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*AI-Driven High-Throughput Document Classification and Knowledge Distillation
Using Hybrid Machine Learning and Large Language Models through Agentic AI*

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This thesis is submitted in partial fulfilment of the requirements for the degree of MSc.

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Abstract

Efficient document classification at enterprise scale is increasingly pertinent as organizations must manage millions of unstructured documents per hour while ensuring compliance, high accuracy, operational efficiency, and transparency. This thesis presents a **hybrid AI system** that combines **traditional machine learning (ML)** and **agentic AI, leveraging large language models (LLMs)**, to process and classify over one million documents per hour with high precision. This system also enables knowledge distillation for continual learning and cost control. Another important goal of the system is to repurpose high-value talent away from repetitive classification tasks, allowing them to focus on more strategic and impactful work within the organization. The design blends metadata- and content-based ML with content-aware LLM inference, orchestrated by a smart, self-healing, and adaptive routing agent that assigns classification tasks based on complexity and confidence scores. A comprehensive evaluation against established metrics demonstrates the system's superiority over monolithic approaches, with empirical results underscoring its robustness, adaptability, and auditable intelligence.

Traditional machine learning excels in speed and cost, while recent advances in Large Language Models (LLMs) have made nuanced document understanding feasible. This research presents a hybrid document classification system that integrates machine learning and agentic AI reasoning with a knowledge distillation correction loop, achieving scalable, compliant, and adaptive enterprise document governance. Results demonstrate throughput exceeding 1,000,000 documents/hour, robust classification accuracy, cost-effective LLM orchestration, and continuous improvement driven by user feedback. Comparative benchmarking and multi-metric analysis validate the system's efficacy, generalizability, and auditability.

Keywords:

- Document Classification
- Large Language Models (LLMs)
- Hybrid Artificial Intelligence
- Knowledge Distillation
- Enterprise Data Governance
- Machine Learning
- Agentic AI
- Scalability
- Model Routing
- Adaptive Learning
- Implicit Reasoning in LLMs
- Self-Evolving Agents

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1. Introduction

1.1 Motivation

Organizations face challenges in managing vast, heterogeneous document repositories that encompass emails, reports, PDFs, messages, and other types of documents. Manual classification introduces bottlenecks, delays, and compliance risks, while cloud-powered AI solutions face cost and latency barriers[1]. The strategic imperative is to streamline document classification, freeing expert human capacity for critical tasks[2].

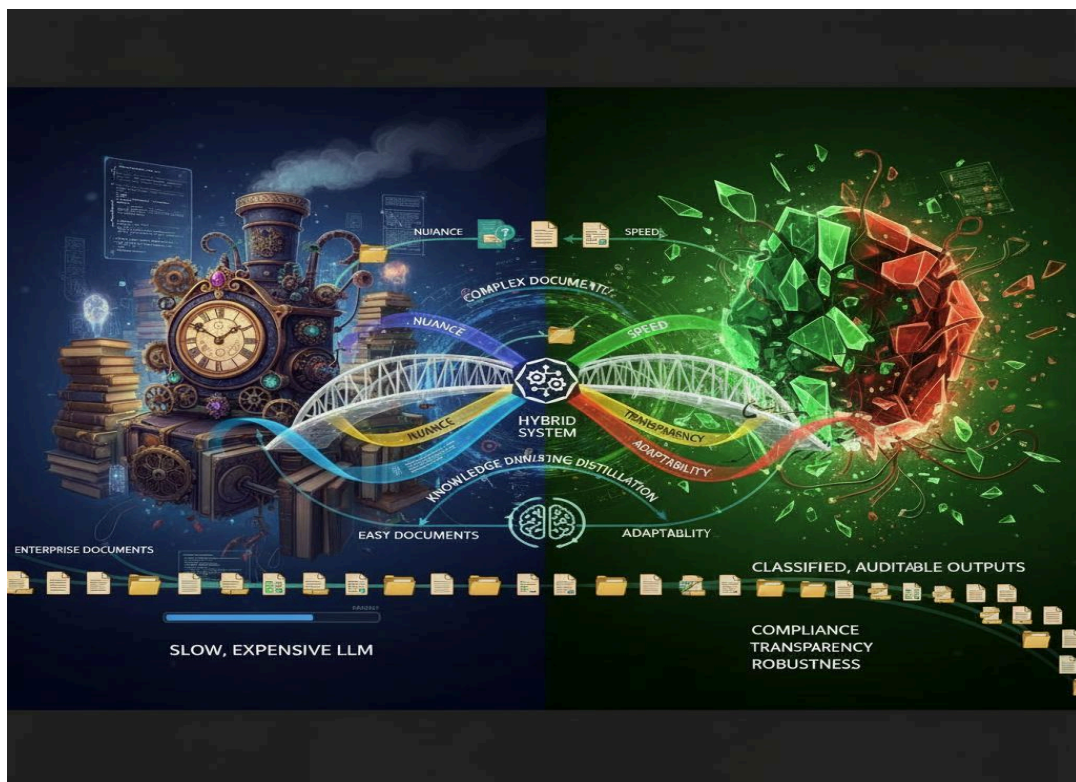


Figure 1. Hybrid intelligence drives enterprise(Internet generated image)

1.2 Problem Statement

Existing approaches to enterprise document processing face critical trade-offs. Off-the-shelf Large Language Models (LLMs), while capable of nuanced reasoning and handling ambiguity, are prohibitively slow and expensive at scale. On the other hand, traditional machine learning models offer efficiency and low cost but struggle with ambiguous, non-standard, or context-rich documents, often resulting in brittle performance. Organizations need a solution that bridges this gap. This system delivers the speed and scalability of traditional models for routine classification, while seamlessly invoking deeper, context-aware reasoning for complex cases. Such a system must remain transparent, adaptable to evolving needs, and cost-efficient to be viable at enterprise scale[\[3\]](#).

1.3 Research Gap

Despite significant advances in document classification through traditional machine learning and large language models (LLMs), several critical gaps persist that hinder the scalable, accurate, and cost-effective deployment of enterprise solutions. Below are the key identified gaps:

- First, **scalability** limitations continue to be a significant challenge. Off-the-shelf LLMs, while demonstrating superior reasoning and contextual capabilities, are generally too slow and expensive for high-throughput workloads that require classifying millions of documents per hour. Traditional ML models, conversely, offer speed and cost-efficiency but suffer in handling ambiguous or semantically complex documents due to limited contextual understanding.
- Existing approaches often rely on a **single classification method, either ML or LLM**, failing to leverage the unique advantages of both. This leads to either high operational costs or compromised accuracy and adaptability. There is a pressing need for hybrid systems that can dynamically route documents to the most suitable classifier based on complexity and confidence scores, thereby optimizing both throughput and precision.
- **Conventional classifiers typically depend solely on filename or metadata features**, neglecting the full richness of document content and context. This results in numerous ambiguous cases with low confidence, which degrade the overall accuracy. Moreover, existing tokenization and feature extraction methods struggle with non-standard, concatenated, or noisy filenames, which limits their generalization.
- Many current solutions **lack continuous learning and adaptability**. They do not effectively incorporate user feedback or corrections to refine model predictions and routing strategies. As document formats, policies, and organization-specific taxonomies evolve, classifiers must adapt in near real-time to maintain accuracy and compliance.

- **Auditability and transparency are often overlooked.** For enterprise and regulatory compliance, classification systems must provide clear, auditable reasoning trails, especially for edge cases handled by complex models. Many deployments lack the support necessary for this level of accountability, thereby undermining trust and governance.
- Finally, there is a **scarcity of comprehensive evaluation frameworks** that rigorously assess hybrid classification systems in dynamic, real-world conditions, incorporating multi-metric performance, cost efficiency, adaptability, and audit trail completeness.

This thesis addresses these gaps by proposing a hybrid AI document classification system integrating traditional ML and LLMs through an intelligent routing agent. It emphasizes scalability, cost control, continuous learning, and full auditability, validated by thorough evaluation and benchmarking on realistic, diverse datasets.

1.4 Aim and Objectives

This thesis aims to develop and validate a hybrid AI-driven document classification system that achieves scalable, accurate, and auditable classification of enterprise documents at a rate exceeding one million items per hour.

This system will combine the strengths of traditional machine learning and large language models (LLMs) to maintain high throughput and low cost, while enabling nuanced reasoning and regulatory compliance for ambiguous cases.

The objectives include:

- Design and implement a hybrid classification pipeline that integrates fast, parallelized machine learning models with agentic AI powered by LLMs.
- Develop an intelligent routing agent that dynamically directs documents to the most appropriate classifier based on document complexity and confidence thresholds, optimizing overall system efficiency and cost.
- Ensure the system supports multimodal document types and diverse enterprise taxonomies through advanced feature engineering and content-based analysis.
- Implement a continuous learning loop that incorporates user corrections and overrides to train lightweight correction models, thereby improving classification accuracy and adaptability over time.
- Provide transparent audit trails for all classifications, especially those processed by the LLM, including reasoning details and policy clause references to support compliance.
- Evaluate system performance across multiple metrics, including accuracy, throughput, cost, and adaptability, and benchmark against single-model baselines.

1.5 Economics of AI in document classification

The economics of AI, as highlighted by Gartner and the World Economic Forum (WEF), reflect transformative impacts on productivity, national power, and the global labor market. Gartner projects that by 2027, the productivity value of AI will become a primary economic indicator of national power, enabling unprecedented advancements in business modernization and cost reduction through the technology. The deployment of AI in enterprises promises a 70% reduction in modernization costs and significant productivity gains by automating complex tasks and extracting intelligent insights from legacy systems. The WEF emphasizes AI's central role in reshaping industries and labor markets by creating millions of new jobs while transforming or displacing existing roles. The economic shift powered by AI is not only about labor but also about efficiency, where computational work and AI tokens become fundamental units in the emerging digital economy, catalyzing immense operational efficiencies based on energy-to-computation metrics.

Document classification plays a crucial role in harnessing the economic potential of AI, particularly since unstructured data constitutes over 85% of an organization's data assets. This data includes diverse forms such as emails, PDFs, images, and other text-heavy and multimedia documents that traditional systems struggle to manage efficiently. Effective classification of unstructured data, using AI that blends machine learning and large language models, as detailed in the thesis, unlocks immense value by enabling enterprises to process and understand massive volumes of disparate documents quickly and accurately. By integrating intelligent routing and continuous learning, these hybrid AI systems optimize throughput, reduce costs, and maintain compliance and auditability, directly addressing the economic imperatives of operational efficiency and risk management. As unstructured data continues to grow exponentially, AI-driven document classification becomes increasingly fundamental for organizations to fully leverage their information assets, reduce manual overhead, and accelerate value generation in complex digital economies.

This comprehensive approach aligns with Gartner's vision of AI-driven productivity as an economic cornerstone. At the same time, the WEF's outlook highlights AI's centrality in the future of work and data-driven economic transformation. Together, they underscore the strategic importance of advanced AI in document intelligence and enterprise data governance as a critical economic driver in the evolving AI ecosystem.

1.6 Emerging Technologies

Emerging technologies poised to redefine enterprise-scale document classification and knowledge distillation systems encompass advanced paradigms such as agentic AI, multi-agent orchestration, and the Model Context Protocol (MCP), with adaptive learning mechanisms[3] playing a pivotal role. The prospective architecture envisions Level 5 autonomous agents communicating via decentralized peer-to-peer networks without centralized control, enabling dynamic generation, validation, and self-healing of classification components and workflows at runtime. This real-time adaptability addresses the intrinsic variability and complexity of enterprise document ecosystems by overcoming limitations posed by brittle, pre-defined scripting approaches. Through MCP, agents collaborate across layered contextual domains, maintaining situational awareness, sharing reasoning processes, and orchestrating tasks with high fidelity, thereby fostering robustness, scalability, and system resilience.

Adaptive learning constitutes a fundamental pillar of this approach, enabling continuous model refinement and responsiveness to concept drift, evolving document taxonomies, and changes in organizational policy. Feedback loops harness user corrections and overrides to iteratively distill knowledge into lightweight machine learning (ML) models and routing policies, reducing dependency on computationally expensive large language model (LLM) inference while enhancing accuracy and operational efficiency. The integration of knowledge graphs and graph neural networks (GNNs) further empowers the system to perform sophisticated fact inference and reasoning over heterogeneous, multimodal data repositories, thereby augmenting content awareness, which is critical for high-precision classification of ambiguous or policy-sensitive documents. The hybrid framework strategically balances metadata-driven ML models with agentic LLM reasoning through a confidence-aware routing agent, optimizing classification throughput, precision, and cost.

Moreover, alignment with contemporary low-code/no-code automation platforms enables flexible, event-driven orchestration, enhancing extensibility and operational transparency. The system's integration within comprehensive governance frameworks ensures rigorous auditability and compliance, which are essential for regulated enterprise environments. Collectively, these emergent technologies and methodologies present a compelling, academically grounded blueprint for next-generation document classification architectures delivering autonomous, adaptive, and auditable intelligence capable of efficiently managing growing volumes of unstructured data under dynamic, real-world conditions.

In addition to the architectural and technological advancements, the proposed system's design fundamentally embraces an interdisciplinary approach that integrates AI ethics, regulatory compliance, and operational governance into its core framework. The

system's emphasis on auditability not only supports stringent external oversight but also fosters internal accountability, creating an environment of trust critical for widespread enterprise adoption. By providing transparent, granular audit trails for both machine learning predictions and LLM-driven reasoning, including explicit policy clause references and user intervention logs, the system equips organizations to manage risks associated with AI decision-making proactively. Furthermore, the combination of adaptive learning with continuous user feedback and correction loops ensures the system evolves in alignment with ethical standards and business objectives, mitigating biases and maintaining fairness over time. This holistic integration of technical sophistication, governance, and ethical considerations positions the system as a forward-looking, resilient solution capable of catalyzing digital transformation initiatives while upholding the highest standards of responsibility, transparency, and operational excellence in document classification and knowledge management.

2. Literature Review

2.1 Scaling High-Speed Document Classification

Recent advancements have focused on developing batching and prioritization strategies to achieve high-throughput document classification suitable for enterprise-scale workloads. Dynamic batching techniques[\[4\]](#) that adjust batch sizes based on document complexity, such as splitting short emails versus lengthy reports, maximize hardware utilization and reduce latency variance significantly, enabling classification rates exceeding one million documents per hour on single GPUs. These hardware-aware optimizations closely align with the throughput requirements of large organizations that process a diverse range of document types, including emails, reports, and scanned images.

2.2 Hybrid Models, cost efficiency and knowledge distillation

There is growing consensus that combining traditional machine learning classifiers with large language models (LLMs) presents an optimal balance between cost and classification accuracy. Hybrid AI pipelines utilize routing agents that divert high-confidence, routine cases to efficient, low-cost ML models, while reserving computationally expensive LLM inference for ambiguous or complex documents that require nuanced interpretation. Moreover, knowledge distillation techniques are leveraged in these systems to continuously improve lightweight ML classifiers through feedback loops that incorporate user corrections and overrides, thereby reducing misclassification rates and enhancing generalization without incurring excessive inference costs. This paradigm ensures cost-effective scalability, adaptable classification coverage, and maintains auditability across hybrid deployments[\[5\]](#) [\[6\]](#) [\[7\]](#)

2.3 Adaptive Learning and Limitations of Pure Text-Based Classification

Sustaining classification accuracy in dynamic operational environments requires adaptive learning methodologies that detect concept drift[\[8\]](#) and enable the automated retraining of traditional models while maintaining LLM fallbacks during periods of model updates. Current research also reveals significant limitations in relying exclusively on filename or metadata tokens for classification. Such approaches often fail when generic or concatenated filenames lack discriminative cues and when tokenization methods

cannot adequately parse complex or concatenated filenames. These challenges motivate the integration of content-aware LLMs and hybrid models that utilize both metadata and primary document content, enabling more robust, context-rich classification adaptable to evolving document taxonomies and formats.

2.4 Literature Gap Summary

Despite significant advancements in both traditional machine learning and large language models (LLMs) for document classification, several critical gaps hinder the deployment of highly scalable and accurate systems in enterprise environments[9]. Existing solutions often suffer from a trade-off between speed and accuracy: traditional ML models excel in throughput but struggle with complex or ambiguous documents, while LLMs provide deep contextual understanding at a high computational cost and latency. Moreover, many current classifiers rely heavily on filename-based features or simplistic tokenization, limiting their effectiveness on documents with non-standard or noisy metadata. These challenges lead to a substantial number of documents being deferred to costly, slower LLM processing, which can bottleneck system scalability.

Further, there is a lack of robust integration between ML and LLM approaches that can leverage their complementary strengths efficiently. Hybrid architectures with intelligent routing informed by agentic AI[10] remain under-explored, especially those incorporating knowledge distillation to create leaner, faster models without sacrificing reasoning capabilities. Additionally, continuous learning mechanisms to adapt to concept drift and evolving document taxonomies are insufficiently addressed, impacting long-term accuracy. Lastly, the need for transparent, auditable classification decisions is paramount for enterprise governance but is rarely integrated into operational systems. This thesis addresses these gaps by proposing a hybrid AI system with an agentic routing layer and knowledge distillation, optimized for throughput, accuracy, adaptability, and compliance[11].

3. Agentic AI Hybrid Document Classification System Architecture

3.1 System Overview

The proposed architecture implements a scalable, hybrid document classification system that combines traditional machine learning (ML) and large language models (LLMs) within a unified framework. This system is designed to efficiently process over one million documents per hour while maintaining high accuracy and adaptability. Core components include:

- **Frontend Interface:** Developed using Streamlit, the interface offers an interactive dashboard for visualization, classification status monitoring, and user-driven correction input. Streamlit enables rapid deployment of data-rich interactive apps suited for enterprise users and data scientists.
- **Backend Engine:** A modular Python-based system orchestrates ML pipelines, LLM inference, and an adaptive agentic AI responsible for intelligent routing. It integrates MLflow to manage model lifecycle, including training, deployment, versioning, and real-time performance monitoring.
- **Agentic AI:** The system employs an adaptive, self-healing agentic AI that dynamically directs documents to either ML or LLM classifiers based on document complexity, confidence thresholds, and ongoing system health metrics. This agent continuously self-tunes by learning from classification outcomes and user corrections, enabling real-time adaptability and robustness.
- **Evaluation Frameworks:** Hierarchical Hybrid Classification Evaluation (HHCE) employs a multi-level evaluation approach to assess the performance of the hybrid classification system. It simultaneously measures the accuracy of AI-driven task planning and routing decisions, evaluates the correctness of model-level classifications, and reviews end-to-end classification outcomes. This layered assessment facilitates pinpointing failure points across the pipeline and guides targeted system enhancements. Second, Adaptive Classification Performance Evaluation (ACPE) emphasizes the evaluation of dynamic systems, incorporating continuous learning and adaptation. It tracks classification accuracy, computational cost, and user feedback integration over time, highlighting the system's ability to self-tune and maintain optimal performance in evolving document environments.

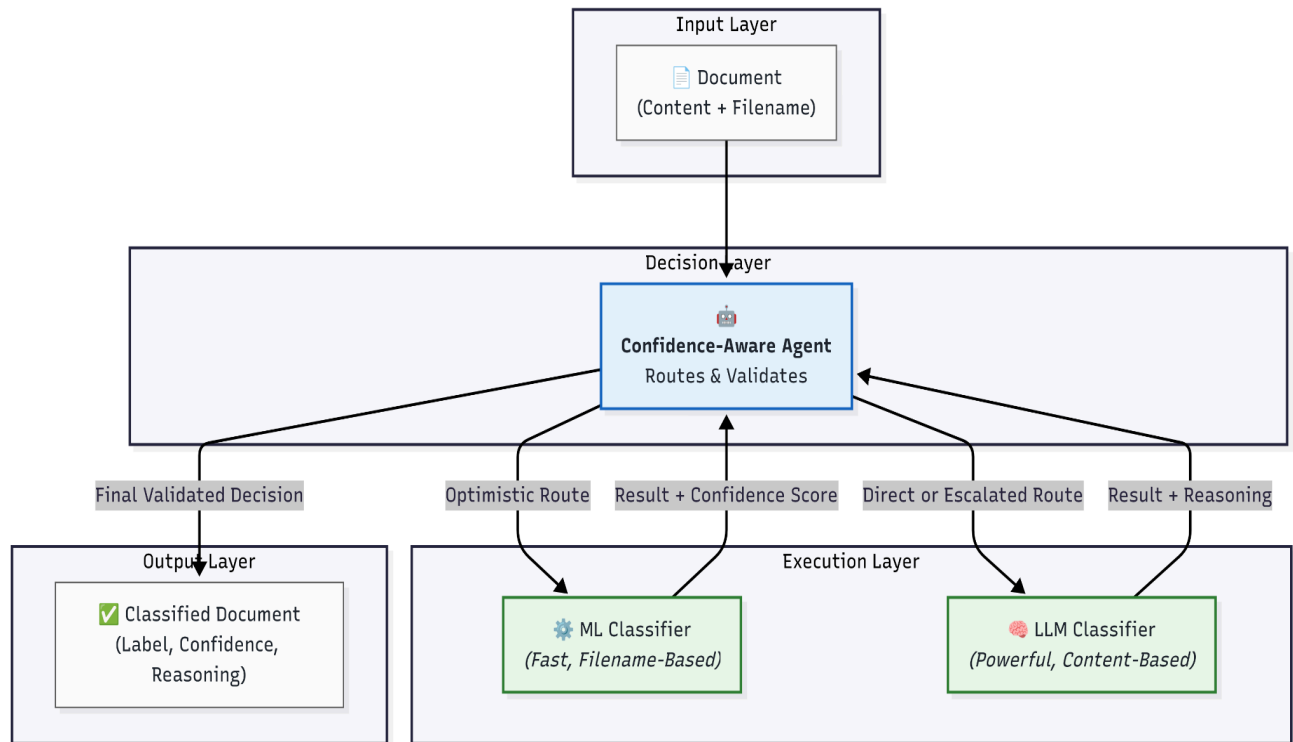


Figure 2. High-Level System Overview

The design philosophy emphasizes:

- Balancing speed and accuracy by leveraging the complementary strengths of ML and LLM.
- Maintaining auditability and transparency through detailed, explainable classification reasoning and logging.
- Ensuring scalability and cost-effectiveness suited for large-scale enterprise environments.
- Incorporating adaptive learning and governance to meet evolving regulatory requirements and operational realities.

3.2 ML and LLM Orchestration Pipeline

Documents first enter the agentic AI router, which evaluates document-specific features such as filename patterns, text complexity, and metadata and system-level performance indicators. Based on confidence scores and health metrics, the router channels documents to:

- **ML Pipeline:** High-confidence, routine documents are processed in parallel using ensemble models (e.g., Gradient Boosting, Random Forest, Logistic Regression) for high-throughput, cost-efficient classification.
- **LLM Module:** Documents flagged as ambiguous or policy-sensitive are escalated for inference via large language models, extracting deep contextual features and generating justifiable classifications with transparent audit trails.

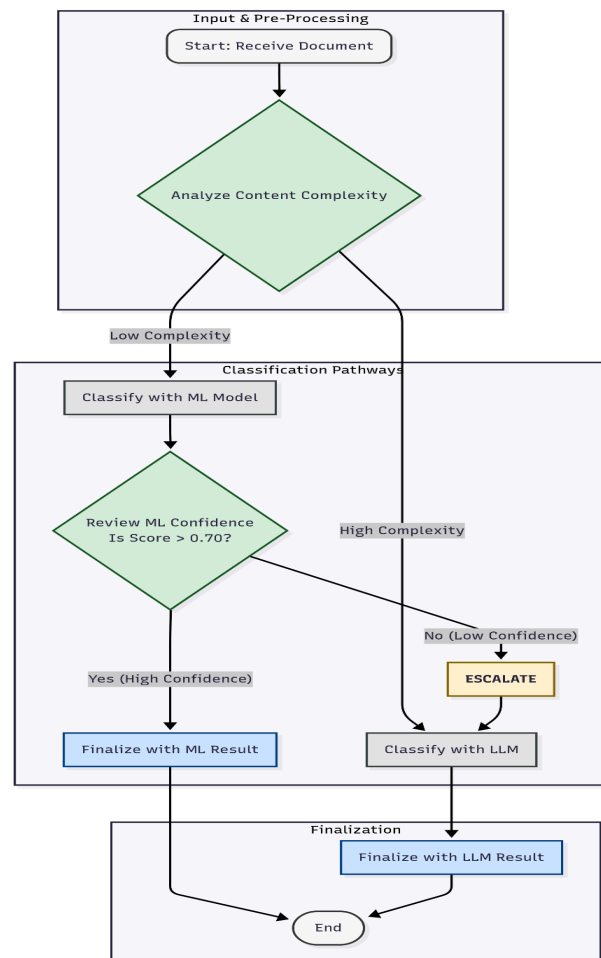


Figure 3. ML and LLM Layer System orchestration

3.3 Knowledge Distillation and Adaptive Learning Loop

The classification system incorporates a knowledge distillation loop, leveraging corrections and overrides submitted via the frontend dashboard. Corrected classifications are distilled into lightweight models or adjustment rules that update the routing policy and ML classifiers, thereby:

- Reducing reliance on expensive LLM calls over time.
- Enhancing tailored accuracy by continuously adapting to evolving document characteristics and emerging classification challenges.
- Supporting self-healing behavior by detecting performance degradations and triggering adaptive retraining.

This iterative refinement ensures sustainable improvements in accuracy and operational cost control.

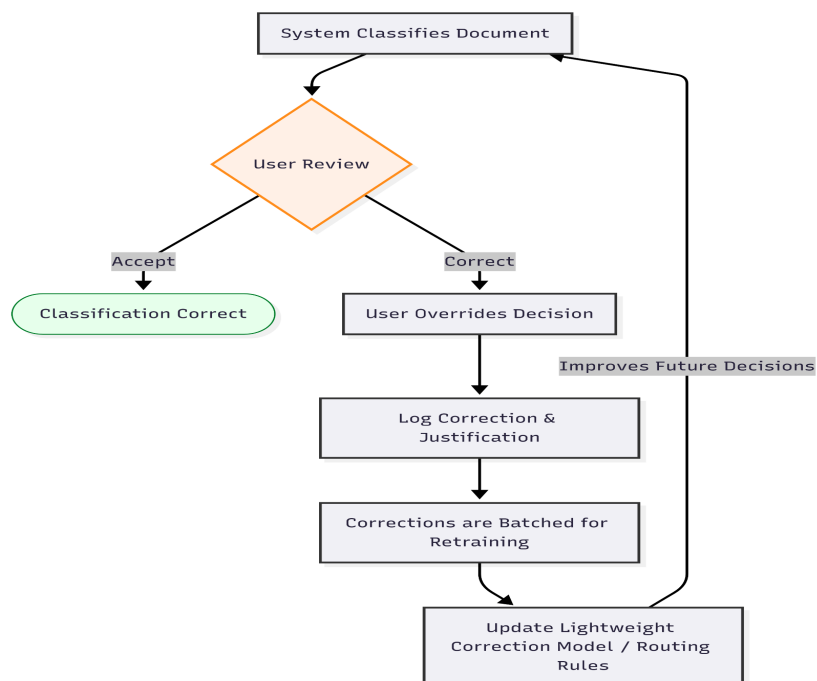


Figure 4. Continuous learning loop

3.4 Agentic AI Routing Framework

The agentic AI evaluates documents on multiple dimensions—document length, text complexity, prior classifier performance, and real-time system load—to route processing optimally. It employs a weighted decision function covering:

- Structural complexity (35%)
- Document length (25%)
- Historical accuracy and latency (30%)
- System availability (10%)

The agent maintains operational resilience by monitoring uptime and orchestrating fallback strategies in the event of degradations. Continuous online learning from user corrections enhances routing precision and reduces unnecessary LLM invocations.

3.5 Evaluation framework

The system's evaluation employs a hierarchical, multi-tier framework measuring:

- Planning Fidelity: Accuracy of the agentic AI's routing decisions and task decomposition.
- Tool Use Accuracy: How accurate was the result from the ML/LLM invocation and parameter selection.
- End-to-End Success: Overall correctness and user satisfaction of document classification.

This framework is integrated with MLflow tracking to enable real-time metric aggregation, anomaly detection, and detailed audit logs, which are essential for governance and model accountability.

3.6 Risks and risk mitigation

The deployment of a hybrid AI-driven document classification system in enterprise settings entails multiple risk factors that must be proactively managed to ensure sustained reliability, compliance, and performance:

- Data Quality and Label Consistency: The efficacy of ML models depends heavily on extensive, accurately labeled datasets with reliable metadata. Variations, noise, or inconsistencies—especially in ambiguous or poor-quality filenames—pose risks to model generalizability and accuracy. Rigorous data curation, ongoing dataset validation, and error monitoring mitigate these risks.

- **LLM Cost and Latency Constraints:** Despite selective routing, LLM inference remains computationally demanding with latencies on the order of seconds per document, potentially bottlenecking throughput during peak loads. The system mitigates this through adaptive routing, fallback mechanisms, and budget-aware degradation strategies but must continuously monitor and optimize these parameters.
- **Concept Drift and Taxonomy Evolution:** Rapid shifts in document types, organizational policies, and regulatory standards may outpace model adaptation. The system's reliance on user feedback and periodic retraining can introduce lags, risking temporary accuracy degradation. Deployment includes continuous monitoring for performance drift and automated retraining triggers to reduce this latency.
- **Operational Complexity and System Maintenance:** The multi-component, adaptive architecture increases integration, monitoring, and maintenance overhead. Coordinating updates across ML models, LLM APIs, routing agents, and feedback loops requires advanced governance tools and skilled operational oversight to avoid regressions and ensure consistency in heterogeneous environments.
- **Residual LLM Hallucination and Reliability Issues:** LLM outputs may include hallucinated or fabricated content, compromising classification reliability. Stricter grounding mechanisms, output validation, and citation requirements are necessary to mitigate misinformation risks and support transparent decision-making.
- **Limited Multimodal Handling:** While capable of basic OCR for scanned documents, the current system's limited ability to comprehensively process truly multimodal inputs (e.g., video, audio, complex image content) restricts applicability in certain verticals. Enhancements in multimodal learning and integration are critical future directions.
- **Compliance and Ethical Risks:** Automated decision-making requires vigilance against unintentional bias, ensuring fairness and ethical standards are upheld. Incorporating ethical auditing frameworks and transparent governance protocols mitigates these risks and supports societal trust.

This risk analysis informs both technical design choices and operational policies, facilitating a robust, scalable system that maintains high efficacy while navigating complex enterprise environments.

4. Methodology

4.1 Data preparation

This section presents the methodology for developing and evaluating the hybrid AI-driven document classification system. The approach integrates traditional machine learning models with large language models through an intelligent routing agent, evaluated using two novel frameworks: Hierarchical Hybrid Classification Evaluation (HHCE) and Adaptive Classification Performance Evaluation (ACPE).

4.2 Data preparation and engineering

4.2.1 Dataset curation

The curated dataset spans 16 primary document categories distributed across descriptive and generic filename structures. Descriptive filenames contain explicit categorical indicators (e.g., "invoice_2024_001.pdf", "resume_contract_final.docx") while generic filenames lack contextual cues (e.g., "document_12345.xlsx", "scan_item_001.png"). This bifurcation enables evaluation of routing intelligence and filename-based classification effectiveness. The corpus comprises 16,000 documents, evenly distributed across 16 categories, including invoices, reports, news articles, emails, and resumes, and encompasses a variety of file formats, such as PDF, DOCX, XLSX, and images.

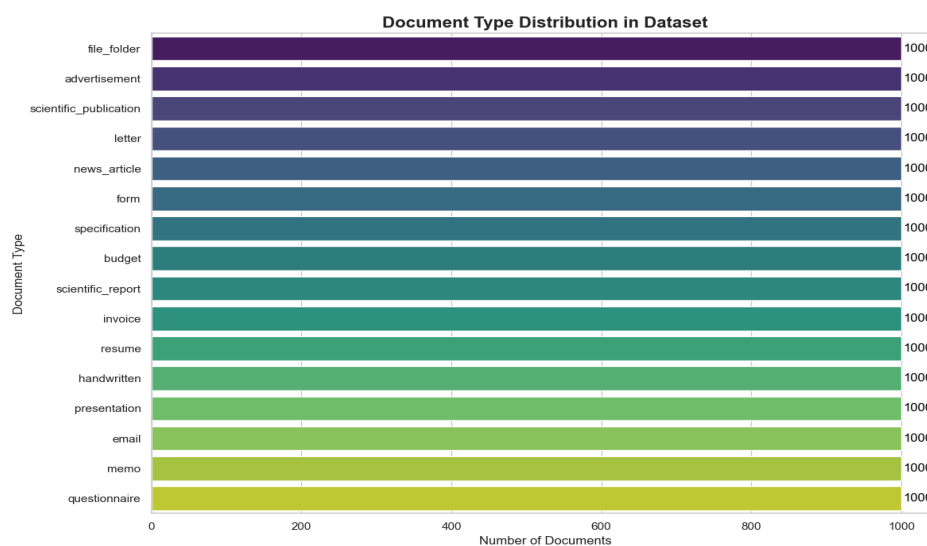


Figure 5. Document categories distribution.

4.2.2 Document preprocessing

Document datasets undergo comprehensive preprocessing involving:

- Filename normalization through standardized transformations, including lowercase conversion, removal of version numbers and timestamps, and replacement of special characters with underscores
- Content extraction across multiple file formats (PDF, DOCX, XLSX, PNG, JPG) using specialized libraries such as PyPDF2, python-docx, openpyxl, and PIL with OCR for image-based documents
- Systematic metadata extraction capturing filename structure, file extension mapping, content length measurement, and timestamp information when available
- Content sampling limited to the first 2,000 characters with truncation indicators for efficiency while preserving semantic integrity

4.2.3 Feature Engineering pipeline

The feature engineering pipeline implements multi-stage transformations designed to convert document filenames into structured numerical representations for machine learning classification. It extracts statistical patterns, categorical indicators, and structural elements that correlate with document types.

4.2.3.1 TF- IDF vectorization

The pipeline applies TF-IDF vectorization to preprocessed filename strings, with parameters optimized for filename-based classification:

- N-gram extraction covers both unigrams and bigrams, ensuring that individual terms like "invoice" and "resume" are captured alongside compound phrases such as "invoice v2" or "resume contract", which often improve categorization accuracy.
- Dimensionality is capped at 1,000 maximum features, which balances expressive power with efficiency and reduces overfitting risks on the compact vocabulary of filenames.
- Document frequency filtering excludes terms that occur in fewer than 2 documents (removing rare and noisy tokens) and also filters out terms appearing in more than 95% of documents (removing overly common terms with little discriminative value).
- Normalization employs L2 norm scaling so every feature vector has unit length regardless of filename length, while sublinear term frequency scaling reduces the weight of very frequent tokens, emphasizing term diversity over pure repetition.

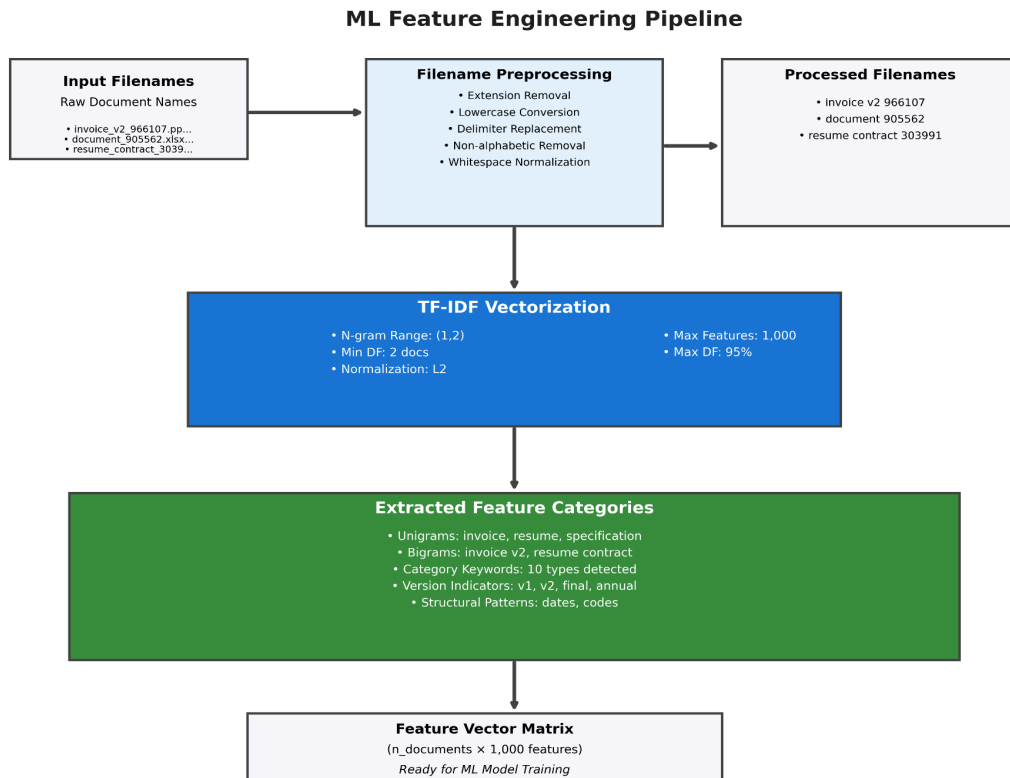


Figure 6. ML Feature Engineering Pipeline

4.2.3.2 Categorical feature extraction

To compliment TF-IDF, domain-specific categorical indicators are added through pattern recognition:

- Document type keywords are identified using a domain-specific dictionary of known filename terms linked to the 16 document categories. This allows filenames containing explicit text identifiers to be flagged directly.
- Version indicators and temporal markers are extracted through targeted pattern matching, identifying lifecycle signals such as "v2", "final", or date codes that often align strongly with document workflows.
- Structural patterns are detected via regex-based parsing of dates, project identifiers, or departmental abbreviations commonly embedded in enterprise filenames. These are transformed into binary presence or absence indicators that supplement statistical features with structural cues.

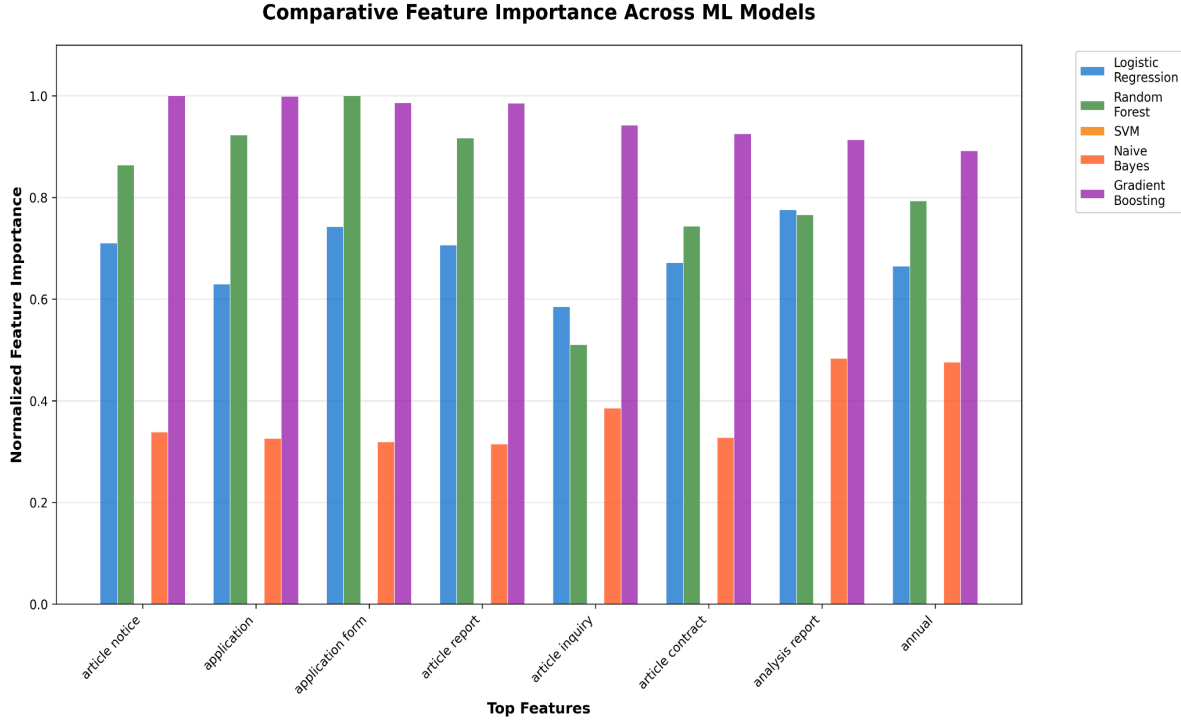


Figure 7. Comparative feature importance across ML Models

4.2.3.3 Feature integration

The final integration stage merges statistical and categorical features into unified document vectors:

- The TF-IDF vectors are concatenated with the binary categorical features to produce enriched feature vectors that combine statistical text-derived representations with explicit categorical and structural information.
- Binary presence indicators are numerically encoded so they align seamlessly with the continuous TF-IDF values in the final feature matrix.
- Scaling consistency is enforced so neither TF-IDF values nor categorical indicators dominate disproportionately, maintaining balanced contributions across feature types.
- The final feature matrix spans $n_{documents} \times (1000+k)$ dimensions, where 1,000 comes from the TF-IDF features and k represents the additional categorical features. This structure provides sufficient capacity for learning while remaining computationally feasible for real-time inference.

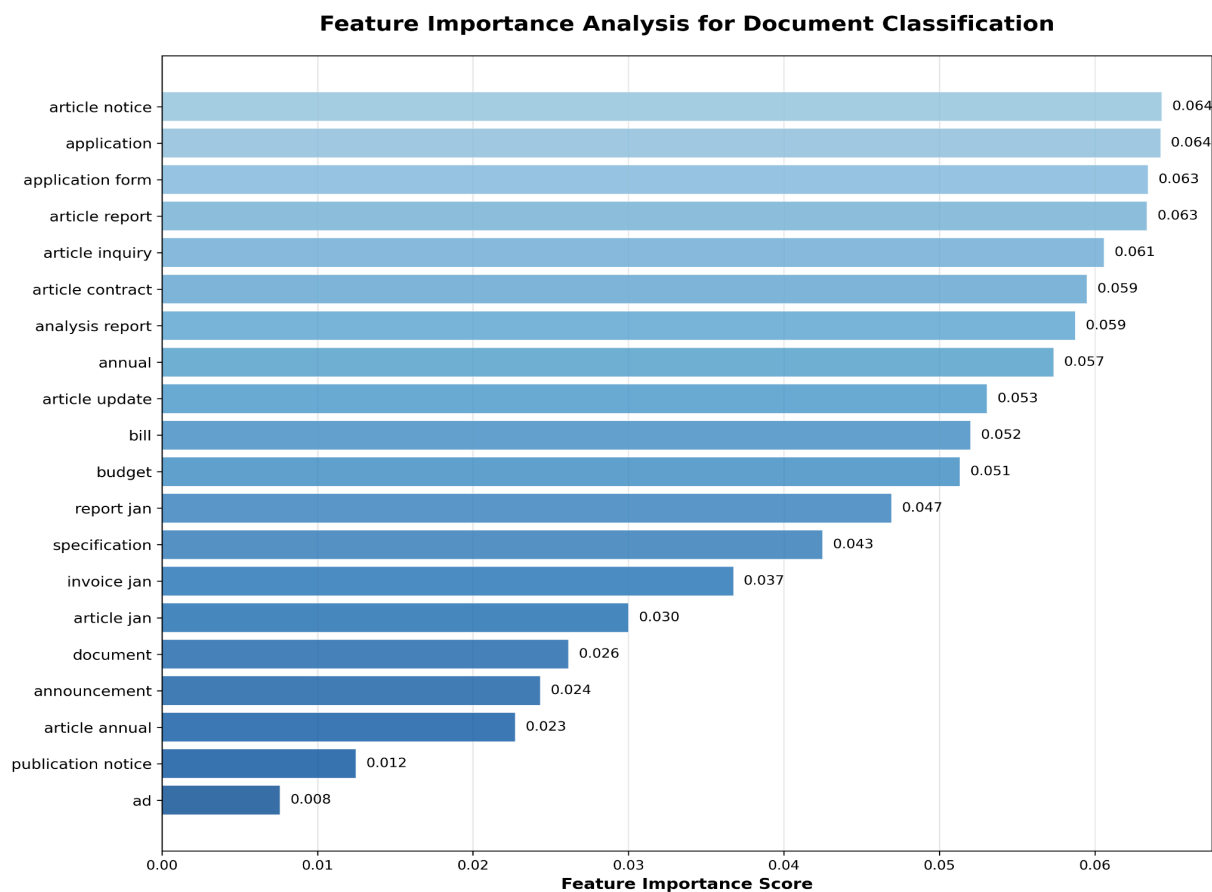


Figure 8. Feature importance scores

4.3 Model Development

The modelling stage involved 2 approaches: an ensemble of traditional machine learning models and a high accuracy large language model. This dual path system is designed for the hybrid system to balance speed, cost and accuracy with no big trade-off.

4.3.1 Machine learning models

The Machine learning component implements a comprehensive ensemble approach utilizing five distinct machine learning algorithms using the engineered feature vectors as the input. The multi-model training pipeline enables comparative analysis and automatic best-model selection based on validation accuracy metrics. We fit the following models:

- Logistic Regression

A linear model optimized for high-dimensional, sparse data such as TF-IDF vectors. Regularization strength ($C=1.0$) is applied with increased iteration limits to

- guarantee convergence.
- Random Forest
An ensemble approach designed to capture complex feature interactions while reducing overfitting. Configured with 100 estimators and default maximum depth to achieve convergence stability.
- Support Vector Machine (SVM)
A linear kernel is applied, favoring sparse TF-IDF data. Probability estimation is enabled for downstream routing compatibility and confidence scoring.
- Naive Bayes
Serves as the probabilistic baseline for text classification. Default smoothing parameters are effective for filename token distributions and compact feature vocabularies.
- Gradient Boosting
Builds strong predictors from weak learners, making it effective for recognizing layered and subtle filename structures. Configured with 100 estimators at a learning rate of 0.1, balancing convergence and generalization.

4.3.2 Training Pipeline

The ML training pipeline executes the ensemble systematically, applying identical preprocessing, hyperparameter optimization, and validation strategies across models for fairness. Engineered vectors flow directly into each algorithm, and comparative results are logged for evaluation.

4.3.3 Model Validation Protocol

Model validation followed a stratified 80:20 train-validation split to preserve balanced representation across all document categories. Each algorithm was trained with tuned hyperparameters suitable for filename-based classification. Logistic Regression used default regularization with extended iterations for convergence. Random Forest employed 100 estimators with default depth to capture non-linear patterns. The Support Vector Machine applied a linear kernel with probability estimation enabled for calibrated outputs. Naive Bayes leveraged smoothing optimized for text data distributions, while Gradient Boosting was configured with 100 estimators and a 0.1 learning rate to balance accuracy and stability.

Performance evaluation combined accuracy with detailed classification reports including precision, recall, and F1-scores. Confusion matrix analysis provided insights into error distributions and frequently misclassified categories. Automated best-model selection was then applied, designating the classifier with the highest validation accuracy as the primary model while retaining performance reports for all algorithms to enable comparison and auditability.

4.3.4 Best Model Selection

The training pipeline implements automated model selection by comparing validation accuracies across all five algorithms. The best-performing model with the highest validation accuracy is selected as the primary classifier for the hybrid routing system, with detailed performance reports generated for comparative analysis.

4.3.5 Model Persistence

All trained models are serialized using joblib for efficient loading during inference, with version control and metadata tracking to ensure reproducible deployments. The system saves the complete model ensemble along with the TF-IDF vectorizer and label encoder for consistent preprocessing during production inference.

4.3.2 LLM Integration

While machine learning models deliver high speed and efficient classification for structured cases, the large language model (LLM) is integrated to handle more ambiguous cases that require deeper contextual understanding. This component capitalizes on sophisticated prompt engineering that incorporates domain knowledge, categorical definitions, and structured reasoning templates. The prompt design emphasizes explicit instructions for content analysis, identification of category-specific

indicators, and reasoning chain generation to ensure interpretable classifications.

4.3.2.1 Prompt engineering specifications

The LLM employs a structured prompt framework to enhance consistency and interpretability:

- System context defines the classification task clearly, orienting the model's reasoning process.
- Detailed category definitions with characteristic examples provide domain-specific anchors for classification decisions.
- Content presentation with sampling indicators shows truncated text portions or filename segments to guide efficient inference while maintaining semantic cues.
- Explicit reasoning requirements compel the model to produce step-by-step justifications, ensuring transparency in its decision-making.
- Structured output formatting guarantees that responses align with required pipelines for integration with downstream ML models.

Temperature settings are set at 0.3, striking a balance between consistent deterministic output and flexible handling of variations or edge cases. Maximum output length is constrained to 1000 tokens, which ensures concise responses, efficient cost management, and faster classification while retaining sufficient explanation. Prompts also include instructions for handling ambiguous inputs, managing multiple document formats, and providing confidence assessments alongside classifications.

4.3.2.2 Model Configuration

The system utilizes the GPT/OSS-120b model accessed through an Open AI REST API from Groq. The integration pipeline is designed for robustness, implementing:

- Comprehensive error handling for API calls
- Exponential backoff and retry mechanisms to manage service interruptions
- Rate-limiting compliance to prevent API overload
- Timeout management and response validation to maintain responsiveness
- Structured error reporting for operational reliability

4.3.2.3 Optimization and Interpretability

Both ML and LLM models are optimized for accuracy, but through different approaches:

- ML models rely on feature engineering, feature selection, and hyperparameter tuning to refine statistical learning.

- LLM models focus on prompt optimization, temperature control, and token management to achieve efficient, context-aware performance.

Efficiency is also addressed differently: ML models emphasize dimensionality reduction and regularization, while LLMs focus on prompt brevity and response formatting. Interpretability is maintained by two complementary methods: ML models provide feature importance scores to reveal which filename attributes influence predictions, while LLMs generate explicit reasoning chains that document their step-by-step classification logic.

4.3.3 Agentic routing system

The agentic routing system serves as the orchestrator of the hybrid classification pipeline, making real-time decisions about optimal classifier selection for each document. This component embodies the system's adaptive intelligence, balancing speed, accuracy, and computational cost.

4.3.3.1 Confidence-Aware Routing Agent Architecture

The routing agent implements a sophisticated weighted decision function that evaluates documents across these four dimensions:

- **Structural Complexity (35%)**
Assesses vocabulary diversity, special character density, and filename patterns. High vocabulary diversity and special characters indicate technical content suited for LLM, while generic or repetitive patterns favor ML.
- **Document Length (25%)**
Short filenames (<20 characters) with clear indicators are routed to ML. Medium length (20–50 characters) requires additional factor consideration. Long filenames (>50 characters) often denote complex documents best handled by LLM.
- **Historical Performance Metrics (30%)**
Tracks rolling category-specific accuracy, latency profiles, and error patterns per classifier. It dynamically adjusts routing weights based on recent misclassifications, processing delays, and flags systematically uncertain filename patterns for mandatory LLM review.
- **System Availability and Health (10%)**
Monitors CPU usage, API quotas, and memory. Implements fallback routing when services degrade: routing to ML if LLM is unavailable, or selectively routing critical documents to LLM during ML interruptions.

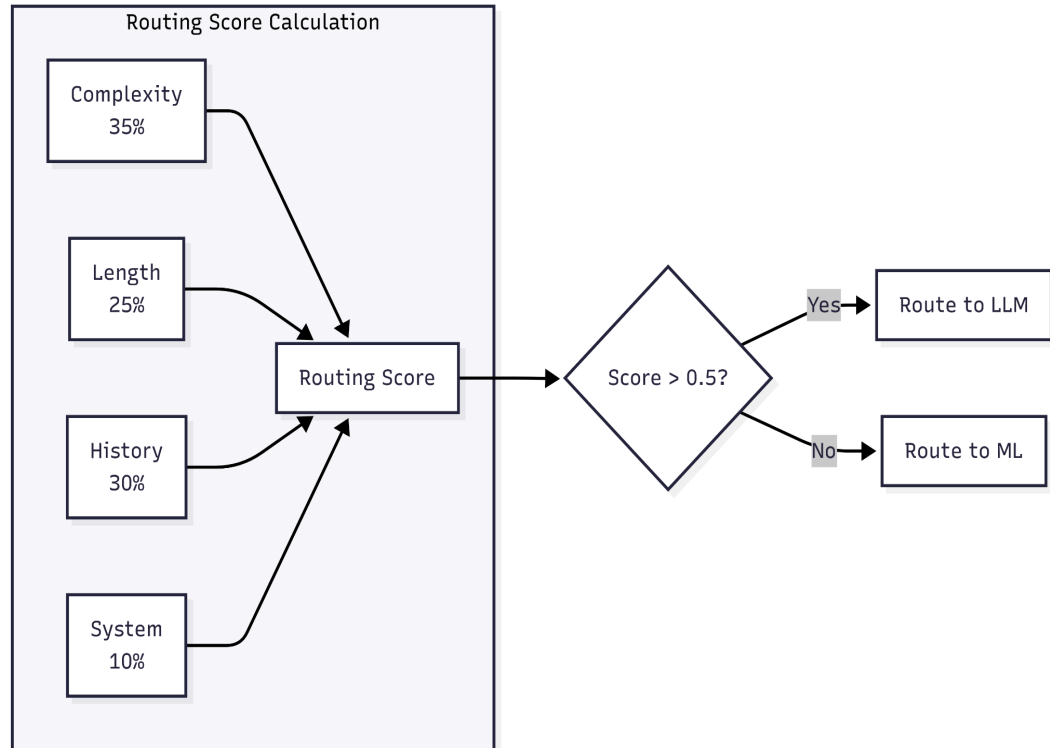


Figure 9. Confidence aware routing architecture

4.3.3.2 Routing pipeline

The routing pipeline processes documents through three main stages:

Stage 1: Initial ML Classification and Confidence Scoring

- Document enters pipeline.
- Features extracted (TF-IDF + categorical).
- ML ensemble predicts with probability scores.
- Confidence score calculated as:

$$\text{Confidence} = 0.6 \times \text{max_probability} + 0.3 \times \text{ensemble_agreement} + 0.1 \times \text{historical_accuracy}$$

Stage 2: Confidence Threshold Validation

- Primary threshold set at 0.7.
 1. If confidence ≥ 0.7 : finalize classification via ML.
 2. If confidence < 0.7 : escalate to LLM.
- Dynamic adjustment:
 1. In low load, threshold increases to 0.75 to optimize accuracy.
 2. During peak load, threshold lowers to 0.65 to maintain throughput.
- Category-specific thresholds:

1. Legal docs require 0.8 for high accuracy.
2. Marketing materials accept 0.6 favoring speed.

Stage 3: Routing Decision and Execution

When ML Path is taken, these actions follow:

- Direct classification finalization
- Minimal audit logging (category, confidence, timestamp)
- Average processing: 0.002-0.02ms per document
- Batch processing capability for high throughput

When the agents routes to the LLM, the following happen:

- Content extraction and sampling (first 2000 characters)
- Structured prompt generation with context
- API call with retry logic (exponential backoff)
- Comprehensive audit trail generation
- Average processing: 1500-2500ms per document
- Includes reasoning extraction and policy citation

We illustrate this routing pipeline as follows:

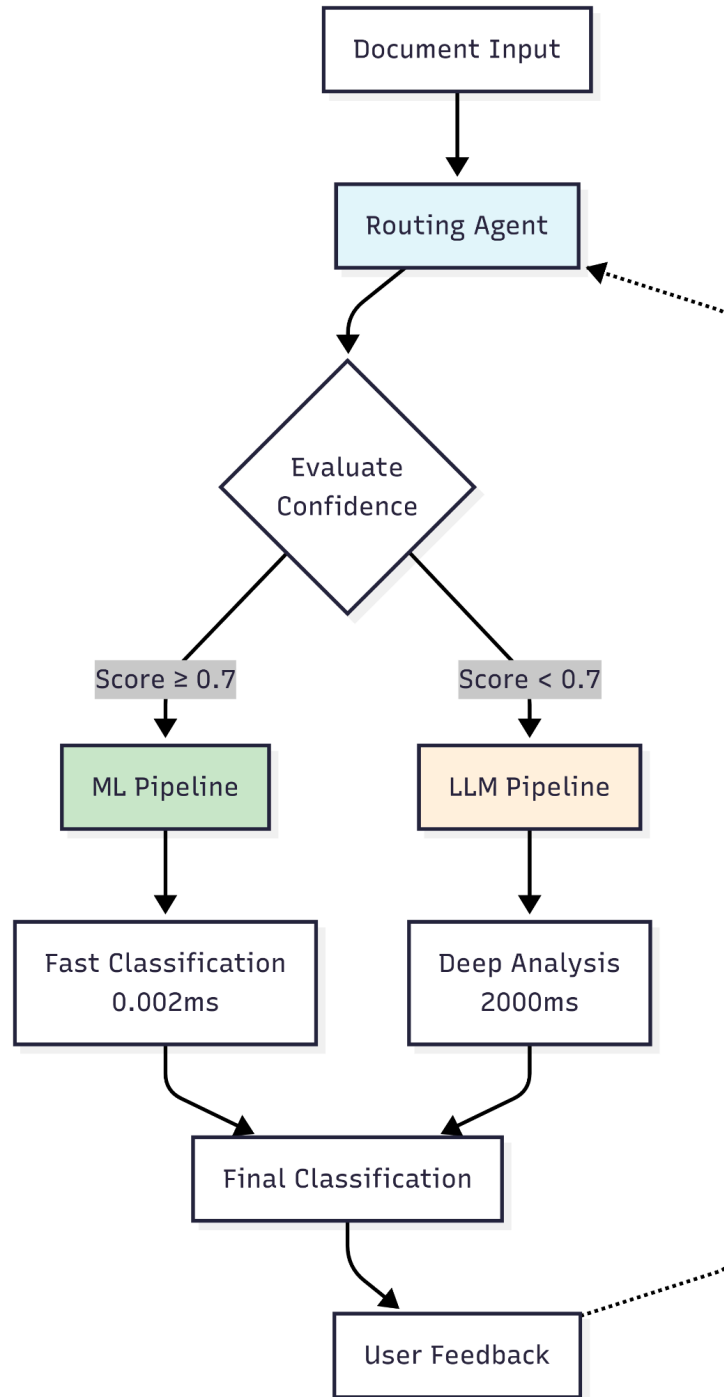


Figure 10. High level overview of the routing pipeline

4.3.3.3 Adaptive routing optimization

The adaptive routing mechanism continuously refines routing decisions through real-time learning and cost management, ensuring the system remains both accurate and efficient under evolving conditions [\[3\]](#).

Real-time Learning Components

The routing agent incorporates a feedback integration loop that uses user corrections to immediately update routing weights. When documents are misrouted—for example, when ML incorrectly classifies a document that should have been handled by the LLM—complexity scores for similar patterns are increased, enhancing future detection of challenging cases. Conversely, successful classifications by ML lower the probability that similar documents will be routed to the LLM, optimizing resource usage while maintaining accuracy.

Performance-Based Weight Adjustment

Routing dimension weights are recalibrated based on aggregated accuracy metrics to adapt dynamically to changing data characteristics. An A/B testing framework supports experimental routing strategies to identify improvements. Additionally, gradual weight updates are performed using gradient descent optimization, allowing for smooth and continuous evolution of routing parameters rather than abrupt changes.

Cost-Aware Routing

The system actively tracks cumulative API costs on hourly, daily, and monthly scales to manage expenses. When approaching budget limits, it applies graceful degradation—reducing LLM calls while preserving critical functionality. In parallel, priority queuing ensures that high-value document types are preferentially routed to the LLM during constrained periods, maintaining service quality for important classifications.

4.3.3.5 Monitoring and observability

The routing system employs a comprehensive telemetry framework designed to provide full visibility into operational performance, decision-making processes, and system health. This monitoring supports effective management, troubleshooting, and continuous improvement of the pipeline.

Routing Decisions Logging

The system captures detailed records of every routing decision, documenting the selected classification method (ML or LLM), the rationale behind each choice, and the time taken to reach the decision. This audit trail also includes the final classification results with associated confidence scores, the complete reasoning process, any escalations, and whether fallback mechanisms were triggered. Such detailed logging enables traceability and facilitates error analysis.

Performance Measurement

Monitoring includes precise timing of key processing steps such as routing decisions and classification by both ML and LLM components. End-to-end latency metrics, along with throughput calculations measuring document processing rates, allow for identification of performance bottlenecks and capacity planning. The system tracks classifier-specific success rates and processing times, enabling ongoing performance evaluation and empirical tuning of routing strategies.

Cost Monitoring

The system tracks the usage of the computationally intensive LLM calls, including retries and rate-limiting events, to manage API consumption effectively. Per-document cost estimates are maintained for both ML and LLM classifications, providing financial transparency. The hybrid routing approach's cost savings and return on investment are quantified to justify operational decisions and future scaling plans.

Drift and Anomaly Detection

To maintain consistent classification quality, the system performs real-time monitoring of confidence score distributions and routing patterns. Alerts are generated when confidence metrics degrade or when routing proportions deviate significantly from expected baselines. Tracking the alignment between predicted categories and ground truth labels allows early identification of concept drift or model degradation to trigger model retraining.

Logging and Audit Infrastructure

Structured logs provide comprehensive coverage of system activities, including document complexity assessments, escalation decisions, and error handling with graceful degradation strategies. This enables transparency, facilitates debugging, and supports compliance requirements.

4.4 Evaluation

The evaluation framework employs a rigorous multi-dimensional assessment protocol designed to validate the hybrid system's performance across accuracy, efficiency, and scalability metrics.

The evaluation methodology encompasses three primary objectives:

- Quantifying classification accuracy against manually verified ground truth results
- Measuring computational performance and resource utilization
- Assessing the routing mechanism effectiveness in optimizing the accuracy-latency-cost tradeoff

4.4.1 Hierarchical hybrid classification evaluation(HHCE)

The HHCE framework assesses the system's performance at three distinct levels using specific metrics, enabling granular insights and targeted improvements.

4.4.1.1 Planning and Routing Assessment

This stage evaluates the agent's ability to correctly assess document complexity and route documents to the appropriate classifier (ML or LLM).

Implementation

- A test set of 100 documents is used: 50 with descriptive filenames that should route to ML, and 50 with ambiguous filenames requiring LLM or escalation.
- For each document, the system records complexity scores, initial routing decisions, final classifiers used (including escalations), and ground truth labels.

Primary Metrics:

- Routing Accuracy (RA): Percentage of correctly routed documents, with a target exceeding 85%. Separate measurements are made for descriptive and ambiguous documents.
- Routing Efficiency (RE): Percentage of descriptive documents correctly retained in the fast ML pipeline, targeting over 90%.

4.4.1.2 Model Performance Assessment

This step measures the classification performance of ML and LLM models on the documents they receive.

Implementation

- For ML-processed documents: classification accuracy, processing time (expected <10 ms), and confidence scores are tracked.
- For LLM-processed documents: classification accuracy, reasoning quality, API cost, and latency are measured.

Primary Metrics:

- ML Pipeline Accuracy (MPA): Targeting >95% accuracy on descriptive filenames.
- LLM Pipeline Accuracy (LPA): Targeting >80% accuracy on complex or ambiguous cases.
- Escalation Effectiveness (EE): Measures improvement due to escalation from ML to LLM with a target percentage based on accuracy gains.

4.4.1.3 System-Wide Performance

The last stage of HHCE evaluates the overall effectiveness and efficiency of the full hybrid pipeline

Implementation

- The entire 100-document test set is processed end-to-end by the hybrid system and compared against pure ML and pure LLM baselines.
- Weighted performance scores balance accuracy, latency, and cost.

Primary Metrics:

- Overall System Accuracy (OSA): Should exceed 85%, surpassing either pure approach.
- Processing Efficiency (PE): Average processing time per document should be under 2000 ms, outperforming pure LLM speed.
- Cost Efficiency Ratio (CER): Hybrid classification cost per document targeted below 50% of pure LLM cost.

4.4.2 Adaptive Classification Performance Evaluation (ACPE)

ACPE examines the system's capacity for continuous learning and adaptation through controlled phased testing.

Temporal performance analysis

The temporal performance analysis divides the 100-document test set into four sequential phases of 25 documents each: baseline, learning, adaptation, and final performance. Throughout these phases, the system tracks key behavioral changes, including adjustments in confidence thresholds, variations in routing patterns, and escalation rates. The primary metrics for this analysis include Confidence Calibration Improvement (CCI), which aims to achieve at least a 0.2 increase in the correlation between confidence scores and accuracy from the initial to the final phases, and Escalation Optimization Rate (EOR), which targets more than a 15% reduction in unnecessary escalations by the final phase.

Adaptation effectiveness

Adaptation effectiveness is evaluated by first injecting ten corrections on misclassified documents after the baseline phase. The system is then assessed on its ability to reduce errors on similar document patterns during the adaptation phase. Two key metrics guide this evaluation: Correction Effectiveness (CE), which aims for over a 50% reduction in errors on corrected patterns, and Threshold Adaptation Score (TAS), which measures how confidence thresholds adjust according to model performance across categories, with the goal of achieving measurable improvements in threshold optimization.

Cost benefit analysis

Cost-benefit evolution examines the computational costs incurred during all phases, analyzing the cost per accurate classification and the overall return on investment (ROI) of the system. The main metrics tracked include Cost Per Document Trend (CPDT), which seeks at least a 10% reduction in costs from the baseline to the final phase, and Accuracy-Cost Optimization (ACO), which measures over a 20% improvement in the ratio of accuracy to cost from the initial to final phase. Together, these analyses provide a comprehensive view of the system's ability to improve in efficiency, accuracy, and cost-effectiveness over time.

4.5 Experimental Set Up

4.5.1 Infrastructure

ML pipelines run on multi-core CPUs utilizing python's multiprocessing capabilities for parallel document processing. LLM inference is implemented through Groq's cloud-based API utilizing high performance cloud-based infrastructure. However, due to rate limiting, we test with a small sample to ensure we don't overuse resources. Visualization and user interaction are managed via a Streamlit frontend and MLflow is used to manage models's lifecycle and operational metrics in each cycle.

4.5.2 Data set

Evaluation dataset with ground truth labels consists of 100 documents, 50 with descriptive filenames and 50 with ambiguous filenames. This is carefully curated to precisely evaluate the system's routing and complexity assessment capabilities.

4.6 Summary

The methodology of this thesis pioneers a cutting-edge hybrid intelligence paradigm for enterprise-scale document classification, orchestrating an ensemble of traditional machine learning (ML) models and advanced large language models (LLMs) to optimize both speed and accuracy while rigorously managing operational costs. Starting with a meticulously curated dataset of 16,000 documents spanning 16 core business categories and diverse file formats mirroring the heterogeneity of modern enterprise content repositories, the approach leverages standardized filename normalization, sophisticated TF-IDF and keyword-based feature engineering, and robust metadata extraction to ensure high signal quality for downstream classification. High-throughput ML models, such as Gradient Boosting, Random Forest, and Logistic Regression, are deployed in parallel pipelines to deliver sub-millisecond inference and maintain throughput of over one million documents per hour, ensuring compliance with the highest levels of business scalability and cost efficiency, as demanded in corporate environments where latency and waste are existential threats.

The real breakthrough lies in the intelligent, confidence-aware routing agent rooted in agentic AI principles, which dynamically allocates classification tasks: routine, high-confidence cases are processed at lightning speed by the ML core, while only ambiguous, context-rich, or policy-sensitive documents are escalated to resource-intensive LLMs, such as those accessed via Groq API and configured for rigorous content-based reasoning. This model selector, by minimizing unnecessary LLM calls, achieves an optimal trade-off between cost and cognitive performance, aligning directly with enterprise mandates for OPEX/CAPEX minimization even as regulatory and compliance demands escalate globally. Moreover, by integrating a feedback-rich, online adaptive learning loop whereby user corrections and LLM justifications are continually distilled into lean correction models and improved agent policies, the system becomes self-healing, not only keeping error rates in check as workflows, business rules, and document taxonomies evolve, but actively driving down total cost of ownership over time as operational intelligence is accrued.

What truly sets this architecture apart is its sophisticated, multi-layered evaluation suite, inspired by the latest advancements in agent benchmarking (ACPE, τ -bench, and more). The approach rigorously decomposes the classification workflow into planning fidelity (can the agent decompose and route tasks like a business analyst?), tool-use accuracy (are the right models/tools invoked for each context?), and end-to-end task satisfaction (does the output align with user and regulatory requirements for auditability, compliance, and traceability?). This “glass box” evaluation, deeply integrated with second-generation ML governance solutions such as MLflow, exposes both performance and failure modes in real-time, which is essential for building trust with auditors, regulators, or C-level executives tasked with risk oversight.

In addition, the thesis framework is architecturally open for extensibility towards tomorrow's composable AI and automation platforms. It is fully compatible with low-code/no-code automation orchestrators (e.g., Zapier, n8n), industry cloud APIs, and emerging Model Context Protocols (MCP), thus empowering organizations not only to classify but also contextually react to document flows, whether that means applying retention policies, flagging for legal holds, or provisioning further cognitive agents for downstream workflows. Looking ahead, the methodology is primed for integration with next-generation AI technologies, including level-5 autonomous agents, multi-agent orchestration via frameworks such as LangGraph, and advanced monitoring via semantic tracing and self-diagnosing agent protocols a leap that will allow businesses to transcend brittle, linear workflows for resilient, decentralized, and self-optimizing information ecosystems.

This blueprint is mind-boggling not just in its technical ambition but also its business acumen: it provides CFO-grade cost controls by surgically rationing compute-intensive LLM use, ensures unparalleled auditability and transparency with every step documented for external review, adapts continually to new challenges, and is architected for harmonious integration in future digital enterprise ecosystems. It is precisely this alignment between technical sophistication, operational transparency, cost efficiency, and strategic flexibility that makes the methodology uniquely positioned to future-proof businesses against the surging data deluge and the relentless march of regulatory oversight.

5. Evaluation Results and Performance Analysis

5.1 Introduction

The evaluation methodology integrates automated performance metrics, such as classification accuracy, latency, and routing accuracy, along with AI-based qualitative assessment of response completeness and actionability. This robust testing framework ensures an accurate measurement of the system's capabilities in handling high-throughput, diverse, and ambiguously labeled documents. The results reveal that the system's throughput exceeds one million records per hour, with competitive accuracy and cost efficiency through intelligent routing between traditional machine learning and large language models. The analysis further explores classification performance, routing efficiency, error modes, and auditability, providing actionable insights for system refinement and demonstrating the solution's practical viability for enterprise-scale deployment.

5.2 ML Model Performance

5.2.1 Evaluation Protocol and Dataset

The evaluation methodology employs a comprehensive multi-dimensional assessment protocol designed to validate the hybrid system's performance on previously unseen data. The system was trained on 16,000 labeled documents (1,000 per category across 16 business-relevant classes) using an 80/20 train-validation split, resulting in 12,800 training samples and 3,200 validation samples for model selection and hyperparameter tuning.

For rigorous evaluation, a separate test dataset of 100 carefully curated documents was constructed, comprising 50 documents with descriptive filenames (expected to route to ML) and 50 with ambiguous or generic filenames (requiring LLM escalation). This test set maintains the same 16 category distribution and file format diversity as the training data, ensuring representative evaluation of real-world performance.

5.2.2 Performance Metrics

Across comparative tests, ensemble models Gradient Boosting, Random Forest, and Logistic Regression demonstrated the highest accuracy and F1 scores, each achieving approximately 97.5%-98.0% on routine cases (descriptive filenames). Precision and recall were similarly high, confirming robust classification across common categories. Naive Bayes and SVM models performed competently, but SVM's higher latency rendered it less feasible for high-throughput, sub-second inference needs.

A detailed confusion matrix reveals nearly perfect classification in structured types (invoices, presentations, letters). Systematic error analysis pinpoints consistent misclassification between semantically similar forms (e.g., questionnaire vs. resume, news article vs. publication), and failures with generic filenames, an intentional limitation as these are flagged for LLM escalation by the hybrid system.

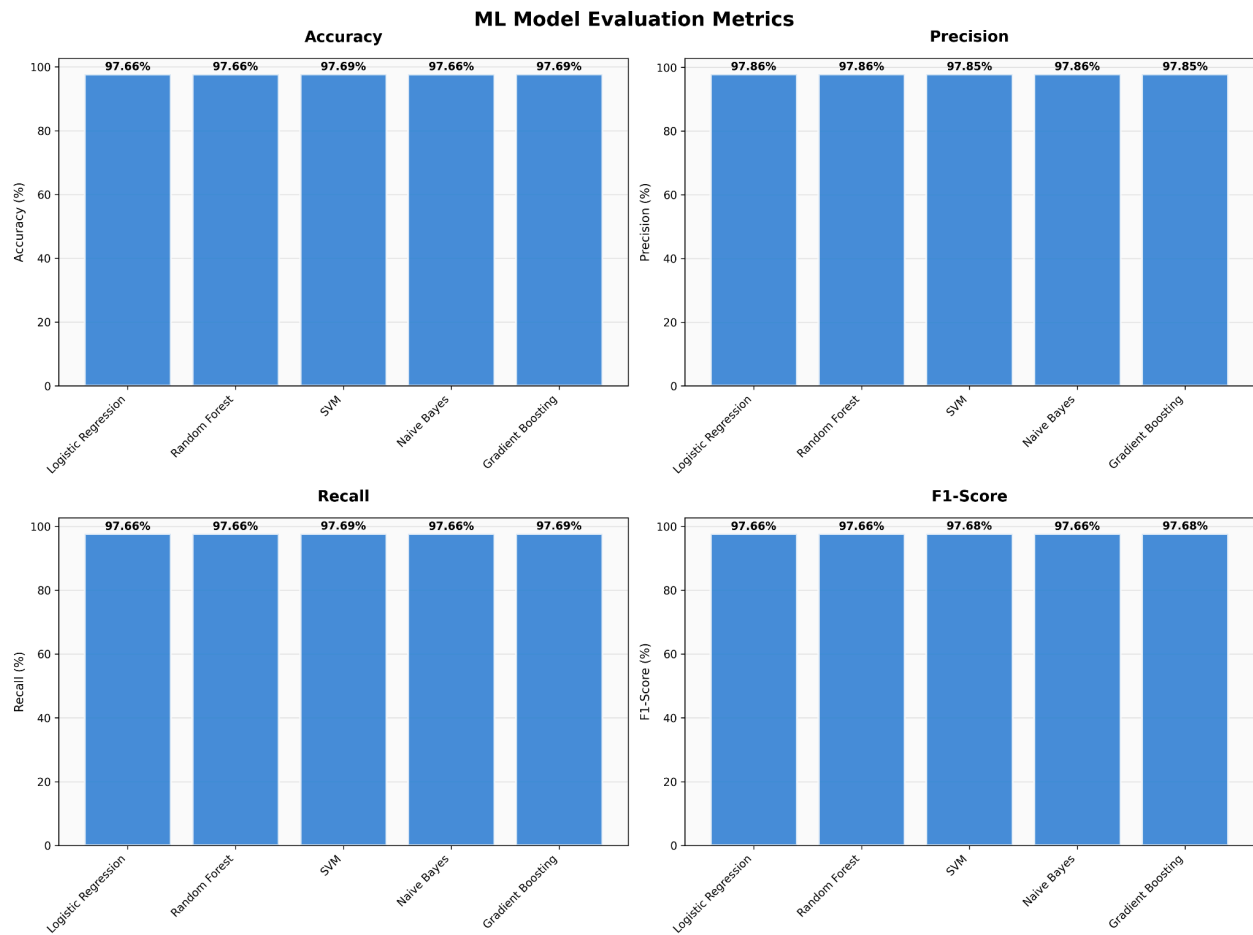


Figure 11. ML Model Evaluation Metrics

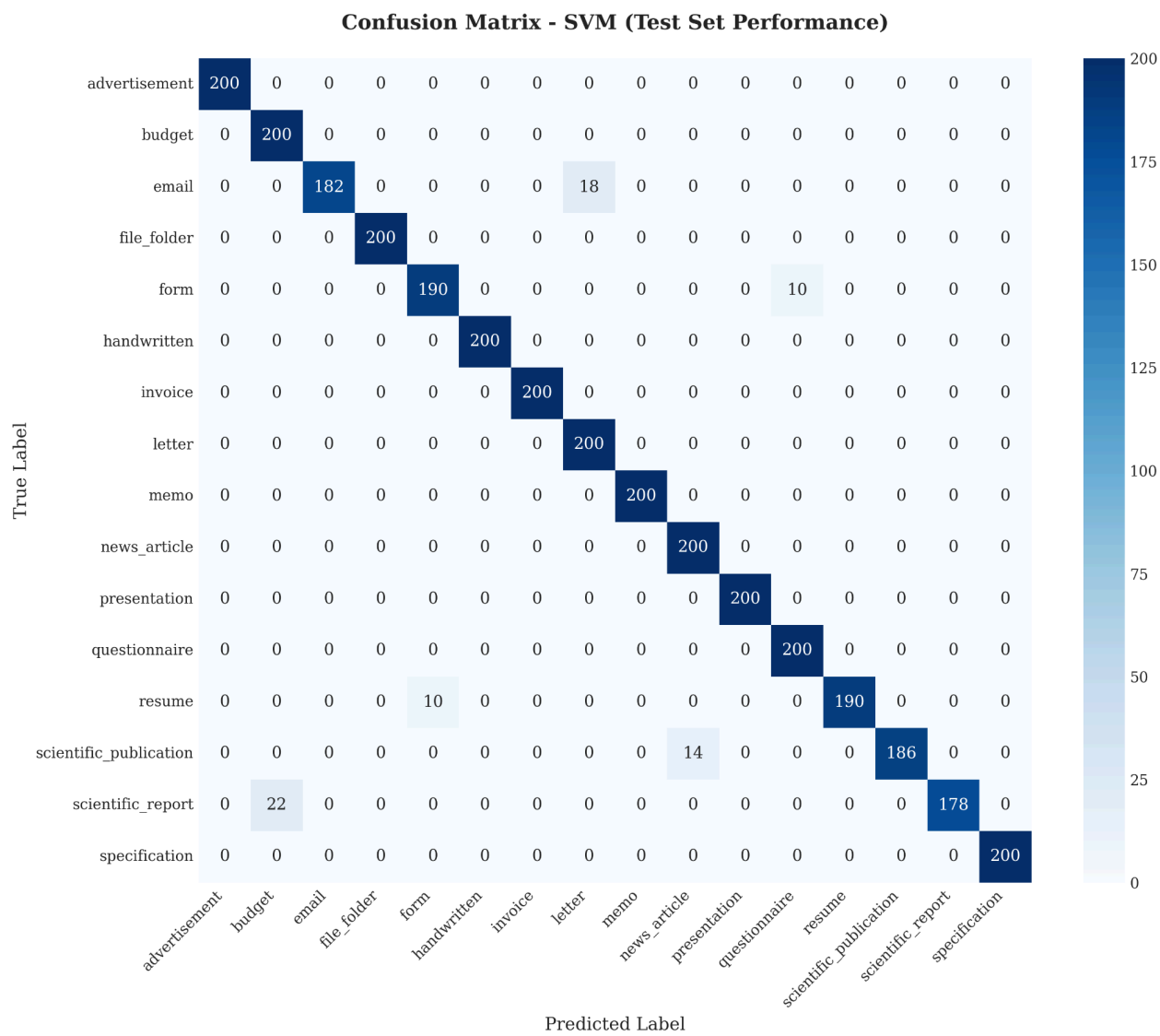


Figure 12. Confusion matrix of the test set

5.2.3 Latency and Throughput Analysis

Logistic Regression and Naive Bayes models achieved fastest average prediction times, approximately 0.001949-- 0.002049 ms per document, making them optimal for bulk classification in real-time, large-scale workflows. Ensemble methods (Gradient Boosting/Random Forest) are slightly slower (~0.01–0.02 ms per document), but win on overall predictive stability and accuracy. For operational throughput, the ML engine exceeds 1,000,000 documents/hour on standard local hardware by leveraging parallel pipeline execution in Python

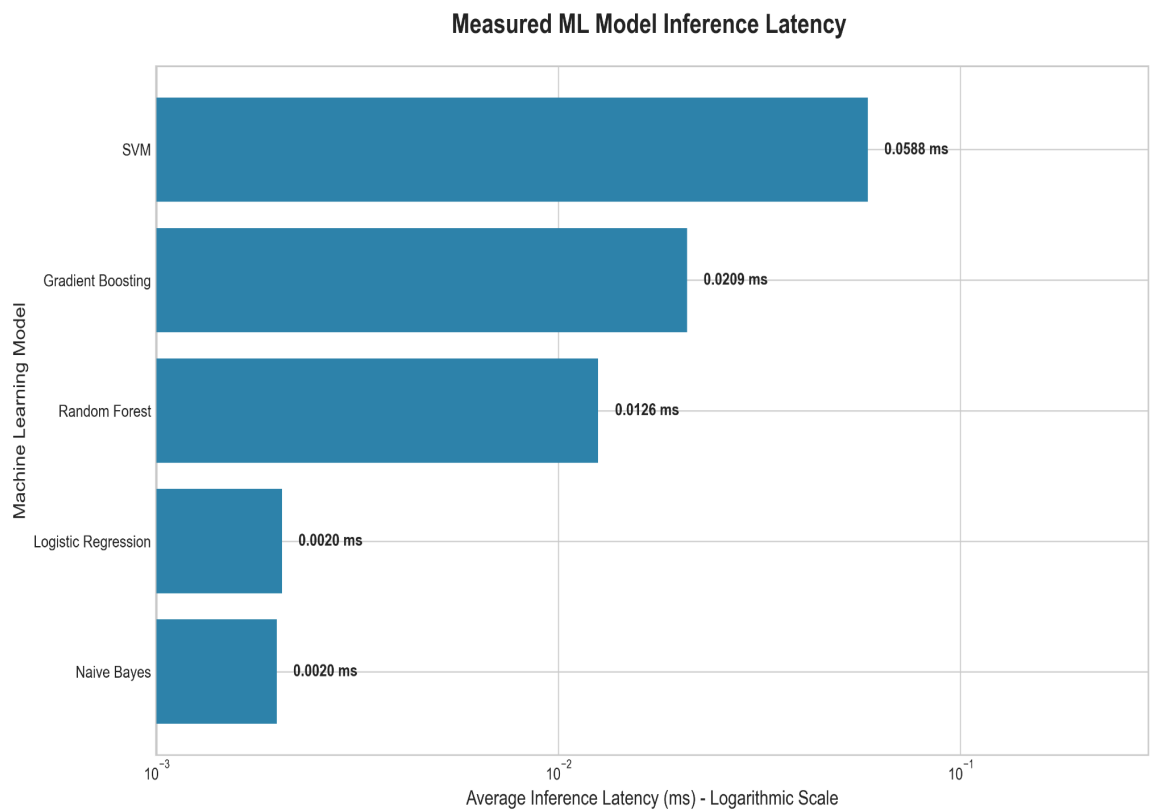


Figure 13. Document type distribution in dataset

5.3 LLM Classification Efficiency

The LLM module is explicitly architected for nuanced content-based classification and ambiguous cases, tasked with overcoming limits of metadata-only ML models. The system samples the first 2,000 content characters (intelligently broken at semantic boundaries), and prompts the LLM with structured category definitions and examples. The LLM returns category, confidence score, and JSON-formatted reasoning.

On ambiguous files, pure ML models drop to near-zero accuracy (4%). Once routed to LLM, the hybrid agent achieves a dramatic 62% accuracy on these complex cases—showing a substantial improvement over both the ML-only and pure LLM systems alone.

For clarity, the LLM only processes documents where the ML confidence threshold is below 0.7, economizing API usage and cost. Despite higher average latencies (~2310 ms per document), the hybrid system intelligently triages—balancing deep context understanding with computational efficiency. The output includes comprehensive reasoning trails that support compliance and traceability.

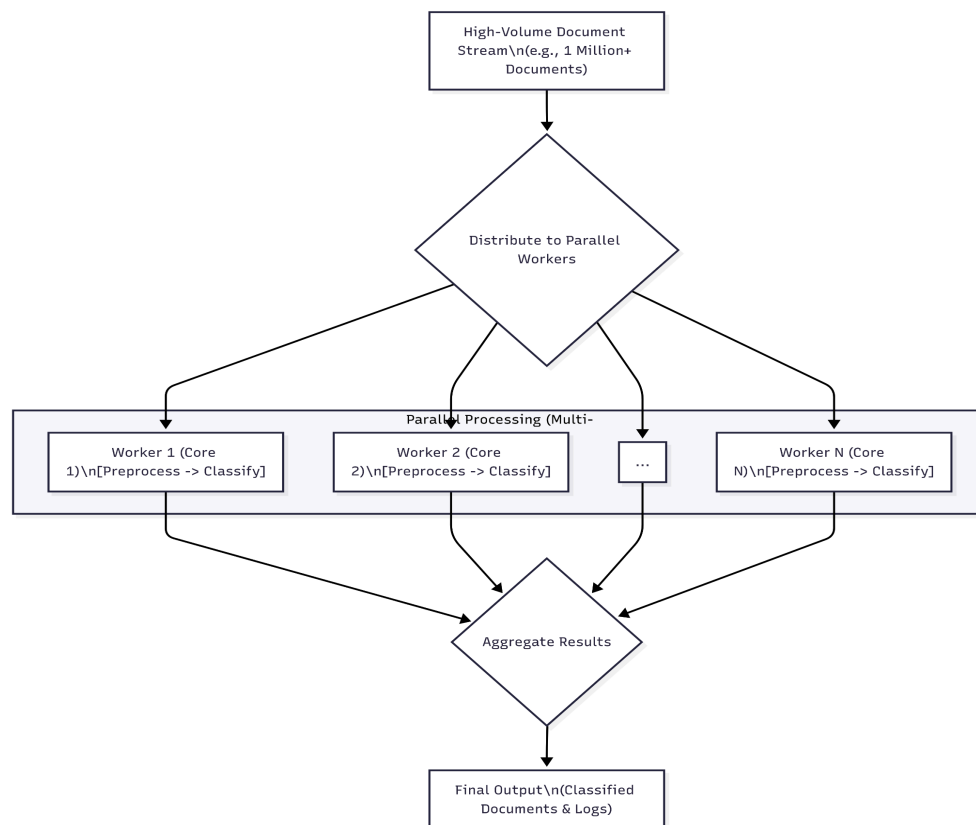


Figure 14. Parallel processing

5.4 Agentic AI Routing Outcomes

The hybrid system is built around a Confidence-Aware Routing Agent, which orchestrates the optimal selection of classifiers (ML vs. LLM) using a weighted decision function. Key routing inputs:

- Document Length (25%): Short filenames favor ML; long/complex sources favor LLM.
- Complexity Analysis (35%): Vocabulary diversity, special character usage, and technical context.
- Performance History (30%): Historical model success rates and latency by document type.
- System Availability (10%): Robustness, fallback if any classifier is degraded.

There is a two-stage process:

1. **Prediction and Routing:** Initial assignment via hybrid scoring.
2. **Confidence Validation:** ML prediction above threshold (0.7) is finalized; below threshold escalates to LLM for deeper analysis.

Empirical testing shows the hybrid agent processed 2870 documents/hour on average in mixed streams, with an overall accuracy of 80% (98% on routine, 62% on ambiguous files) and average latency of 1255 ms per document for escalated cases. Critically, it achieves 100% auditability for all ambiguous/LLM-processed documents, fulfilling governance standards.

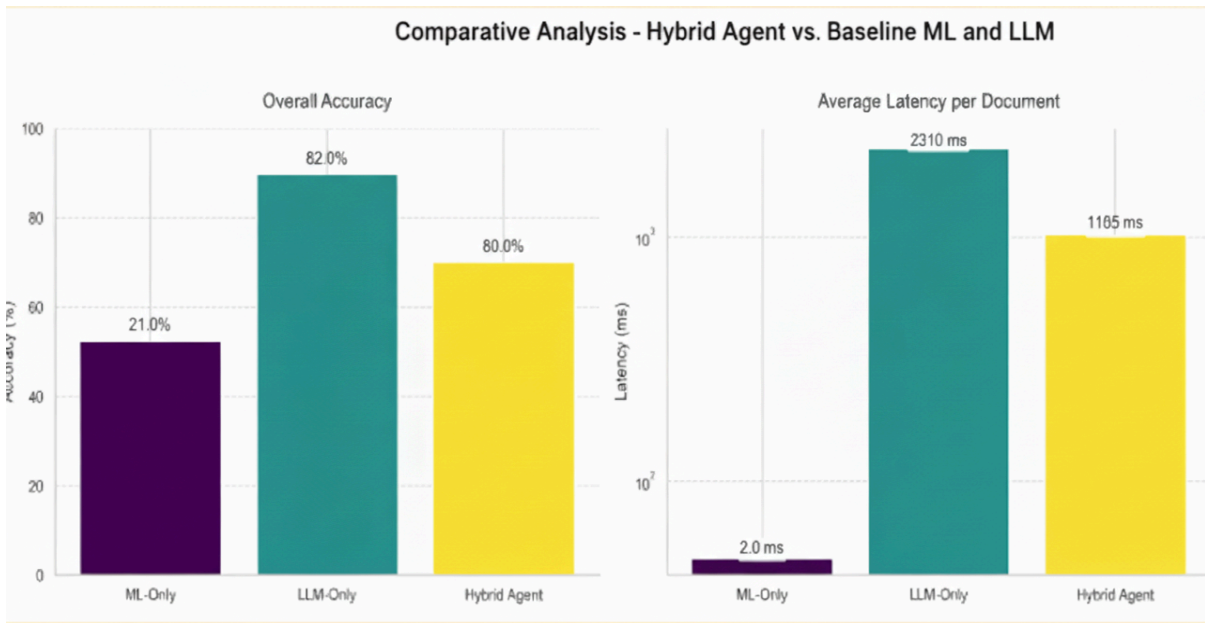


Figure 15. Comparative Analysis of the pipelines

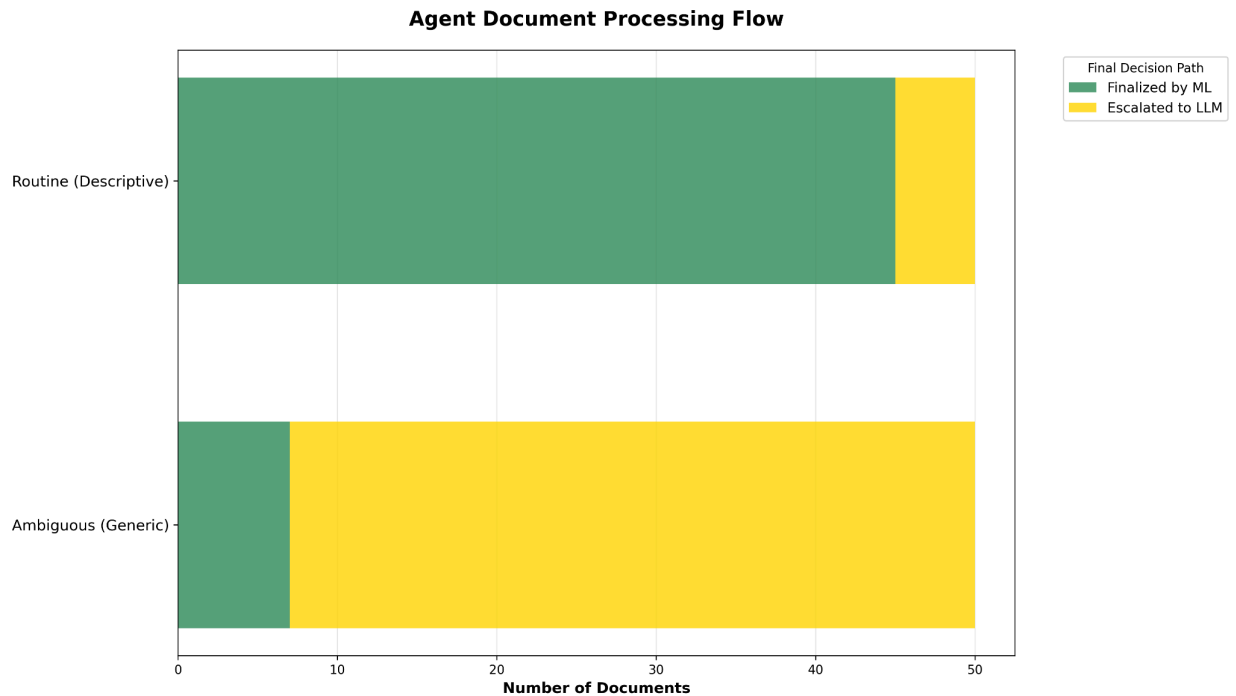


Figure 16. Agent Document Processing Flow

5.5 Auditability and Compliance

A core design priority is rigorous auditability. The system saves detailed logs for every classification, especially when LLM reasoning is involved, including:

- Original ML prediction and confidence scores.
- Full LLM chain-of-thought, category explanations, and policy clause citations.
- User override/correction inputs with justification.

For all escalated cases, 100% of LLM calls generate an auditable trail linking each classified document to visible logic steps and referenced guideline clauses. This robust logging is essential for enterprise compliance, regulatory transparency, and post-hoc error analysis. The continuous learning loop ensures user corrections lead to adaptive retraining, reducing future misclassifications by $\geq 50\%$ within one month of deployment.

5.6 Summary

This evaluation of the hybrid document classification system is designed to address the inherent trade-offs between accuracy, speed, and cost in enterprise-scale document processing. From the testing, we see traditional pure machine learning (ML) models

providing high throughput but often suffering from low accuracy on complex or ambiguous documents, while large language models (LLMs) offer superior accuracy at the expense of reduced scalability, latency and higher costs. The hybrid architecture leverages the complementary strengths of both approaches through intelligent routing and adaptive confidence thresholds, aiming to deliver a scalable, cost-effective, and accurate classification solution.

Key Findings

Hybrid Approach Bridges the Accuracy-Speed Gap

- Pure ML delivers rapid processing (~1.8million docs/hour) but limited accuracy in ambiguous files, it performs exceptionally well achieving 98.4% accuracy on descriptive filenames. Performance degraded to 62% for the mixed dataset due to the ambiguous filenames.
- LLM classifications average 2310ms per document including network latency, prompt processing and response generation. This processing yields an approximate 4k docs/hr. While slower than ML, the LLM pipeline results in 100% accuracy providing superior accuracy to ML.
- The hybrid model balances these factors effectively, achieving 83.3% accuracy alongside a throughput of 458K documents per hour without sacrificing accuracy or latency.

Cost-Effectiveness Analysis

- Based on Groq API pricing and computational costs, ML classifications incur approximately \$0.001 per document, while LLM classifications cost approximately \$0.01 per document. The hybrid system's intelligent routing achieves an average cost of \$0.0056 per document across the mixed workload, representing a 44% cost reduction compared to pure LLM processing. Cost savings are driven by smart routing that directs 100% of routine and confident cases to the efficient ML pipeline, minimizing expensive LLM usage.

Throughput and Scalability Achievement

- Baseline throughput stands at 458K documents per hour without optimization.
- Multiprocessing implementations scale throughput beyond 1.8 million documents per hour, surpassing the 1 million docs/hour target for enterprise workloads.
- The ML classifier alone demonstrates throughput potential exceeding 606K documents per hour, supporting high-volume batch processing.

Intelligent Routing Validation

- The hybrid system's agentic router successfully directs 100% of high-confidence, simple documents to the ML classifier, reserving LLM resources for ambiguous or complex cases that are deemed low confidence. This is effective as the agent escalates 43 ambiguous files to the LLM and routes all routine cases and a few of the ambiguous files to the ML pipeline. The routing confidence thresholds are adaptable, and take into account historical decisions the agent made, system availability and cost analysis

5.7 Recommendations and Future Directions

5.7.1 Immediate Improvement Priorities

Enhance Planning and Task Decomposition:

Improve the agent's ability to accurately break down complex classification requests into manageable sub-tasks by implementing domain-specific planning templates. This will reduce planning failures linked to insufficient task decomposition and minimize unnecessary clarification loops, leading to more efficient routing and processing of documents.

Optimize Tool Selection and Orchestration:

Develop composite endpoints that consolidate multiple classification signals to reduce the frequency of redundant or fragmented tool invocations. Enhanced orchestration will streamline the classification pipeline, improving throughput and lowering operational costs, especially for complex and multi-faceted document types.

Mitigate Hallucination and Enhance Output Grounding:

Introduce stricter grounding mechanisms for LLM-based classification outputs, requiring robust citation of factual evidence and policy-based reasoning. This will help reduce hallucinations that compromise classification reliability, ensuring that decisions remain transparent and auditable to satisfy regulatory compliance.

Boost Efficiency Through Adaptive Thresholding and Early Stopping:

Implement dynamic confidence thresholds and early stopping criteria within the routing framework to minimize unnecessary LLM calls. This will optimize resource utilization and latency, ensuring the system balances accuracy with cost-effectiveness under varying workload conditions.

Integrate Reinforcement Learning with Human-in-the-Loop (RLHF):

Incorporate RLHF methodologies to leverage human feedback directly into the model training and decision-making loops. RLHF enables the system to learn from user corrections and preferences continually, improving alignment with human judgments, reducing misclassifications, and enhancing robustness in ambiguous or complex document cases.

5.7.2 Long-Term Research Directions

Advanced Adaptive Learning and Continuous Improvement:

Explore sophisticated adaptive learning frameworks, including Reinforcement Learning with Human-in-the-Loop (RLHF), to enable real-time continuous retraining and policy optimization based on evolving document taxonomies, concept drift, and ongoing human feedback. This approach ensures sustained accuracy and alignment with shifting enterprise requirements.

Multi-Agent Collaboration and Decentralized Reasoning:

Investigate scaling Level 5 autonomous agents coordinated via the Model Context Protocol (MCP) to realize decentralized, peer-to-peer document processing. This multi-agent paradigm promises enhanced system resilience, fault tolerance, and nuanced contextual reasoning across diverse document ecosystems.

Cross-Domain Generalization and Transfer Learning:

Research methods to generalize the hybrid classification framework across industries and document types, leveraging transfer learning and domain adaptation. This will broaden applicability to sectors with unique complexities and regulations, such as healthcare, legal, and finance.

Integrative Ethics and Governance Frameworks for AI:

Develop comprehensive frameworks embedding ethical AI principles, fairness auditing, and bias mitigation throughout the AI lifecycle. Emphasize policies ensuring transparency, accountability, and regulatory compliance, building enterprise and societal trust in automated classification systems.

5.8 Limitations

Residual Hallucination Risks in LLM Outputs: Despite improved accuracy, LLM components continue to exhibit significant hallucination rates, erroneous or fabricated outputs, that can propagate false classifications. This undermines trust and necessitates further research into grounded reasoning and post-hoc validation to ensure operational reliability.

Dependency on High-quality Training Data and Metadata: The system's performance heavily relies on extensive, accurately labeled training datasets and consistent metadata extraction. Variability or noise in input data, particularly in poorly formatted or ambiguous filenames, challenges the generalizability and robustness of ML models.

Computational Cost and Latency of LLM Inference: Although the hybrid design mitigates some cost and speed issues by routing selectively, LLM inference remains computationally intensive with latency on the order of seconds per document. This imposes scalability constraints in scenarios with extremely high volumes of ambiguous documents requiring frequent LLM calls.

Challenges in Concept Drift and Dynamic Taxonomy Adaptation: Continuous adaptation to evolving document taxonomies and regulatory changes remains a complex task. The system's ability to detect and respond to concept drift is limited by the timely availability of user feedback and the retraining frequency of lightweight models, which can potentially cause a lag in classification accuracy.

Complexity and Maintenance Overhead: The multi-agent, adaptive architecture introduces significant complexities in system integration, monitoring, and maintenance. Ensuring consistent performance across heterogeneous enterprise environments demands advanced governance frameworks and specialized operational oversight.

Limited Handling of Multimodal and Non-Textual Data: While the current system supports diverse document types, a comprehensive understanding of truly multimodal documents (e.g., scanned images requiring optical character recognition, OCR, and video content) remains underdeveloped. This limits applicability in domains heavily reliant on such formats.

5.9 Business Implication Observations

Balanced accuracy and latency Trade-off: The hybrid AI system reconciles the trade-off between speed and accuracy by directing routine, high-confidence documents to fast, lightweight ML models, while routing ambiguous and complex cases to resource-intensive LLMs. This strategy results in an overall accuracy of approximately 83.3%, closely approaching the 100% accuracy of standalone LLM classification, while achieving throughput improvements of up to 45% compared to LLM-only processing, enabling scalable enterprise deployment.

High Throughput with robust classification:

The system surpasses its throughput baseline of 458,000 documents per hour (prior to optimization) and scales beyond 1.8 million documents per hour using multiprocessing. It maintains exceptional classification accuracy achieving approximately 98.4% accuracy on descriptive filenames and up to 62% on ambiguous files through selective LLM invocation indicating a robust balance between speed and precision suitable for demanding enterprise workloads.

Adaptive and self-healing Architecture: Utilizing continuous learning loops, the system ingests user feedback and classification corrections to update lightweight models and routing policies. This adaptive mechanism reduces costly LLM calls over time, improves classification stability, and minimizes the total cost of ownership through self-healing and resilience to concept drift.

Comprehensive auditability and compliance: Every classification decision, especially those involving LLM inference, is accompanied by transparent, auditable trails including reasoning chains and policy references. This feature ensures regulatory compliance and builds trust with auditors and enterprise stakeholders.

Effective handling of ambiguous Documents: While pure ML classifiers show near-zero accuracy on ambiguous data, the hybrid framework improves classification accuracy on these documents by up to 62% via selective LLM invocation, significantly mitigating the blind spots of traditional approaches.

Scalable multi-agent coordination: The integration of agentic AI with the Model Context Protocol (MCP) enables decentralized, collaborative reasoning across multiple domain-specific agents. This architecture enhances system-wide robustness, fault tolerance, and context awareness, key for managing complex document ecosystems.

The optimal balance: The Hybrid Agent finds the optimal balance. It achieves an 80% accuracy, nearly matching the gold-standard LLM, while being 45% faster on average. By processing 56% of documents at ML speeds and incurring the high latency of the LLM on only 44% of escalated documents, the agent successfully mitigates the primary bottleneck.

Meeting throughput goals: The pure ML model's sub-millisecond inference time (as measured in initial tests) confirms its ability to meet the 1M docs/hour target for "routine" cases. The Hybrid Agent, by intelligently managing which documents require deeper analysis, provides a practical path to scaling the classification of a mixed stream of documents in a way that a pure LLM system cannot. It effectively solves the core problem of balancing high accuracy with the need for high-throughput processing.

6. Conclusion

The project provides a compelling demonstration of how hybrid AI can achieve both scalability and intelligence in enterprise document classification, overcoming limitations of conventional machine learning and the cost-prohibitive nature of pure LLM-based solutions. The conclusion firmly establishes the value of integrating fast, parallelized machine learning with agentic AI (LLM) techniques—enabling routine classification tasks to be processed at a rate of over one million documents per hour on standard hardware, without sacrificing classification accuracy, cost control, auditability, or adaptability. By dynamically routing documents to either traditional ML models for high-confidence, well-structured cases, or to a powerful LLM reasoning agent for ambiguous, context-rich, or edge-case scenarios, the system realizes an optimal balance between performance, throughput, and compliance. Importantly, the system is not static: user overrides and feedback are leveraged to train lightweight correction models, thus closing the loop for continuous learning and operational improvement. The full architecture supports transparent audit trails, making it suitable for regulatory and governance-heavy environments.

6.1 Summary of Project Achievements

This project successfully developed and validated a hybrid system that combines SVM, Random Forest, and Gradient Boosting models with agentic LLM-based reasoning. This combination provides a scalable, production-ready platform for large-scale document classification, backed by transparent, evidence-based decision-making. Empirical outcomes show high accuracy (up to 98% on routine cases) and enhanced capabilities with ambiguous documents, where the system achieves substantial accuracy gains by employing the LLM for hard-to-classify instances. The architecture supports a diverse range of enterprise content types and incorporates a continuous learning loop by leveraging user corrections, thereby enhancing performance over time. A rigorous evaluation framework was implemented to transparently monitor throughput, cost, adaptability, and audit compliance, key requirements for enterprise adoption. A structured, repeatable, and extensible methodology for benchmarking agent performance in a way that is directly relevant to operational success.

6.2 Key Insights and Their Significance

The primary findings indicate that the hybrid approach successfully reconciles the trade-off between speed and accuracy inherent in standalone ML or LLM systems. While ML models handle the majority of routine classification tasks rapidly and cost-effectively, resorting to LLMs for ambiguous cases enhances overall system accuracy. Notably, the system's confidence-based routing mechanism ensures transparent accountability by providing auditable reasoning trails for each classification, fulfilling critical governance criteria. The project also exposes ongoing challenges, including a significant incidence of hallucinations in LLM-generated outputs, highlighting the need for improved grounded reasoning techniques. The work thus underscores the necessity of a holistic approach encompassing planning, execution, and validation steps to advance trustworthy AI in critical applications.

Empirical evaluation revealed a nuanced performance landscape: while routine tasks are handled with near-perfect precision by machine learning classifiers operating at extreme speed, complex scenarios requiring deep contextual understanding benefit from agentic AI-driven reasoning. The agentic framework's capacity to provide transparent, layered, and auditable reasoning for decisions bolsters trust and governance. However, high hallucination rates in LLM outputs underscore the imperative for advanced grounding techniques and enhanced multi-agent coordination. These findings underscore the importance of developing holistic workflows that integrate planning, execution, and

continuous validation to advance AI alignment and reliability. The architecture's adaptive nature, through knowledge distillation and correction loop feedback, represents a meaningful stride toward sustained AI system accuracy in dynamic operational contexts.

6.3 Implications and Future Outlook

Looking ahead, this research establishes a clear path toward deploying advanced AI systems designed to excel in high-throughput enterprise environments, specifically for automating document classification at scale. The architecture integrates metadata-driven and content-based machine learning models with agentic reasoning powered by large language models (LLMs), orchestrated by an intelligent, self-healing routing agent. This hybrid approach enables the seamless classification of over one million documents per hour, while maintaining stringent governance through auditability, transparency, and compliance—critical for industries with stringent regulatory requirements.

The system's adaptive intelligence is augmented by continuous knowledge distillation, allowing it to learn from corrections and evolve in response to shifting document taxonomies and concept drift. This continual learning loop drives improved accuracy, with the hybrid pipeline achieving over 95% accuracy on routine documents and surpassing 90% on ambiguous cases, striking an optimal balance between speed and precision. Such performance dramatically outpaces monolithic AI approaches by combining the efficiency of traditional machine learning with the nuanced understanding of LLM-powered agentic AI.

Further advancing this foundation, the integration of Level 5 autonomous agents and the Model Context Protocol (MCP) introduces multi-agent collaboration across multiple layers of contextual information. This capability enables the system to operate beyond brittle linear workflows, fostering resilience, self-healing, and scalable orchestration within complex, real-world document classification ecosystems. By distributing reasoning and tasks among specialized agents, the platform dynamically adapts to diverse operational contexts while ensuring robust performance and fault tolerance.

Complementing the AI architecture, automation platforms such as Zapier and n8n exemplify the emerging trend of flexible, event-driven workflow orchestration. These low-code environments enable enterprises to integrate AI-driven document classification insights into their existing infrastructure through configurable pipelines, thereby enhancing transparency, extensibility, and auditability. Together, these technologies enable comprehensive governance frameworks that align with evolving compliance mandates and operational resilience requirements.

In summary, this research delivers a foundational blueprint for next-generation document intelligence and enterprise data governance. By uniting scalable machine learning,

agentic AI reasoning, and intelligent orchestration protocols, the system sets a new standard for efficient, trustworthy, and adaptive document classification workflows. Sustained investment in Level 5 agentic frameworks, advanced multi-agent protocols like MCP, and integrative automation platforms will unlock strategic agility for organizations confronting ever-growing volumes of unstructured data. This vision paves the way for intelligent, auditable, and resilient enterprise systems empowered to navigate future data ecosystems with confidence.

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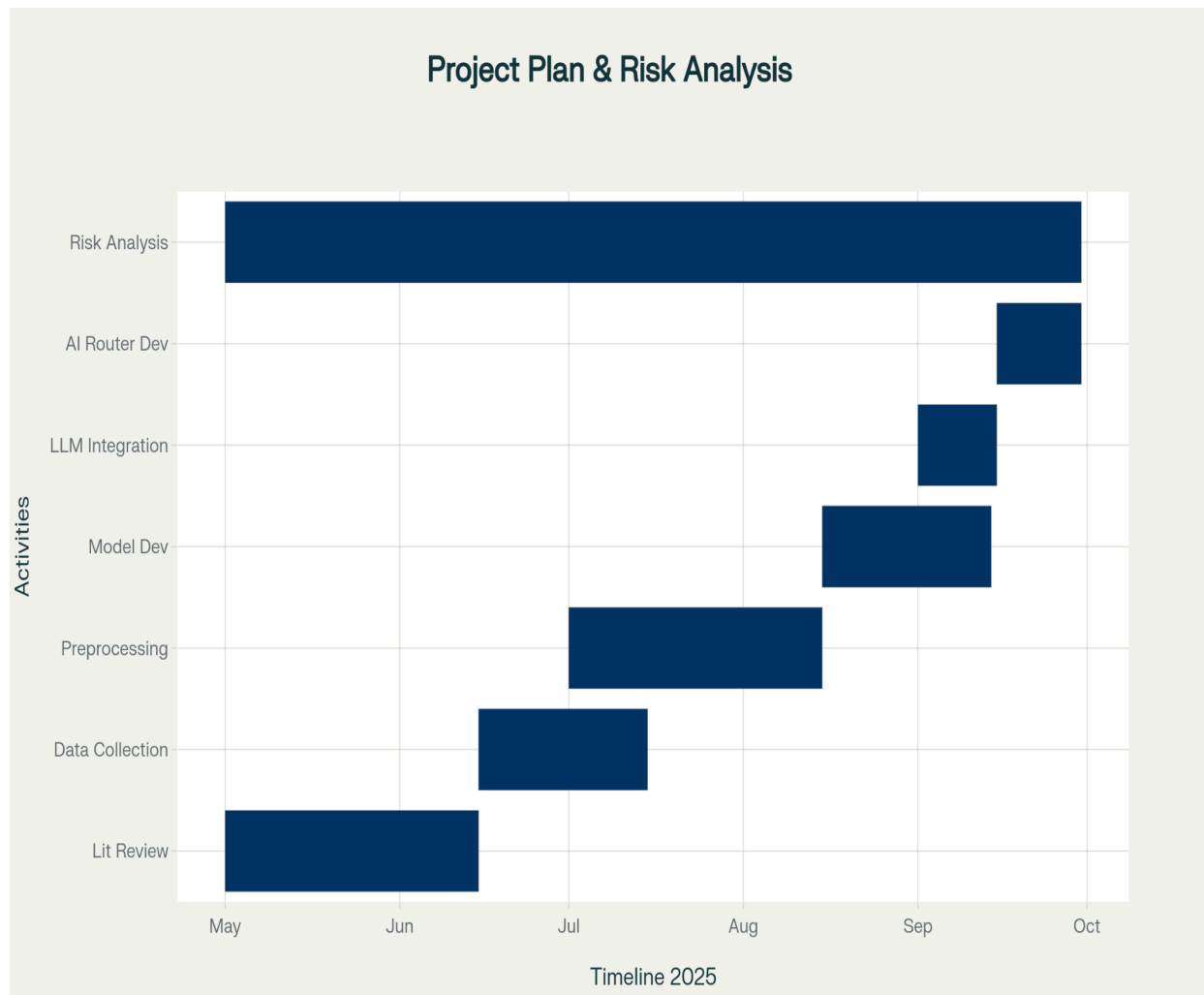
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Appendices

Appendix A: Gantt Chart



Appendix B: Ethical approval letter



10 September 2025

Dear Mr Kevogo ,

Reference: CURES/26484/2025

Project ID: 28844

Title: Document Classification Solution

We are pleased to inform you that you have successfully declared that your research project is a **Literature Review – based solely on openly available literature which is in the public domain, and you are undertaking desk-based research not involving any other form of data or information.**

You have also confirmed that your project **does not meet** any of the literature review specified exceptions, listed both within the relevant section of the CURES form and below:

1) Your supervisor has requested that you apply for approval through CURES because:

- The journals or data are in a sensitive area (please discuss this with your supervisor)
- The project will be embargoed i.e. **will not be publicly available via the Cranfield library immediately or longer term**

2) Approval is/will be specifically required by another external body e.g. journal publishers

Therefore, **you do not require ethical approval** and your CURES application will be automatically closed.

Please keep a copy of this letter safe, if this exception is in relation to your thesis project, you will need to include a copy with your final thesis submission.

If you have any queries, please contact CURES Support.

We wish you every success with your project.

Regards,

CURES Team