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APEX AI — MULTI-MODEL HYBRID CHATBOT ASSISTANT FOR HYBRID ONLINE AND OFFLINE ENVIRONMENTS

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ABSTRACT
APEX AI is a full-stack, multi-model hybrid chatbot assistant designed to deliver intelligent conversational capabilities in both online and offline environments. Built on a FastAPI backend and a single-page responsive frontend, the system integrates four large language models — Groq Llama 3.3 70B, Google Gemini Flash 1.5, Ollama Phi-3, and Ollama TinyLlama — providing seamless automatic switching between cloud-based and locally hosted inference engines depending on internet availability. The platform supports multimodal inputs including text, images (via Gemini vision), and file uploads, real-time DuckDuckGo web search, and browser-native voice input. Session state is managed entirely in-memory using Python dictionaries, ensuring zero-database overhead and rapid deployment. Experimental evaluation confirms sub-500 ms latency for online models and graceful offline degradation without user-visible interruption, making APEX AI a practical solution for connectivity-constrained environments.

Index Terms —
APEX AI, Multi-Model LLM, Hybrid Chatbot, FastAPI, Groq, Gemini, Ollama, Phi-3, TinyLlama, Offline AI, Web Search, Voice Input, Multimodal AI, Python

I. INTRODUCTION

The proliferation of large language models (LLMs) has fundamentally transformed human-computer interaction over the past several years. Intelligent chatbot systems powered by LLMs are now deployed across domains ranging from customer service and education to software development and healthcare advisory. Despite this rapid adoption, the overwhelming majority of deployed systems depend entirely on stable internet connectivity to access cloud-hosted inference endpoints. This introduces critical failure modes in bandwidth-limited, intermittently connected, or air-gapped environments — scenarios that are particularly prevalent in developing regions, field operations, and enterprise networks with strict egress restrictions.

APEX AI addresses this gap by implementing a hybrid model-routing architecture that automatically selects the most capable available model at inference time — cloud models when online, local Ollama models when offline — without user intervention or session disruption. The routing decision is made transparently at the API layer, ensuring continuity of the conversational experience regardless of network state. Beyond connectivity resilience, APEX AI provides multimodal input handling, real-time web search augmentation, and browser-native voice input, all within a zero-database, single-command deployable stack built on Python and FastAPI.

The key design philosophy of APEX AI is simplicity without sacrifice: the entire backend is a single Python file; the frontend is a self-contained HTML document; and deployment requires only a single terminal command. This minimal infrastructure approach makes APEX AI uniquely accessible for research institutions, small teams, and developers in resource-constrained settings, while still delivering state-of-the-art conversational AI capabilities through integration with leading cloud and open-weight language models.

The system is further distinguished by its support for multimodal inputs — combining text, image, and file context within a single unified chat interface — and its real-time web search augmentation layer, which grounds model responses in current information without requiring a vector database or embedding pipeline. Voice input via the browser SpeechRecognition API rounds out the interaction modalities, making APEX AI accessible to users who prefer or require hands-free operation. Together, these capabilities position APEX AI as a reference implementation for the next generation of lightweight, connectivity-resilient AI assistant architecture.

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II. LITERATURE REVIEW

2.1 Multi-Model LLM Architectures

Ensemble and routing strategies for LLMs have been extensively explored in the literature. Shazeer et al. (2017) introduced the Sparsely-Gated Mixture-of-Experts (MoE) architecture, demonstrating that routing inputs to specialized sub-models can yield significant capacity improvements without proportional increases in inference cost. Model cascade systems, as studied by Dohan et al. (2022), extend this paradigm by routing queries of varying complexity to models of appropriate scale, reducing average inference cost while maintaining quality. APEX AI extends the routing paradigm to the connectivity dimension: model selection is conditioned on network availability rather than query complexity alone, enabling a new class of resilience-aware LLM systems.

2.2 On-Device and Edge LLM Inference

The emergence of small, quantized open-weight models has made on-device inference feasible on consumer-grade hardware. Microsoft's Phi-3 Mini (Abdin et al., 2024) demonstrates that a 3.8B parameter model trained on high-quality synthetic data can achieve reasoning performance competitive with much larger models on standard benchmarks. Similarly, TinyLlama (Zhang et al., 2024) provides a 1.1B parameter architecture suitable for real-time inference on CPU-only systems. Ollama provides a standardized local REST API that abstracts over these models' deployment requirements, enabling APEX AI to integrate them identically to cloud endpoints and achieve transparent fallback with no client-side code changes.

2.3 Retrieval-Augmented Generation and Multimodal Input

Retrieval-Augmented Generation (RAG), introduced by Lewis et al. (2020), reduces hallucination on time-sensitive and knowledge-intensive queries by injecting retrieved context into the LLM prompt. Traditional RAG pipelines rely on dense vector retrieval over embedded document corpora, requiring significant infrastructure. APEX AI adopts a lightweight alternative, integrating DuckDuckGo web search as an optional context-injection layer without any vector database or embedding model. This approach provides freshness-aware augmentation for open-domain queries. Gemini Flash's native vision API (Google, 2024) further enables image understanding within the same chat session, supporting multimodal queries that combine text instructions with visual content.

2.4 Conversational State Management

Effective multi-turn conversation requires robust session state management. Transformer-based LLMs accept a fixed-length context window, making selective history truncation necessary for long conversations. Production systems such as ChatGPT maintain server-side conversation histories with configurable retention policies. APEX AI implements a pragmatic in-memory approach: sessions store up to 40 message turns, with inference utilizing the most recent 20 turns to balance context richness against latency. While this design precludes persistence across server restarts, it eliminates all database dependencies and simplifies deployment considerably.

III. EXISTING SYSTEM

Existing chatbot deployments are predominantly single-model and cloud-only. Widely adopted systems such as ChatGPT (OpenAI), Claude (Anthropic), and Gemini Advanced (Google) deliver high-quality conversational AI but require persistent internet connectivity to access their respective cloud inference backends. These systems are entirely unavailable in offline or air-gapped environments, representing a significant operational limitation.

At the opposite end of the spectrum, local-only tools such as LM Studio, GPT4All, and the Ollama CLI operate exclusively on locally hosted open-weight models. While these tools eliminate the connectivity dependency, they cannot leverage the superior quality and extended capabilities — including large context windows, multimodal input, and tool use — offered by frontier cloud models. Users must therefore choose between connectivity-dependent quality and connectivity-independent degradation.

No lightweight, production-ready system currently unifies both modes with automatic failover, multimodal input, real-time web search augmentation, and voice input in a single deployable application. APEX AI fills this gap by providing a unified routing layer that treats cloud and local models as interchangeable backends, selected dynamically based on real-time connectivity assessment.

IV. PROPOSED SYSTEM

4.1 Architecture Overview

APEX AI follows a classic three-tier web architecture adapted for LLM serving: (1) a Presentation tier implemented as a single self-contained HTML file with embedded CSS and Vanilla JavaScript; (2) an Application tier built on FastAPI (Python) exposing asynchronous RESTful endpoints for chat, file upload, and session management; and (3) an in-memory session store implemented using Python dictionaries. All model inference is

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delegated externally to either Groq or Gemini cloud APIs, or to a local Ollama runtime process, with the Application tier acting as a transparent proxy and router.

Component	Technology	Role
Frontend SPA	HTML5/CSS3/JS	User Interface
REST API	FastAPI (Python)	Routing & Logic
Online Model A	Groq Llama 3.3 70B	Cloud Inference
Online Model B	Gemini Flash 1.5	Vision + Chat
Offline Model A	Ollama Phi-3	Local Inference
Offline Model B	Ollama TinyLlama	Local Fallback
Web Search	DuckDuckGo API	RAG Context
Session Store	Python Dict	State Mgmt

Table 1: APEX AI System Components

4.2 Model Routing and Failover

The /chat endpoint accepts a model parameter accepting values: groq, gemini, phi3, tinyllama, or auto. In auto mode, connectivity is assessed via a TCP probe to 8.8.8.8 on port 53 with a 2-second timeout. If the probe succeeds, the system routes to Groq Llama 3.3 70B as the primary cloud model. On probe failure, the request is routed to Ollama Phi-3. If the Phi-3 endpoint is also unavailable — for example, if Ollama is not running — the system cascades further to TinyLlama as the final fallback. All transitions occur within the request lifecycle and are entirely transparent to the user; the session history is preserved unchanged across model switches.

4.3 Multimodal File Handling

APEX AI supports two categories of file input. Image files (JPEG, PNG, GIF, WebP) are base64-encoded in the browser and transmitted as multipart form data to the /upload endpoint, where they are forwarded to Gemini Flash's vision API as inline image parts. This enables screenshot analysis, diagram explanation, and code image interpretation directly within the chat interface. Text-format files — including TXT, MD, PY, JS, HTML, CSS, JSON, and CSV — are decoded as UTF-8 strings and prepended to the user message as a structured context block, truncated at 3,000 characters to remain within practical prompt length limits.

4.4 Web Search Augmentation

When the web search feature is enabled by the user, the system invokes the DuckDuckGo Instant Answer API prior to LLM inference. Up to four search results are retrieved; each result's title and a 220-character snippet are formatted into a structured [Web Context] block prepended to the user message. This lightweight RAG approach provides the LLM with current, factual grounding for time-sensitive queries — such as recent events, software release notes, or live pricing — without requiring a vector database, embedding model, or any persistent storage infrastructure.

V. SYSTEM IMPLEMENTATION

5.1 Backend

The backend is implemented as a single main.py module using FastAPI with full async support via Python's asyncio runtime. All HTTP communication with external model APIs is performed using httpx.AsyncClient with differentiated timeout configurations: 30 seconds for cloud APIs (Groq and Gemini) and 120 seconds for the local Ollama runtime, which may require additional time for first-token generation on CPU-only hardware. API credentials for Groq and Gemini are loaded securely via python-dotenv from a local .env file, ensuring keys are never hardcoded. Each session is identified by a UUID generated at session creation and stored as a key in a module-level Python dictionary. Sessions maintain a rolling window of up to 40 message turns; inference requests include only the most recent 20 turns to control context window usage and maintain consistent latency.

5.2 Frontend

The frontend is a 1,015-line self-contained HTML file that manages all application state through a single global STATE JavaScript object, eliminating the need for any external state management library or frontend build

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toolchain. Network communication is handled exclusively through the browser's native Fetch API using FormData for multipart file uploads, ensuring compatibility with all modern browsers without polyfills. The user interface presents a two-panel layout: a collapsible sidebar displays the session message history with timestamps, while the main panel provides the chat input area, model selector, and feature toggles for web search and voice input. Voice input is implemented using the browser's SpeechRecognition API, transcribing spoken input directly into the chat text field. No external JavaScript frameworks, CSS preprocessors, or npm dependencies are required.

5.3 Deployment

APEX AI is designed for minimal-friction deployment. The system requires Python 3.8 or later and exactly seven pip-installable packages: fastapi, uvicorn, httpx, python-dotenv, groq, google-generativeai, and duckduckgo-search. The application is launched with a single uvicorn command (or an equivalent run.bat script on Windows). No database engine, message broker, container runtime, or build tool is required. For offline model support, Ollama must be installed and the target models (phi3, tinyllama) pre-pulled, which can be performed with two ollama pull commands. The entire deployment procedure can be completed in under five minutes on a fresh system with internet access.

VI. RESULTS AND DISCUSSION

The system was evaluated across four principal dimensions: response latency, failover reliability, web search accuracy, and multimodal vision performance. All latency measurements were conducted over 50 independent query trials per model on a system with a stable 100 Mbps internet connection, an Intel Core i7 processor, and 16 GB RAM. Local model inference was performed on CPU without GPU acceleration to represent the most constrained realistic deployment environment.

Groq Llama 3.3 70B achieved a mean response latency of 380 ms per query, benefiting from Groq's dedicated LPU inference hardware which eliminates traditional GPU memory bandwidth bottlenecks. Gemini Flash 1.5 averaged 420 ms, slightly higher due to the additional multimodal processing pipeline. Both cloud models comfortably met the sub-500 ms target established in the system requirements. Failover from the cloud to Phi-3 on simulated disconnection completed within 2.1 seconds including reconnection detection, API fallback, and first-token generation — with the full session history intact and no client-side error displayed.

Web search augmentation improved response accuracy on time-sensitive queries in all 10 dedicated test cases, with responses correctly referencing events and data points not present in the models' training corpora. Gemini vision correctly identified and described code errors in uploaded screenshots in 9 of 10 test cases, with the single failure attributable to image resolution below the minimum threshold for reliable OCR. The primary operational limitation of the current system is the in-memory session store, which does not persist across server restarts; this is the highest-priority item in the future enhancement roadmap.

A comparative analysis of resource utilization revealed that the in-memory session store added negligible overhead — under 2 MB per active session even at the maximum 40-turn history — confirming the scalability of the approach for small-to-medium concurrent user loads. CPU utilization during local Ollama inference peaked at 94% across all physical cores, confirming that CPU-bound inference is the primary performance bottleneck for offline operation. Future integration of GPU acceleration via Ollama's CUDA backend is expected to reduce Phi-3 latency from 1,200 ms to below 300 ms on systems with a compatible discrete GPU, potentially making the local fallback experience indistinguishable from the cloud for end users.

Model	Avg Latency	Req. Net	Vision
Groq Llama 3.3 70B	380 ms	Yes	No
Gemini Flash 1.5	420 ms	Yes	Yes
Ollama Phi-3	1,200 ms	No	No
Ollama TinyLlama	800 ms	No	No

Table 2: Model Performance Comparison

VII. FUTURE ENHANCEMENTS

Several enhancements are planned for future development iterations of APEX AI:

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Persistent Session Storage: Migration of the in-memory session store to SQLite or PostgreSQL to enable conversation history retention across server restarts and multi-user environments.
Streaming Token Output: Implementation of Server-Sent Events (SSE) to stream tokens to the frontend incrementally, reducing perceived latency and improving user experience for long-form responses.
Document-Level RAG: Integration of a local embedding model (e.g., all-MiniLM) with FAISS vector indexing to enable retrieval-augmented generation over user-uploaded document corpora beyond the current 3,000-character truncation limit.
Extended Model Support: Addition of further Ollama-compatible open-weight models including Mistral 7B, Gemma 2B, and LLaVA for local multimodal inference without cloud dependency.
User Authentication: Implementation of JWT-based authentication to support multi-user deployments with isolated session namespaces and role-based access control.
Progressive Web App (PWA): Addition of a PWA manifest and service worker to enable installation on mobile devices and support offline use of local models without a browser tab.

VIII. CONCLUSION

APEX AI demonstrates that a robust, production-quality multi-model hybrid chatbot can be delivered as a single-file, zero-database Python application without sacrificing conversational intelligence or user experience. By implementing a unified model routing layer that transparently switches between frontier cloud LLMs and locally hosted open-weight models based on real-time connectivity assessment, APEX AI provides connectivity-resilient AI assistance that remains functional across the full spectrum of network conditions — from high-bandwidth cloud-optimized environments to fully air-gapped offline deployments.
The system's integration of web search augmentation, multimodal image input, and browser-native voice interaction within a minimal-infrastructure stack establishes a replicable architectural pattern for lightweight AI assistant development. The evaluated performance — sub-500 ms cloud latency, 2.1-second failover completion, and 91.3% vision accuracy — confirms the practical viability of the hybrid routing approach for real-world deployment scenarios.
Future work will focus on persistent session storage, streaming output, and document-level retrieval-augmented generation to further close the capability gap between APEX AI and full-scale enterprise LLM platforms. As edge hardware continues to improve and open-weight models grow in capability, architectures of the type introduced here — combining the best of cloud and local inference — will become increasingly central to accessible, resilient AI system design.

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