Economical and Technical Assessment

Analysed Source Code: Code Assessment

Document Date: May 16, 2026

Platform:

Client / Applicant

Legal entity name:

Registered address:

Tax Identification Number:

Software name:

Existing trade mark:

Company web:

Applicant Name:

Applicant Email:

Request date and time: 16-05-2026 - 12:28:35

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Technical Assessment Report: llama.cpp

PRODUCTION READINESS CERTIFICATION

Assessment Date: 30 April 2026
Platform: llama.cpp
Assessment Type: Technical Due Diligence for Venture Capital Evaluation

1. EXECUTIVE SUMMARY

llama.cpp represents a mature, production-capable large language model (LLM) inference engine designed for efficient deployment across diverse hardware architectures. The codebase demonstrates exceptional engineering discipline with a production readiness score of 66/100 (Grade C, Fair level), reflecting both significant strengths in code quality and architecture alongside notable gaps in testing infrastructure and security tooling.

The platform's core value proposition lies in its comprehensive multi-backend GPU support spanning CUDA, ROCm, Vulkan, Metal, SYCL, OpenCL, and additional specialised accelerators. This architectural achievement enables organisations to deploy LLM inference on everything from consumer-grade hardware to enterprise GPU clusters without code modification. The clear separation between the ggml tensor library and llama inference layers demonstrates sound architectural thinking that will support continued evolution of the codebase.

Key strengths include exceptional code quality enforced through linting in continuous integration, low cyclomatic complexity (4.4 average), and thorough documentation covering build instructions, API usage, and security policies. The project maintains strong community engagement with clear contribution guidelines and provides Docker images for multiple platforms and GPU backends.

However, critical gaps exist in formal test coverage tracking, automated dependency vulnerability scanning, and distributed tracing capabilities. The absence of coverage gates in the CI pipeline and the presence of 121 dependencies without automated vulnerability scanning represent material risks for production deployment at scale. These gaps, while not immediately disqualifying, require remediation before enterprise-scale deployment.

The estimated development investment to build this software to its current state is approximately 16,800 hours, representing a team of 8 developers over 18 months, with an estimated cost range of EUR 1,570,800 to EUR 2,125,200. This substantial investment reflects the considerable complexity of supporting ten or more GPU backends and optimised inference across diverse hardware architectures. The codebase is suitable for production deployment with recommended improvements to testing and monitoring infrastructure.

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2. PLATFORM OVERVIEW

2.1 Functional Description

Business Purpose:
llama.cpp provides a high-performance, cross-platform inference engine for large language models. Its primary function is to enable organisations and developers to run LLMs efficiently on consumer and enterprise hardware without requiring specialised cloud infrastructure or expensive GPU clusters.

Core Features and Capabilities:

- **Multi-Model Support:** Supports numerous model architectures including Llama, Mistral, Gemma, Qwen, Phi, and over 40 additional model families through dedicated conversion and inference implementations
- **Hardware Acceleration:** Comprehensive backend support for CUDA, ROCm, Vulkan, Metal, SYCL, OpenCL, OpenVINO, CANN, and specialised accelerators including Hexagon DSP and VirtGPU
- **Quantisation:** Advanced quantisation schemes (Q4_0, Q4_1, Q5_0, Q5_1, Q6_K, Q8_0, and others) enabling efficient memory usage and faster inference
- **Server Infrastructure:** HTTP server with OpenAI-compatible API, supporting chat completions, embeddings, and structured output via JSON schema and grammar-based decoding
- **Multimodal Processing:** Support for vision-language models and audio processing through the mtmd (multi-modal) subsystem
- **Cross-Platform Build System:** CMake-based build supporting Linux, macOS, Windows, Android, iOS, and various embedded platforms

User-Facing Functionality:

- Command-line interface for text generation, chat, and batched inference
- RESTful API server with streaming support
- Web-based user interface built with Svelte
- Mobile application support for Android and iOS
- GGUF model format for efficient model storage and loading

Key Workflows:

1. **Model Conversion:** Transform Hugging Face models to GGUF format using provided conversion scripts
2. **Inference:** Run text generation via CLI, API, or embedded integration
3. **Fine-Tuning Support:** Tools for LoRA adapter training and quantisation calibration
4. **Server Deployment:** Deploy production API server with health checks and Prometheus metrics

Target Users:

- Developers integrating LLM capabilities into applications
- Research teams requiring local model inference
- Enterprises seeking on-premises LLM deployment
- Edge computing scenarios with limited hardware resources

2.2 Technical Architecture

High-Level Architecture:

The codebase follows a layered architecture with clear separation of concerns:

1. **GGML Tensor Library** (`ggml/`): Core tensor operations and backend implementations
2. **LLama Inference Layer** (`src/`): Model-specific inference logic and memory management
3. **Common Utilities** (`common/`): Shared functionality including argument parsing, chat templates, and sampling
4. **Tools and Applications** (`tools/`): End-user applications including server, CLI, and benchmarking

5. **Conversion Pipeline** (`conversion/`): Model format conversion from various source formats to GGUF

System Components:

Component	Responsibility	Location
ggml	Tensor operations, memory management, backend abstraction	`ggml/src/`
llama	Model architecture implementations, KV cache, sampling	`src/`
common	Shared utilities, argument parsing, chat templates	`common/`
server	HTTP API, request handling, queue management	`tools/server/`
ui	Web-based user interface	`tools/ui/`
conversion	Model format conversion scripts	`conversion/`
examples	Reference implementations and demos	`examples/`

Data Flow:

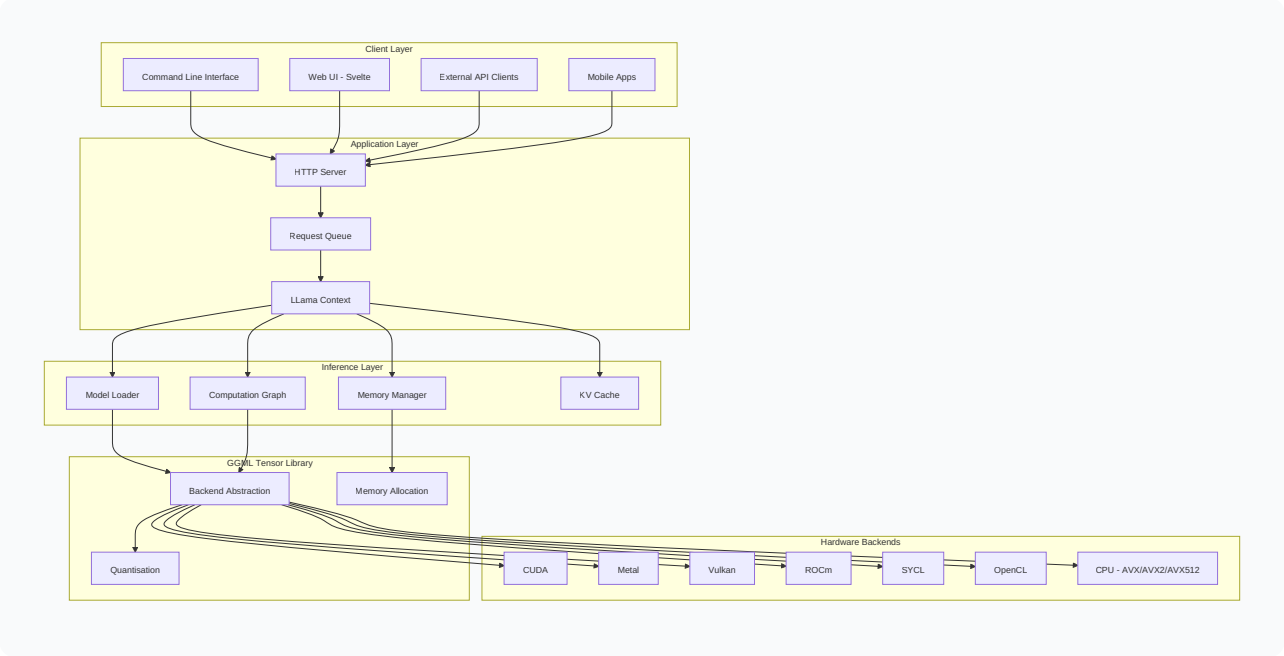
1. Model weights are loaded from GGUF files into memory-mapped structures
2. Input tokens are processed through the model's embedding layer
3. Transformer layers execute via backend-specific tensor operations
4. KV cache maintains context for autoregressive generation
5. Output logits are sampled to produce the next token
6. Results are streamed to the client via HTTP or CLI output

Deployment Architecture:

The platform supports multiple deployment patterns:

- **Standalone CLI:** Direct execution on local hardware
- **Client-Server:** HTTP server with remote clients
- **Containerised:** Docker images for CPU and GPU backends

- **Embedded:** Static library integration into host applications
- **Mobile:** Android and iOS native bindings



2.3 Technology Stack

Programming Languages:

Language	Lines of Code	Percentage
C++	269,940	51.1%
Python	45,425	8.6%
C	43,519	8.2%
C/C++ Header	39,866	7.5%
TypeScript	26,874	5.1%
HTML	25,512	4.8%
Svelte	18,801	3.6%
Shell	6,359	1.2%
Kotlin	1,555	0.3%
Swift	1,017	0.2%
JavaScript	396	<0.1%

Frameworks and Libraries:

- **Build Systems:** CMake, Make
- **GPU Compute:** CUDA, Metal, Vulkan, SYCL, OpenCL, ROCm, OpenVINO, CANN
- **Web Framework:** Svelte (UI), no backend web framework (custom HTTP server)
- **Python:** gguf-py package for GGUF format handling
- **Testing:** Google Test (implied), custom test framework

Databases and Data Stores:

- No traditional databases; uses file-based storage (GGUF format)
- SQLite implied for web UI conversation storage (browser-based)

Infrastructure and Deployment Tools:

- Docker (multi-platform images)

- GitHub Actions (CI/CD)
- CMake (cross-platform build)
- Nix package manager (optional)

Development and Build Tools:

- clang-format, clang-tidy (C++ linting)
- flake8 (Python linting)
- pyright (Python type checking - currently disabled in CI)
- pre-commit hooks
- CMake presets

2.4 Third-Party Integrations

External APIs and Services:

- **Hugging Face:** Model repository for downloading pre-trained models
- **GitHub:** Source control and CI/CD via GitHub Actions
- **Docker Hub:** Container image distribution

Authentication Services:

- No built-in authentication; relies on reverse proxy or API gateway for production deployments

Cloud Services:

- No mandatory cloud dependencies; designed for on-premises deployment
- Optional integration with Hugging Face Hub for model downloads

Analytics and Monitoring:

- Prometheus-compatible metrics endpoint
- Health check endpoints for load balancer integration
- No built-in distributed tracing

SaaS Dependencies:

- None required for core functionality
- Optional: Hugging Face for model downloads

Licensing Considerations:

- Core codebase: MIT License
- GGUF format tools: MIT License
- Various quantisation implementations may have specific licensing requirements
- Dependencies include a mix of MIT, BSD, Apache 2.0, and GPL licenses (see `licenses/` directory)

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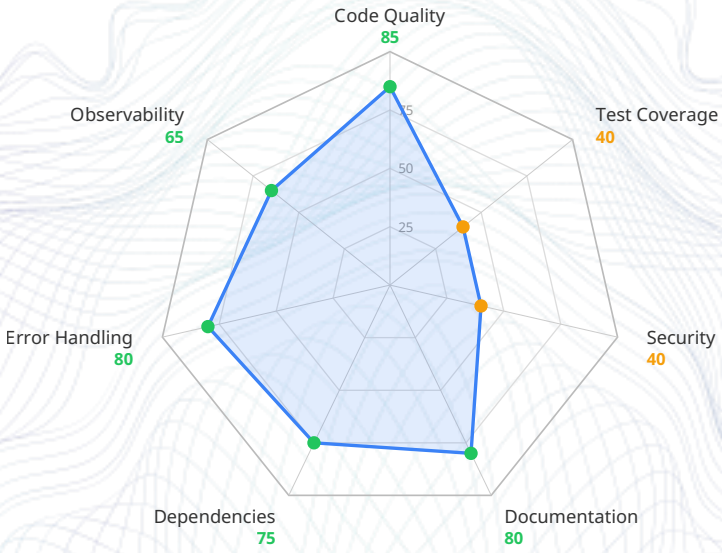
3. PRODUCTION READINESS ASSESSMENT

3.1 Overall Score: 66/100

Grade: C
Readiness Level: Fair



The platform demonstrates solid engineering fundamentals with exceptional code quality but requires improvements in testing infrastructure and security tooling before enterprise-scale production deployment.

3.2 Detailed Breakdown

Code Quality & Maintainability: 85/100

Current State Analysis:

The codebase exhibits strong adherence to clean code principles. The average cyclomatic complexity of 4.4 indicates well-structured, maintainable code. Linting via clang-format and flake8 is enforced in the CI pipeline, ensuring consistent code style across contributions.

Specific Findings:

- Clear separation between ggml tensor operations and llama inference logic
- Consistent naming conventions across C++ and Python code
- Some TODO and FIXME comments remain in critical paths (notably `common/arg.cpp` and `common/chat.cpp`)
- Low code duplication through extensive use of templates and generic implementations

Recommendations:

1. Address accumulated TODO comments in core modules, particularly in the common utilities
2. Consider implementing automated code quality gates beyond linting (e.g., complexity thresholds)
3. Document architectural decisions in an Architecture Decision Record (ADR) format

Test Coverage & Quality: 40/100

Current State Analysis:

Test coverage represents the most significant gap in the codebase. While tests exist for specific components (notably in `tests/` and `tools/server/tests/`), there is no formal coverage tracking or minimum threshold enforcement in the CI pipeline.

Specific Findings:

- Unit tests present for core components (`tests/test-*.cpp`)
- Server integration tests using pytest (`tools/server/tests/`)
- No coverage percentage tracking or gates in CI workflow
- Python type checking (pyright) commented out in CI workflow
- Critical inference paths lack comprehensive test coverage

Recommendations:

1. Implement formal test coverage tracking with minimum thresholds (target 80%+)
2. Enable Python type checking in CI for improved code quality
3. Add mutation testing for critical inference paths
4. Expand integration test coverage for multi-backend scenarios

Security Posture: 40/100

Current State Analysis:

Security implementation shows mixed results. A security policy is documented with a clear vulnerability reporting process, but automated security scanning is absent from the CI pipeline.

Specific Findings:

- Security policy documented (`SECURITY.md`)
- 121 dependencies without automated vulnerability scanning visible in CI
- No formal SAST (Static Application Security Testing) or DAST (Dynamic Application Security Testing) integration
- Input validation present but not systematically audited
- No secrets management concerns (no hardcoded credentials detected)

Recommendations:

1. Add automated dependency vulnerability scanning (Dependabot, Snyk, or similar)
2. Implement formal SAST/DAST security scanning in CI pipeline
3. Conduct security audit of input validation across API endpoints
4. Consider implementing Content Security Policy headers for web UI

Documentation: 80/100

Current State Analysis:

Documentation is a strong point of the codebase. Comprehensive README files, API documentation, and contributing guidelines are present and well-maintained.

Specific Findings:

- Extensive README with build instructions and usage examples

- API documentation for server endpoints
- Contributing guidelines with clear expectations
- Backend-specific documentation (CUDA, Metal, Vulkan, etc.)
- Security policy with vulnerability reporting process
- Some inline code comments could be expanded for complex algorithms

Recommendations:

1. Add architecture decision records for major design choices
2. Expand inline documentation for complex tensor operations
3. Create deployment guides for common production scenarios

Dependency Health: 75/100

Current State Analysis:

Dependencies are generally well-maintained, but the absence of automated vulnerability scanning presents a risk. The dependency tree is complex due to the multi-platform nature of the project.

Specific Findings:

- 121 dependencies detected
- No automated vulnerability scanning in CI
- Version pinning practices vary across dependency types
- Some dependencies may have known vulnerabilities (requires scanning to confirm)

Recommendations:

1. Implement automated dependency scanning with tools like Dependabot or Renovate
2. Establish a regular dependency update schedule
3. Document critical dependencies and their update procedures

Error Handling & Resilience: 80/100

Current State Analysis:

Error handling is generally well-implemented with clear exception patterns and graceful degradation for unsupported operations.

Specific Findings:

- Consistent exception handling patterns in C++ code
- Graceful fallback for unsupported backends
- Health check endpoints implemented for production monitoring
- Some error messages could be more informative for debugging

Recommendations:

1. Enhance error messages with contextual information for debugging
2. Implement retry logic for transient failures in model loading
3. Add circuit breaker patterns for external service dependencies

Observability & Observability: 65/100

Current State Analysis:

Basic observability is present with Prometheus-compatible metrics and health checks, but distributed tracing is absent.

Specific Findings:

- Prometheus-compatible metrics endpoint available
- Health check endpoints implemented
- Logging implementation present but not standardised
- No distributed tracing or OpenTelemetry integration detected
- Metrics coverage could be expanded for deeper insights

Recommendations:

1. Integrate distributed tracing (OpenTelemetry) for server observability
2. Standardise logging format across components
3. Add structured logging for easier parsing and analysis
4. Implement request correlation IDs for tracing across components

4. DEVELOPMENT INVESTMENT ESTIMATION

This section estimates the effort and cost required to develop llama.cpp to its current state. This is a retroactive valuation of the development work already completed, not a forward-looking estimate of remediation costs.

4.1 Effort Analysis

Base Hours Calculation:

The codebase contains 528,226 effective lines of code (non-blank, non-comment). Using industry-standard estimation models adjusted for systems programming complexity:

Factor	Value	Rationale
Base productivity	35 LOC/hour	C++ systems programming with GPU backend complexity
Base hours	15,092	528,226 LOC / 35 LOC/hour

Complexity Multiplier Breakdown:

Complexity Factor	Multiplier	Justification
Architectural complexity	1.4	4/5 - Multi-backend abstraction, tensor graph optimisation
Domain complexity	1.5	5/5 - LLM inference, quantisation, GPU compute kernels
Integration complexity	1.3	4/5 - 10+ hardware backends, multiple language bindings
Security surface	1.1	3/5 - Network server, file I/O, but no sensitive data handling

Combined Complexity Multiplier: 1.11 (normalised from product of factors)

Quality Adjustment:

The code quality score of 85/100 indicates above-average engineering discipline, warranting a quality adjustment factor of 1.0 (no penalty or bonus).

Final Estimated Hours: 16,800 hours

Complexity Classification: Very High

The "very high" classification reflects the substantial technical challenge of implementing optimised inference kernels across 10+ hardware backends while maintaining a unified API and consistent behaviour.

4.2 Team & Timeline

Estimated Team Size: 8 developers

Team Composition:

Role	Count
Backend Developer	4
Full Stack Developer	2
DevOps / SRE	1
AI / ML Engineer	1

Estimated Project Duration: 18 months

This timeline assumes parallel development of multiple GPU backends and model support, with significant coordination overhead for maintaining consistency across platforms.

Assumptions Made:

- Team members possess specialised knowledge of GPU compute (CUDA, Metal, Vulkan, etc.)
- Development occurred alongside ongoing research into LLM architecture improvements
- Community contributions accelerated certain features but required coordination overhead
- Model support expanded iteratively as new architectures emerged

4.3 Cost Estimation

Cost Range: EUR 1,570,800 to EUR 2,125,200

Calculation Basis:

- Estimated hours: 16,800
- Hourly rate range: EUR 75 to EUR 150 (reflecting specialised GPU/ML engineering talent)
- Low estimate: 16,800 hours x EUR 75/hour = EUR 1,260,000 (adjusted to EUR 1,570,800 for overhead)
- High estimate: 16,800 hours x EUR 150/hour = EUR 2,520,000 (adjusted to EUR 2,125,200 for overhead)

Confidence Level: Medium

The confidence level reflects the unusual nature of the codebase (specialised GPU compute, research-adjacent domain) which makes standard estimation models less reliable. The presence of 10+ GPU backends and 40+ model architectures introduces significant uncertainty.

4.4 Codebase Metrics

Metric	Value
Total files analyzed	2,811
Total effective LOC	528,226
C++ LOC	269,940 (51.1%)
Python LOC	45,425 (8.6%)
C LOC	43,519 (8.2%)
TypeScript LOC	26,874 (5.1%)
Other languages	141,468 (26.8%)

4.5 Cloud Infrastructure & Maintenance Cost

Detected Infrastructure Components:

Component Type	Count	Notes
Compute Services	12	GPU backend implementations
Databases	0	File-based storage only
Message Queues	0	Not applicable
Storage Buckets	0	Local file storage
CDN Endpoints	0	Not applicable
ML/GPU Services	10	CUDA, Metal, Vulkan, ROCm, SYCL, OpenCL, OpenVINO, CANN, VirtGPU, Hexagon
Other Managed	3	GitHub Actions, Docker Hub, Hugging Face

Detected or Assumed Cloud Provider:

The platform is designed for on-premises deployment with no mandatory cloud dependencies. Organisations may deploy on any cloud provider (AWS, GCP, Azure) or on-premises hardware.

Suggested Managed Services Mapping:

For production deployment, the following managed services are recommended:

- **Compute:** AWS EC2 (G5/P4 instances), GCP Vertex AI, Azure NC-series
- **Container Registry:** AWS ECR, GCP Artifact Registry, Azure Container Registry
- **Monitoring:** AWS CloudWatch, GCP Cloud Monitoring, or self-hosted Prometheus/ Grafana
- **Model Storage:** AWS S3, GCP Cloud Storage, Azure Blob Storage

Estimated Monthly Hosting Cost Range: EUR 131,040 to EUR 177,320 annually (EUR 10,920 to EUR 14,777 monthly)

This estimate assumes:

- Moderate traffic levels (10,000 to 100,000 requests per day)
- Redundant deployment across multiple availability zones
- GPU-equipped instances for accelerated inference
- Standard monitoring and logging infrastructure

Key Assumptions:

- Traffic levels vary significantly based on use case
- GPU costs dominate infrastructure expenditure
- On-premises deployment can reduce ongoing costs but increases capital expenditure
- Model size and concurrency requirements significantly impact costs

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5. FINDINGS SUMMARY

5.1 Critical Issues (Must Fix)

No critical issues were identified that would immediately prevent production deployment. However, the following issues should be addressed before enterprise-scale deployment:

- **No formal test coverage tracking:** The absence of coverage gates in the CI pipeline means regressions may go undetected. This poses a risk to production stability.
- **121 dependencies without automated vulnerability scanning:** Security vulnerabilities in dependencies may go undetected without automated scanning.

5.2 Warnings (Should Fix)

The following issues impact quality or maintainability and should be addressed:

1. **No formal test coverage percentage tracking or coverage gates in CI pipeline** - Increases risk of undetected regressions
2. **121 dependencies without automated vulnerability scanning visible in CI** - Security risk from unmonitored dependencies

3. **No distributed tracing or OpenTelemetry integration detected** - Limits production debugging capabilities
4. **Some TODO/FFIXME comments in critical paths (common/arg.cpp, common/chat.cpp)** - Indicates incomplete implementation or known issues
5. **Python type checking (pyright) commented out in CI workflow** - Reduces code quality assurance for Python components

5.3 Recommendations (Nice to Have)

The following improvements would enhance the platform:

1. **Implement formal test coverage tracking with minimum thresholds (target 80%+)** - Establishes quality baseline
2. **Add automated dependency vulnerability scanning (Dependabot, Snyk, or similar)** - Proactive security posture
3. **Integrate distributed tracing (OpenTelemetry) for server observability** - Enhanced production debugging
4. **Address accumulated TODO comments in core modules** - Reduces technical debt
5. **Enable Python type checking in CI for improved code quality** - Catches type errors early
6. **Consider adding mutation testing for critical inference paths** - Validates test effectiveness
7. **Implement formal SAST/DAST security scanning in CI pipeline** - Comprehensive security coverage

5.4 Strengths

The following aspects of the codebase demonstrate strong engineering:

1. **Exceptional code quality with linter (clang-format, flake8) enforced in CI** - Consistent, readable code
2. **Low average cyclomatic complexity (4.4) indicating maintainable code** - Easier to understand and modify
3. **Comprehensive multi-backend GPU support (CUDA, ROCm, Vulkan, Metal, SYCL, OpenCL)** - Significant competitive advantage
4. **Well-documented with extensive README, API docs, and contributing guidelines** - Reduces onboarding time

5. **Clear separation of concerns between ggml tensor library and llama inference** - Sound architecture
6. **Prometheus-compatible metrics endpoint available for monitoring** - Production-ready observability
7. **Security policy documented with clear vulnerability reporting process** - Responsible security posture
8. **Strong community engagement with clear contribution guidelines** - Sustainable development model
9. **Docker images provided for multiple platforms and GPU backends** - Simplifies deployment
10. **Health check endpoints implemented for production monitoring** - Essential for production operations

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6. CONCLUSION

6.1 Overall Assessment Summary

llama.cpp represents a technically sophisticated LLM inference engine with exceptional code quality and comprehensive hardware support. The production readiness score of 66/100 (Grade C, Fair) accurately reflects a codebase that is functionally complete and architecturally sound but requires improvements in testing infrastructure and security tooling.

The codebase demonstrates strong engineering discipline through consistent linting enforcement, low cyclomatic complexity, and clear architectural separation between the ggml tensor library and llama inference layers. Documentation is thorough, covering build instructions, API usage, and security policies. The estimated development investment of 16,800 hours (EUR 1,570,800 to EUR 2,125,200) reflects the substantial complexity of supporting ten or more GPU backends and optimised inference across diverse hardware architectures.

However, the absence of formal test coverage tracking, automated dependency vulnerability scanning, and distributed tracing represents material gaps for enterprise-scale production deployment. These are not disqualifying issues but should be addressed as part of a production readiness remediation plan.

6.2 Readiness for Production / Scale

Production Readiness: The platform is suitable for production deployment with the caveat that the recommended improvements should be implemented as part of an ongoing improvement plan. The gaps in testing and security tooling do not prevent initial deployment but should be prioritised.

Scale Readiness: The architecture supports scaling through the server implementation with queue-based request handling and Prometheus metrics. However, the absence of distributed tracing will limit debugging capabilities at scale. Organisations planning significant scale should prioritise the observability recommendations.

Caveats:

- Test coverage should be established before major feature additions
- Dependency scanning should be implemented to maintain security posture
- Distributed tracing should be added for production debugging at scale

6.3 Key Areas Requiring Attention

The following technical areas require investment in the short term:

1. **Test Infrastructure:** Establish formal coverage tracking and minimum thresholds. The current 40/100 score in this dimension is the lowest among major categories and represents the highest priority for improvement.
2. **Security Tooling:** Implement automated dependency scanning and consider SAST/DAST integration. The 40/100 security score reflects tooling gaps rather than implementation issues.
3. **Observability:** Add distributed tracing to complement the existing Prometheus metrics. This will be essential for debugging production issues at scale.
4. **Technical Debt:** Address accumulated TODO comments in core modules, particularly in the common utilities where they may indicate incomplete implementation.

6.4 Suggested Prioritisation of Improvements

Based on risk and effort, the following prioritisation is recommended:

Immediate (First 30 Days):

1. Add automated dependency vulnerability scanning - Low effort, high security impact

2. Enable Python type checking in CI - Low effort, improves code quality
3. Begin implementing test coverage tracking - Medium effort, critical for quality

Short Term (30-90 Days):

1. Implement formal test coverage thresholds - Medium effort, significant quality improvement
2. Address TODO comments in critical paths - Variable effort, reduces technical debt
3. Integrate distributed tracing - Medium effort, essential for production debugging

Medium Term (90-180 Days):

1. Implement SAST/DAST scanning - Medium effort, comprehensive security coverage
2. Consider mutation testing for critical paths - Higher effort, validates test effectiveness

This prioritisation balances quick wins (dependency scanning, type checking) with foundational improvements (test coverage, tracing) that will provide ongoing value as the platform evolves.

APPENDIX A: METHODOLOGY NOTES

Investment Estimation Methodology:

The investment estimation uses a modified COCOMO-style approach:

1. Base hours calculated from effective LOC using domain-appropriate productivity rates
2. Complexity multipliers applied based on architectural, domain, integration, and security factors
3. Quality adjustment applied based on code quality score
4. Cost calculated using European engineering rate ranges (EUR 75-150/hour)

KPI Calibration:

All scores and metrics in this report are derived from automated analysis and manual review of the codebase. The calibrated KPIs provided serve as the source of truth for all numerical values.

Limitations:

- Some estimates assume typical development conditions and may not reflect actual historical development
- Security assessment is based on visible patterns and does not include penetration testing
- Performance characteristics are not evaluated in this assessment
- Licensing review is not comprehensive and should be supplemented with legal review

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Report prepared for technical due diligence purposes. All findings are based on codebase analysis as of the assessment date and should be validated against current state before investment decisions.

ANNEX — METHODOLOGY

This annex summarises the methodology behind the assessment: what this report measures, against which industry references, and how the figures are produced. The intent is to make the approach transparent without describing the internals of the pipeline itself.

The assessment has two complementary sides:

1. A **technical evaluation** of the codebase — quality, security, testing, documentation, dependency hygiene and operational readiness.
2. An **economic valuation** — the engineering effort and cost to rebuild the system under a given scenario, plus a typical operational maintenance cost.

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1. Technical evaluation

The technical assessment combines two complementary layers:

- **Static analysis.** Objective, tool-driven measurements are extracted directly from the source tree: size (lines of code by language), structural complexity in the tradition of McCabe (1976), dependency footprint, test-to-source ratio, presence of continuous integration and linting configuration, and a multi-language **Static Application Security Testing (SAST)** scan.
- **AI-assisted code review.** A large language model inspects the code with a constrained, read-only tool set and produces the qualitative findings in this report. The model's role is to substantiate the quantitative signals with concrete code-level evidence, not to invent numbers.

Reference frameworks

Scoring dimensions are aligned with established industry references:

Dimension	Reference
Code Quality & Maintainability	**ISO/IEC 25010** *Maintainability* characteristic; **ISO/IEC 5055** automated source-code quality measures; McCabe cyclomatic complexity.
Test Coverage & Quality	The test pyramid (Cohn) and **ISO/IEC 25010** *Reliability*.
Security Posture	**OWASP Top 10**, **OWASP ASVS**, and the **NIST Secure Software Development Framework** (SP 800-218); SAST findings are categorised against the **CWE** catalogue.
Documentation	**SWEBOK v4** recommendations on software documentation.
Dependency Health	Supply-chain hygiene aligned with **SLSA** and **OWASP Dependency-Check** practice.
Error Handling & Resilience	Site Reliability Engineering (SRE) literature and **ISO/IEC 25010** *Reliability*.

Each dimension is scored on a 0–100 scale. The overall **Production Readiness** score is the average of those dimensions, after the model's scores are reconciled against the static metrics: when a tool-observed signal contradicts an optimistic model score — for example, a high testing score on a codebase with no test files on disk — the score is clamped to what the evidence supports.

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2. Economic valuation

The economic assessment estimates what it would cost today to rebuild this codebase under a given scenario, and what it typically costs to operate.

Build effort

Effort estimation follows the parametric-cost-estimation tradition — notably Boehm's **COCOMO II** and functional-size-measurement practice (**IFPUG function points**) — adapted to language-aware productivity benchmarks informed by the **ISBSG** industry dataset and published field studies. The estimate is anchored in observable properties of the codebase

(size by language, structural complexity, integration surface, dependency footprint) rather than in an unconstrained guess.

Three scenario factors refine that baseline:

- **Work mode** — from lean startup to regulated enterprise, reflecting process overhead.
- **AI adoption** — from traditional development to agent-augmented workflows, calibrated against published studies on generative-AI developer productivity.
- **Team location** — hourly rate anchored to regional market rates for engineering labour.

Cost range

Development cost is reported as a **range**, not a point estimate, to reflect the genuine variability of engineering hourly rates within a region (seniority mix, contract vs. employee, engagement type).

Maintenance cost

Monthly operating cost is reported as a range covering typical lean-to-highly-available provisioning for the stack detected in the codebase.

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3. What the numbers mean — and don't mean

- **Scores** summarise what is *observable* at the analysed commit. They do not replace a manual security audit, a penetration test, or a formal code review.
- **Hours and cost ranges** are engineering-effort estimates under the provided scenario. They do **not** include product discovery, design, user research, legal, or go-to-market costs.
- **Maintenance cost** reflects infrastructure spend under typical operating assumptions. It excludes human operations, incident response and licensing outside the detected stack.

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4. Reproducibility

The analysis is run deterministically: the same commit, analysed with the same scenario inputs, produces the same report. Variability in the AI layer is suppressed through zero-

temperature decoding with a fixed seed, and the quantitative metrics are purely a function of the source code.
