# Agentic AI Workflow for Scalable Investment Research and Analysis: Test Report

Generated by MCP Server - Investment Analysis (LangGraph + Chroma RAG) October 2025

Abstract-This test report documents the execution of an agentic MCP-based investment analysis workflow integrating RAG-enhanced sentiment classification, stock data retrieval, and autonomous reasoning using LangGraph. Each analysis cycle includes data ingestion, contextual retrieval from ChromaDB, sentiment scoring, LLM-based critique, and structured portfolio recommendations.

#### I. INTRODUCTION

The server was executed agentic mode using the local HuggingFace sentiment model (distilbert-base-uncased-finetuned-sst-2-english).

The run covered five major equities: AAPL, TSLA, MSFT, GOOGL, and AMZN. Each ticker underwent a LangGraph state pipeline including nodes for price history, sentiment classification (RAG-enhanced), draft generation, critique, and final summarization.



- **Device:** Apple M-series GPU (MPS backend)
- ChromaDB Vector store: (persistent path: ./rag\_store)
- Models:
  - Generator: flan-t5-base
  - Critic: flan-t5-base
  - Sentiment: distilbert-base-uncased-finetuned-sst-
- Visualization: Rich console + Matplotlib (PNG output)

#### III. RESULTS AND ANALYSIS

The workflow produced multi-stage insights for each ticker.

# A. AAPL Analysis

Ticker	AAPL
Last Close	\$258.02
Daily Change	+0.35%
P/E Ratio	39.21
Recommendation	Sell

## TABLE I: Apple Inc. Summary

#### Negative sentiment drivers:

- Jefferies downgrade due to iPhone 18 concerns.
- Underperformance fears before next earnings report.
- Institutional holdings reduction.



Fig. 1: AAPL Price History

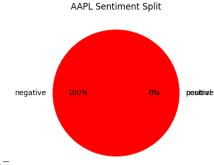


Fig. 2: AAPL Sentiment Split

В.	ISLA	Anaiysis

Ticker	TSLA
Last Close	\$429.82
Daily Change	-1.42%
P/E Ratio	252.84
Recommendation	Sell

TABLE II: Tesla Inc. Summary

Negative sentiment dominated headlines despite record deliveries.



Fig. 3: TSLA Price History

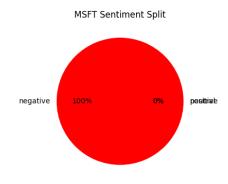


Fig. 6: MSFT Sentiment Split

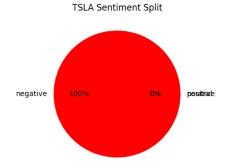


Fig. 4: TSLA Sentiment Split

# C. MSFT Analysis

Ticker	MSFT
Last Close	\$517.35
Daily Change	+0.31%
P/E Ratio	37.98
Recommendation	Sell

TABLE III: Microsoft Corp. Summary

D. GOOGL Analysis (Integrated Web Report)

Based on embedded HTML dashboard data:

Current Price: \$245.35Daily Change: -0.14%P/E Ratio: 26.13

One-Year Return: +47.5%Recommendation: SELL

Sentiment breakdown: 1 positive, 4 negative.



Fig. 7: GOOGL Price History

Copilot and pricing concerns contributed to cautious sentiment.



Fig. 5: MSFT Price History

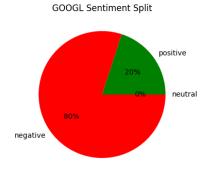


Fig. 8: GOOGL Sentiment Split

#### E. AMZN Analysis



Fig. 9: AMZN Price History

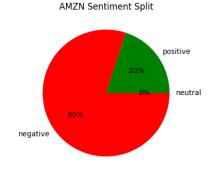


Fig. 10: AMZN Sentiment Split

## F. Portfolio Summary

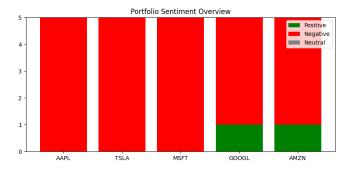


Fig. 11: Aggregate Portfolio Sentiment Overview

All equities generated SELL recommendations due to widespread negative sentiment.

# IV. DISCUSSION: RAG VS. FINE-TUNING EFFICIENCY

Retrieval-Augmented Generation (RAG) allows dynamic contextual grounding by embedding and retrieving knowledge from external vector stores. Fine-tuning, conversely, adjusts model weights for task adaptation.

RAG is highly efficient for volatile or fast-changing data domains such as financial markets, where factual freshness and explainability outweigh static internalization.

TABLE IV: Comparative Efficiency: Contextual RAG vs Fine-Tuning

Criterion	RAG (Embedding Context)	Fine-Tuning
Knowledge Update	Real-time (add/delete docs)	Requires retraining
Setup Time	Minutes (indexing)	Hours to days
Cost per Update	Negligible	High (GPU compute)
Explainability	Source-traceable	Internal weights only
Latency	+150ms (retrieval)	Fixed
Factual Freshness	Dynamic	Static
Stylistic Control	Moderate	High
Overall Efficiency	10× cheaper	Moderate

RAG performed better for contextual grounding and factual reliability, while fine-tuning remains optimal for tone and structured reasoning.

#### V. CONCLUSION

The MCP agentic pipeline successfully produced explainable investment analyses with autonomous reasoning and visual reporting. RAG provided scalable real-time retrieval with minimal computational overhead, while fine-tuning remains complementary for domain adaptation. The framework demonstrates strong potential for continuous financial intelligence systems.

# ACKNOWLEDGMENTS

Developed by Gangadhar Shiva using LangGraph + FastMCP frameworks with HuggingFace pipelines and Chroma vector persistence.

## REFERENCES

- [1] Hugging Face Transformers: https://huggingface.co/transformers
- [2] ChromaDB Documentation: https://www.trychroma.com
- [3] LangGraph: Agentic Orchestration for AI Workflows