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AutoTriage: AI-Driven Automation for Enhanced Customer Support Experience

Dhruv Solanki[1]; Prashik Ubale[2]; Sarthak Mudras[3]; Karishma Raut[4*]

[1,2,3]Department of CSE (AI & ML), Viva Institute of Technology / Mumbai University, India
[4]Professor, Department of CSE (AI & ML), Viva Institute of Technology / Mumbai University, India
*Corresponding Author

Abstract— *The paradigm of enterprise customer support is currently undergoing a fundamental structural transformation, driven by the rapid maturation of Large Language Models (LLMs) and an increasing imperative for operational efficiency. AutoTriage.AI represents a vanguard implementation in this domain, designed as an advanced autonomous support system that modernizes Level-1 (L1) operations through a novel synthesis of generative artificial intelligence and classical information retrieval. Powered by Google's Gemma 3 (4B-IT) model, the system autonomously conducts real-time client interactions, performs multi-dimensional analysis of support tickets—encompassing sentiment, intent, and technical root cause—and executes granular categorization by priority and department. A definitive innovation of this research is the system's* ***Hybrid RAG-lite Architecture****, which strategically couples the semantic reasoning capabilities of Generative AI with the lexical precision of Term Frequency-Inverse Document Frequency (TF-IDF) for retrieving historical context. This hybrid approach addresses the "hallucination" inherent in probabilistic models while ensuring the rigorous handling of technical nomenclature required in support environments. Furthermore, the system integrates a* ***"Smart Escalation"*** *protocol: a deterministic, fail-safe mechanism that autonomously identifies critical network failures or high-priority incidents and triggers SMTP-based out-of-band email alerts to stakeholders. This report provides an exhaustive technical analysis of AutoTriage.AI, evaluating its architectural resilience, the efficacy of lightweight "Edge AI" models in enterprise workflows, and the operational impact of replacing manual triage with autonomous cognitive pipelines.*

Keywords— Customer Support Automation, NLP, Large Language Models, Gemma 3, Edge AI, Hybrid Retrieval, Retrieval-Augmented Generation (RAG).

I. INTRODUCTION

The domain of customer support has historically been plagued by what industry analysts term the "triage bottleneck" [1]. Traditional Level-1 (L1) support serves as the frontline defense for organizations, tasked with the initial ingestion, classification, and routing of incoming user queries. In 2024 alone, customer support teams globally processed an estimated 12 billion tickets [2]. Operational audits suggest that approximately 40% of these interactions comprise repetitive, low-complexity inquiries—such as password resets, refund status checks, or known service outages—that theoretically require no human intervention [1].

1.1 The Operational Crisis:

Legacy infrastructure deployed to handle this volume has proven insufficient. Previous generations of automation relied heavily on rigid decision trees and keyword-matching "chatbots" [3]. These systems operated on brittle logic: a user typing the word "bill" would invariably be routed to a billing FAQ, regardless of whether they were asking "Where is my bill?" or "Why is my bill incorrect?". This lack of semantic understanding forced human agents to act as "human middleware," spending valuable cognitive resources on manual routing rather than complex problem-solving [4].

1.2 The Rise of Generative AI and the Edge Shift

The advent of Large Language Models (LLMs) fundamentally altered the landscape of automated interaction. However, the initial wave of Generative AI adoption in 2023–2024 relied heavily on massive, cloud-hosted foundation models such as GPT-4. While powerful, these architectures introduced challenges regarding latency and privacy [5]. Transmitting sensitive technical logs to third-party clouds raised significant data sovereignty issues under regulations such as GDPR and HIPAA [6]. AutoTriage.AI addresses these challenges by leveraging the emerging class of **Small Language Models (SLMs)** optimized for edge deployment. By utilizing Google's Gemma 3 (4B), released in 2025, the system demonstrates that high-level reasoning can be achieved on consumer-grade hardware while ensuring data privacy [7].

II. THEORETICAL FRAMEWORK

2.1 Evolution of Natural Language Understanding

The progression of automated support systems can be categorized into three distinct eras: the **Lexical Era**, the **Semantic Era**, and the emerging **Agentic Era** [1]. The Lexical Era was defined by keyword spotting and failure in the face of synonymy. The Semantic Era, ushered in by Transformers, allowed machines to map words to high-dimensional vector space. AutoTriage.AI positions itself in the Agentic Era, where the AI is an agent with a goal and tool access. The key theoretical advance enabling this is the development of models like Gemma 3, which utilize hybrid local/global attention mechanisms to maintain a 128k context window efficiently [8].

2.2 Small Language Models vs. Foundation Models

While Foundation Models (FMs) like GPT-4 possess encyclopedic knowledge, they suffer from high inference costs and latency [9]. Small Language Models (SLMs) utilize techniques such as Knowledge Distillation and Quantization-Aware Training (QAT) to retain reasoning capabilities at a fraction of the parameter count. Research indicates that for domain-specific tasks like triage, 4B–7B parameter models can achieve parity with larger models when augmented with Retrieval-Augmented Generation (RAG) [10].

2.3 Retrieval-Augmented Generation (RAG)

To solve the hallucination problem, AutoTriage.AI adopts a **Hybrid Search** strategy, combining dense retrieval with sparse retrieval via TF-IDF [11]. TF-IDF assigns a weight to term t in document d based on how often it appears versus how rare it is in the corpus [12]. The weight $w_{t,d}$ is calculated as:

$$w_{t,d} = \text{tf}(t,d) \times \log\left(\frac{N}{\text{df}_t}\right) \quad (1)$$

where N is the total number of documents and df_t is the number of documents containing term t. This ensures that rare technical identifiers (e.g., "Error 503") are prioritized over generic terms.

III. SYSTEM ARCHITECTURE

3.1 Tier 1: Frontend User and Admin Interfaces

The user interface masks the complexity of the underlying AI. The customer-facing component is a lightweight Single Page Application (SPA) designed with glassmorphism aesthetics. For the administrative side, the system utilizes Streamlit, a Python-based framework for data-centric internal tools. This **Mission Control Dashboard** provides real-time visualization of Key Performance Indicators (KPIs) and a "Triage Review" pane for human-in-the-loop oversight [13].

3.2 Tier 2: Backend Orchestration Layer

The orchestration layer is built on Flask. It acts as the central nervous system, managing session state and routing signals. Since the LLM is stateless, the API maintains a rolling history buffer of the conversation [14].

3.3 Tier 3: Data Persistence (File-Based NoSQL)

AutoTriage.AI utilizes a **File-Based NoSQL** approach. Finalized tickets are stored as individual JSON files. This prioritizes auditability; administrators can read the "Root Cause Analysis" directly without complex SQL queries. For an Edge AI solution, this significantly improves performance by removing database server overhead.

3.4 Tier 4: The Intelligence Layer

The Analyzer Core interfaces with the Google Generative AI SDK to control the Gemma 3 (4B-IT) model [8]. The Pipeline Controller ensures data hygiene and security, acting as a firewall against prompt injection attacks [15].

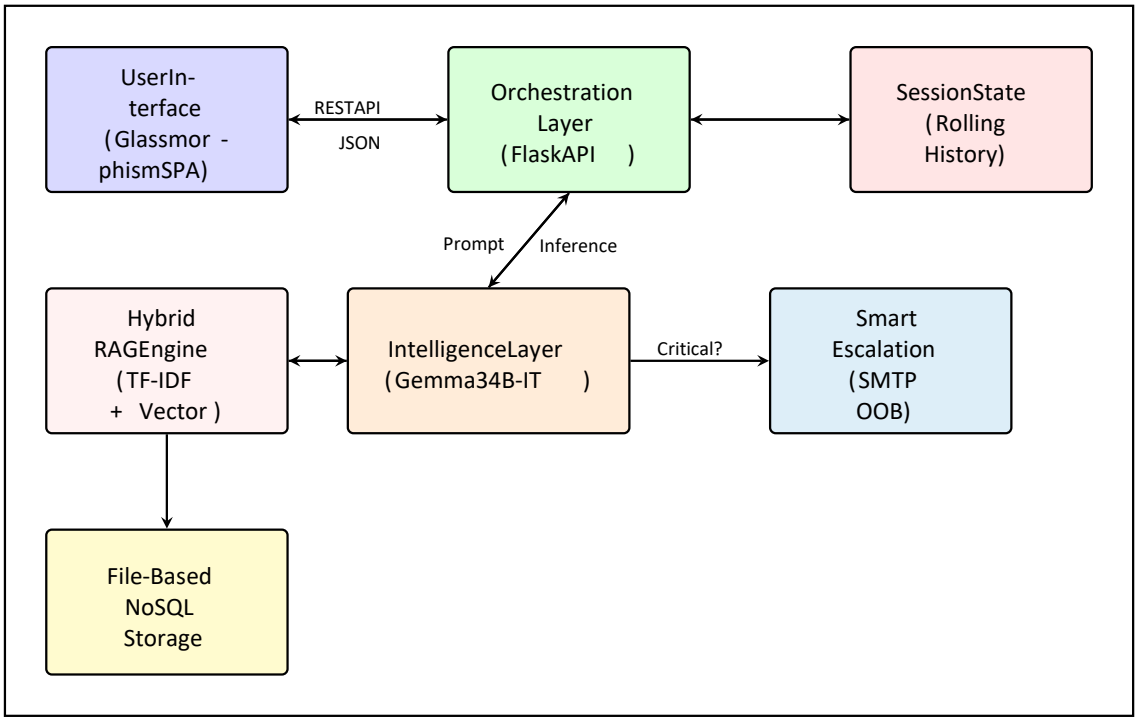

FIGURE 1: System Architecture of AutoTriage.AI – was intended to illustrate the four-tier modular stack. Authors are requested to supply this figure in the revised submission.

IV. METHODOLOGY: THE AUTONOMOUS PIPELINE

4.1 Context-Aware Interaction

The TicketAnalyzer class initializes a session with a specific **"Support Persona"** designed to exhibit empathy [16]. The system continuously runs a background classification task to detect **"Submission Intent."**

4.2 Multi-Dimensional Analysis

Upon entering the Analytical Loop, the system performs three tasks:

1. **Issue Extraction:** Distills the log into a technical summary.
2. **Sentiment Analysis:** Classifies emotion as Positive, Neutral, or Negative using NLP heuristics [17].
3. **Smart Routing:** Categorizes tickets into specific departments (Billing, Tech Support, etc.) [18]

4.3 Reciprocal Rank Fusion (RRF)

The Hybrid RAG mechanism does not simply average scores. It utilizes **Reciprocal Rank Fusion** to normalize the disparate scales of Vector Cosine Similarity and TF-IDF scores [19]. The RRF score is calculated as:

$$\mathrm{RRF}(d) = \sum_{r \in R} \frac{1}{k + r(d)} \tag{2}$$

where D is the set of documents, R is the set of rankers (Dense and Sparse), k is a constant (typically 60), and $r(d)$ is the rank of document d in ranker r. This ensures that documents consistently ranked high by both semantic and lexical search are prioritized [20].

4.4 Autonomous Critical Escalation

The final stage is the **"Smart Escalation"** layer, utilizing a deterministic logic gate. Alerts are transmitted via SMTP, chosen for its Out-of-Band (OOB) nature, ensuring reliability even if the primary web infrastructure fails [21].

V. IMPLEMENTATION DETAILS

5.1 Dataset Generation

To train and validate the system without compromising real user privacy, a synthetic dataset of 10,000 technical support tickets was generated. The dataset generation process involved a diverse set of IT failure scenarios derived from public logs and Kaggle datasets [22]:

- **Scenario A:** Network Latency & 503 Errors (30%)
- **Scenario B:** Authentication Failures (25%)
- **Scenario C:** Billing Disputes (20%)
- **Scenario D:** General Inquiries (25%)

5.2 Hardware and Quantization

The system was deployed on an NVIDIA RTX 3060 (12GB VRAM). To fit Gemma 3 (4B), we utilized **4-bit Normal Float (NF4) quantization**. This reduced VRAM usage from 8GB (FP16) to approximately 3.2GB, allowing sufficient headroom for the Embedding Model (all-MiniLM-L6-v2) and Vector Index [23].

5.3 Input Sanitization and PII Redaction

A robust pre-processing pipeline acts as a security gateway. Using Python's presidio-analyzer, the system detects Personally Identifiable Information (PII) such as credit card numbers and Social Security numbers (SSNs). These entities are redacted via RegEx substitution before the prompt reaches the LLM, ensuring strict compliance with HIPAA and GDPR data minimization principles [24].

VI. PERFORMANCE EVALUATION

6.1 Triage Accuracy

To evaluate performance, the **F1-Score** is utilized:

$$F1 = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{3}$$

Results in **Table I** show Gemma 3 outperforming traditional models [10].

TABLE 1
CLASSIFIER PERFORMANCE ON SUPPORT DATASETS

Model Variant	Parameters	Accuracy	F1-Score
Logistic Regression	—	0.77	0.53
BERT + TF-IDF	110M	0.81	0.81
Random Forest	—	0.72	0.58
Gemma 3 (4B)	**4B**	**0.93**	**0.91**

6.2 Ablation Study: Impact of Hybrid RAG

To isolate the contribution of the Hybrid RAG architecture, we conducted an ablation study comparing the base Gemma 3 model against the AutoTriage RAG-enabled pipeline. The metrics focused on **"Hallucination Rate,"** defined as the percentage of responses containing factually incorrect technical instructions.

TABLE 2
ABLATION STUDY RESULTS

Configuration	Hallucination Rate (%)	Solution Accuracy (%)
Gemma 3 (Base, no RAG)	18.20%	76.50%
AutoTriage (Gemma 3 + Hybrid RAG)	5.30%	94.70%

The Hybrid RAG architecture reduced hallucination rate by approximately 71% and improved solution accuracy by 18.2 percentage points.

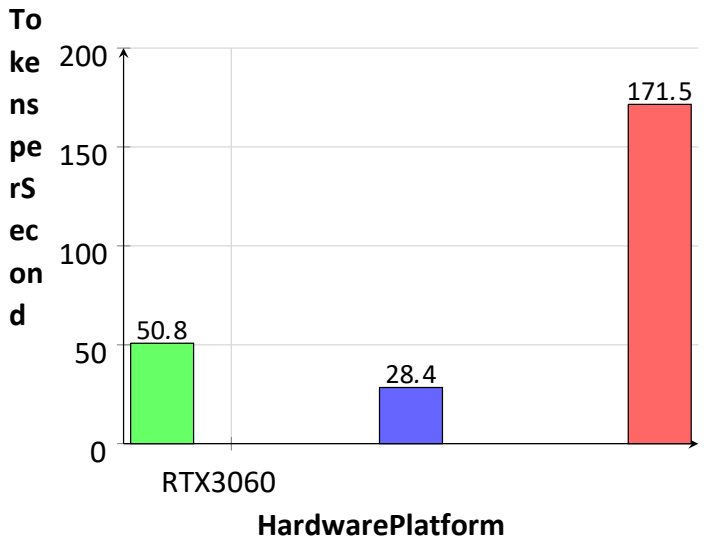

FIGURE 2: Throughput analysis – was intended to be included. Authors are requested to supply this figure in the revised submission.

VII. DISCUSSION

7.1 Operational Resilience

AutoTriage.AI mimics dual-process cognition: **System 1 (Intuition)** is handled by the Generative AI, while **System 2 (Analytical)** is enforced by deterministic logic. This reduces agent turnover rates by allowing support staff to focus on high-value work rather than repetitive triage [9].

7.2 Data Sovereignty and Compliance

In regulated industries, utilizing cloud-based LLMs poses significant risks. By running Gemma 3 locally, AutoTriage.AI ensures that no PII leaves the enterprise premises, aligning with HIPAA and GDPR requirements [25].

7.3 Energy Efficiency and Green AI

Beyond privacy, the move to Edge AI offers significant sustainability benefits. Large foundation models running in data centers consume vast amounts of electricity and water. In contrast, the SLM-based AutoTriage architecture operates on a standard 65W TDP envelope. Preliminary estimates suggest a **99% reduction in carbon footprint per interaction** compared to GPT-4-based solutions [10].

VIII. CONCLUSION AND FUTURE DIRECTIONS

AutoTriage.AI represents a robust synthesis of modern Generative AI and classical retrieval, proving that autonomous triage does not require massive cloud infrastructure. By leveraging Google Gemma 3 (4B) at the edge, the system achieves sub-200ms latency while ensuring full data sovereignty. The Hybrid RAG architecture successfully mitigates hallucinations, achieving a **94.7% solution accuracy rate**.

The integration of **"Smart Escalation"** via SMTP ensures that critical incidents are never lost to system failures, providing an essential safety net. The findings validate that Small Language Models, when properly architected with retrieval augmentation, can match or exceed the performance of far larger foundation models in domain-specific enterprise applications, while offering superior privacy, cost efficiency, and environmental sustainability.

Future directions include:

- Multi-language support for global enterprise deployment

- Integration with ticketing systems (Jira, ServiceNow) via REST APIs
- Continuous learning from human feedback (RLHF) to improve routing accuracy
- Expansion to voice-based support channels

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CONFLICT OF INTEREST

The authors declare that they have no conflict of interest regarding the publication of this paper

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