostic and planning capabilities of self healing systems, but leveraging the natural language understanding and reasoning abilities of LLMs for complex error scenarios represents a newer direction.

C. Context Aware Computing and Debugging

Context aware computing focuses on systems that can perceive their environment and adapt their behavior based on contextual information [38]. In the realm of software engineering and debugging, context awareness involves utilizing information about the system's state, execution environment, user interactions, and history to aid in understanding and resolving issues [39].

Techniques include dynamic slicing, state tracing, and environmental monitoring to gather relevant context. While these techniques are powerful for providing visibility into the system, the challenge remains in effectively processing and reasoning about potentially vast and complex contextual data to pinpoint the root cause of an error and devise an appropriate solution. Our work utilizes context management techniques but enhances the analysis capabilities by feeding this context into a powerful LLM.

D. Large Language Models in Software Engineering

Large Language Models have rapidly emerged as powerful tools for a variety of software engineering tasks, including code completion [40], code generation [8], code summarization, and vulnerability detection [41]. Their ability to understand and generate human language and code has opened possibilities for more intelligent automated tools.

However, directly applying general purpose LLMs to real time, performance critical tasks like runtime error remediation requires careful consideration of latency, cost, and data privacy. The use of smaller, specialized, or locally hosted models is an active area of research to address these challenges [42], [43]. Our approach specifically investigates the practical application of a locally hosted, instruct tuned model (Qwen 2.5 7B Instruct 1M) for a critical software reliability task.

RuntimeErrorSage distinguishes itself from existing work by combining the strengths of local LLM inference, advanced context management, and a formal system model within a

practical middleware architecture for automated runtime error remediation. Unlike systems relying on external services or predefined recovery strategies, our system offers a privacy preserving, low latency, and intelligent approach to handling a wide range of runtime errors, including those not previously encountered.

IX. Conclusion

This paper has presented RuntimeErrorSage, an approach to runtime error handling in .NET applications that leverages local LLM inference for intelligent error analysis and remediation. The system's architecture combines runtime monitoring, context management, and local LLM processing to provide privacy-preserving error resolution capabilities without relying on external services.

While our implementation is still in the prototype stage, theoretical analysis suggests potential for meaningful improvements in error handling efficiency. We anticipate that with continued development and empirical validation, the system could achieve approximately 60% accuracy in error classification and 50-55% success rate in automated remediation suggestions, with resolution times of 10-15 seconds on commodity hardware. The mathematical model provides a foundation for error classification, context management, and remediation decision-making processes that will require thorough validation through real-world testing.

The local LLM approach addresses key limitations of existing solutions by eliminating network dependencies, ensuring data privacy, and potentially providing faster response times than cloud-based alternatives. The modular architecture enables extensibility and integration with existing .NET applications through standard middleware patterns.

We acknowledge several limitations in the current implementation. The Qwen 2.5 7B model, while promising, has inherent constraints in reasoning capabilities, particularly for complex system-specific architectural patterns. Our remediation execution system requires significant safety enhancements before production deployment, including comprehensive rollback mechanisms and formal validation procedures. Additionally, our performance and accuracy claims require rigorous benchmarking against established baselines.

Key future research directions include:

- Comprehensive empirical validation through controlled testing
- Implementation of robust safety mechanisms for remediation execution
- Development of a formal security threat model
- Integration with multiple LLM models to improve reliability and coverage
- Enhanced context management for distributed systems
- Improved remediation strategies through user feedback loops
- Support for additional programming languages beyond .NET

The system's design principles provide a foundation for future work in intelligent runtime error handling systems. The potential of local LLM integration for production error handling opens promising avenues for research in autonomous application reliability management, though significant challenges remain to be addressed before widespread production adoption.

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