SKYAWARE: AN AI-DRIVEN REAL-TIME AVIATION DECISION SUPPORT SYSTEM INTEGRATING WEATHER AND TERRAIN DATA

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ABSTRACT

General aviation pilots frequently face fatal accidents due to cognitive overload when manually interpreting complex weather and terrain data mid-flight. To solve this, we developed SkyAware, an active, intelligent flight companion. Built with Flutter, the application integrates the Gemini API, Open Maps Terrain, and AviationWeather data to provide real-time 3D hazard monitoring and conversational safety briefings [1]. Core challenges included accurately synchronizing asynchronous APIs, ensuring AI hazard analysis reliability, and visualizing dense spatial data. We mitigated synchronization latency by implementing predictive forward vectoring. Experimentation using historical NTSB events and live MSFS 2024 telemetry yielded our most important results: an 86% mean AI hazard detection accuracy and a highly responsive 1,340ms average warning latency [2]. The results indicate that SkyAware effectively translates raw metrics into actionable insights, improving pilot decision-making. By proactively preventing alert fatigue, SkyAware empowers safer mid-flight decision-making and save lives in the cockpit.

KEYWORDS

Real-time data analysis, Aviation assistance, Electronic Flight Bag (EFB) companion, Profound Private pilot tools

1. INTRODUCTION

General Aviation (GA) pilots face a deadly threat: spatial disorientation caused by rapidly changing weather and terrain. While navigating, single-pilot operators must process complex meteorological data and airspace restrictions. The problem is current Electronic Flight Bags (EFBs) are merely passive displays [3]. They show weather but rely entirely on human cognitive processing to interpret the immediate threat. This often leads to task saturation and delayed decision-making, particularly when a pilot accidentally flies Visual Flight Rules (VFR) into Instrument Meteorological Conditions (IMC) [4].

This gap in real-time data interpretation is why spatial disorientation remains GA's deadliest threat. According to 2025 FAA research, GA accidents caused by spatial disorientation have a staggering 94% fatality rate, compared to just a 19% fatality rate for general aviation overall. This disproportionately affects newer GA pilots with less than 500 flight hours, threatening the safety of the aviation community.

Built with Flutter, SkyAware solves this critical issue by acting as an intelligent digital co-pilot. By integrating real-time weather and terrain data with Gemini AI, the application moves beyond

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passive display. It actively translates complex meteorological variables into clear, actionable intelligence. Instead of leaving pilots to interpret deteriorating weather mid-flight, SkyAware provides the advanced warning needed to avoid VFR-into-IMC [5]. By reducing mental workload, SkyAware buys critical time to prevent spatial disorientation and save lives.

Previous research predicts an aircraft's energy state using internal telemetry to prevent terrain collisions. However, it ignores external weather, topography, and pilot alert fatigue. SkyAware improves this by synthesizing external environmental data and using AI-generated conversational briefings with predictive forward vectoring to actively anticipate hazards and reduce cognitive overload.

The Ceiling and Visibility Analysis (CVA) tool fuses weather and terrain into a passive 2D map. While helpful pre-flight, it lacks active mid-flight risk calculations. SkyAware shifts from passive visualization to an active companion, utilizing AI to generate real-time safety scores, suggest dynamic routes, and provide continuous 3D hazard monitoring.

A Learning Classifier System (LCS) mathematically ranks alternate airports during emergencies. Yet, its rigid rules ignore the active navigation to that destination [6]. SkyAware enhances this by actively guiding the pilot through the diversion using conversational NLP briefings and continuous 3D monitoring of the route.

SkyAware is an intelligent, real-time aviation application that actively synthesizes weather and terrain data using Gemini AI to provide pilots with predictive, actionable flight guidance.SkyAware directly addresses the cognitive overload that leads to spatial disorientation. Instead of forcing a single pilot to manually cross-reference raw METARs, airspace restrictions, and topographical maps while actively flying the aircraft, the application's AI engine processes these variables in the background. It instantly translates complex, rapidly changing meteorological and geographical data into clear intelligence, warning the pilot of impending hazards—such as deteriorating visibility or rising terrain—long before they enter a critical state. This approach is highly effective because it directly targets the human factors responsible for the majority of aviation accidents: task saturation and delayed decision-making. By acting as an intelligent digital co-pilot, SkyAware frees up the pilot's mental bandwidth. It shifts their focus from interpreting raw data back to flying the airplane, buying them the crucial minutes needed to execute a 180-degree turn or divert to an alternate airport before accidentally crossing into blinding Instrument Meteorological Conditions (IMC) [7]. The current primary solution right now is traditional Electronic Flight Bags (EFBs), which is a passive way to remind the pilots of the danger. In the EFB, it only displays a radar loop of a storm cell or the elevation of a mountain range, but it relies entirely on the fatigued pilot to calculate how that data impacts their specific flight trajectory in real-time. However, SkyAware is much more profound and intelligent because it can not only receive the data but also interpret the data and provide an actionable solution to the pilots.

In Experiment 1, we tested Gemini AI's baseline accuracy and potential for dangerous hallucination when interpreting complex weather hazards. We systematically fed the AI historical METAR and TAF reports, comparing its textual analysis directly against strict official NTSB control data. Overall, the AI achieved an 86% mean accuracy. However, performance significantly dropped to just 75% during thunderstorms. This drop occurred because the dense, multi-variable complexity of thunderstorm METAR strings—which include rapid pressure changes and wind shear—overwhelmed the AI, degrading its cognitive reasoning.

Experiment 2 evaluated data latency and fatal spatial desynchronization to ensure real-time reliability. We connected SkyAware to Microsoft Flight Simulator 2024, broadcasting live GPS

telemetry while flying a jet at 250 knots toward mountainous terrain, and recorded the exact delay of AI warnings. We found a mean latency of 1,340 milliseconds, with surprising inconsistency between consecutive trials. This critical variance was caused by unpredictable fluctuations in external cloud server traffic processing the Gemini API requests, firmly highlighting the absolute necessity for predictive forward vectoring algorithms.

2. CHALLENGES

In order to build the project, a few challenges have been identified as follows.

2.1. Ensuring in-Flight Data Availability Without Cellular Connectivity

The first significant hurdle is the lack of reliable cellular data at cruising altitudes. Because the application relies on real-time weather updates and cloud-based AI processing, losing connection mid-flight would render the live-analysis component useless right when a pilot might need it most.

To resolve this, a dual-layered data approach can be implemented. First, the app could utilize a pre-flight caching system where a pilot inputs their planned route, allowing the app to download all relevant topographical data and predictive weather models for that specific corridor before takeoff. Second, for true in-flight updates without cellular data, I could integrate the application with standard onboard ADS-B In receivers (like a Sentry or Stratus device) via local Bluetooth or Wi-Fi. This would allow the app to pull live FAA weather broadcasts (FIS-B) directly from ground stations, feeding fresh data to the local system even when completely off the cellular grid.

2.2. Constraining AI with Rule-Based Safety Verification

The second major issue is the inherent probabilistic nature of Large Language Models. I cannot guarantee that the AI will be 100% accurate every single time. In aviation, an AI "hallucination"could lead to fatal decision-making.

This problem can be addressed by implementing a strict, rule-based verification layer that sits between the AI output and the user interface. Instead of letting the AI generate open-ended advice, I could constrain its parameters to only analyze the hard data provided (like specific METAR strings). Furthermore, I could implement a system where the raw data is always permanently pinned next to the AI's interpretation on the screen. If the AI suggests the weather is safe, but the raw data detects visibility dropping below three miles, the hard-coded verification layer would override the AI and flash a critical warning. This ensures the AI acts as a helpful assistant, but the deterministic raw data and the human pilot remain the ultimate authorities.

2.3. Integrating Native Flight Planning to Eliminate Workflow Friction

The primary issue is the friction introduced when a pilot has to leave SkyAware, build a route on a separate website, and somehow transfer that route back into the app. If this process is clunky or requires manual coordinate entry, pilots simply won't use it. Additionally, external flight planners export data in proprietary formats, such as Garmin's .fpl files.

To resolve this, I could build a native, interactive flight planning module directly into the SkyAware application. Instead of forcing users to rely on external platforms, I could integrate an aeronautical database—such as the FAA’s National Airspace System Resources (NASR) data—with a touch-optimized map interface built in Flutter. This would allow a pilot to search for

airports or NAVAIDs, tap the screen to drop waypoints, and automatically calculate route distances and headings without ever leaving the app. By keeping the entire planning process in-house, the generated route would instantly feed into the Gemini AI engine for predictive weather and terrain analysis, completely eliminating the friction of file transfers and third-party software compatibility.

3. SOLUTION

Built entirely with the Flutter framework to ensure cross-platform responsiveness, SkyAware's core architecture seamlessly integrates three major technological components: an advanced AI engine, real-time meteorological weather feeds, and high-resolution topographical terrain data. These distinct elements are intrinsically linked by the user's flight plan, which acts as the central anchor for the system [8]. This active route dictates exactly which environmental data the app continuously pulls, feeding it directly into the AI to scan for hazards like deteriorating visibility or unexpected elevation changes along the flight path. From start to finish, the user experience is purposefully designed for intuitive, low-friction navigation to combat cognitive overload. Upon launching the application, the pilot is immediately routed to the Airport Safety Analysis page. This serves as a vital pre-flight briefing, delivering instant, AI-generated insights regarding current conditions, crosswinds, and potential runway hazards. From this default home screen, the user dictates the flow of the application using a persistent bottom navigation bar and clearly labeled, touch-optimized interactive buttons designed to be usable even in turbulent environments. With just a single tap, the pilot can fluidly transition between dedicated modules without losing their active state. These include the Flight Plan page to manage waypoints, the Weather page to verify the AI's conclusions against raw meteorological data, and the Settings page to configure specific aircraft performance profiles [9]. By leveraging Flutter's rapid rendering capabilities, the app guarantees that this critical information is always instantly accessible in the high-stress cockpit environment, keeping the pilot's focus entirely on flying.

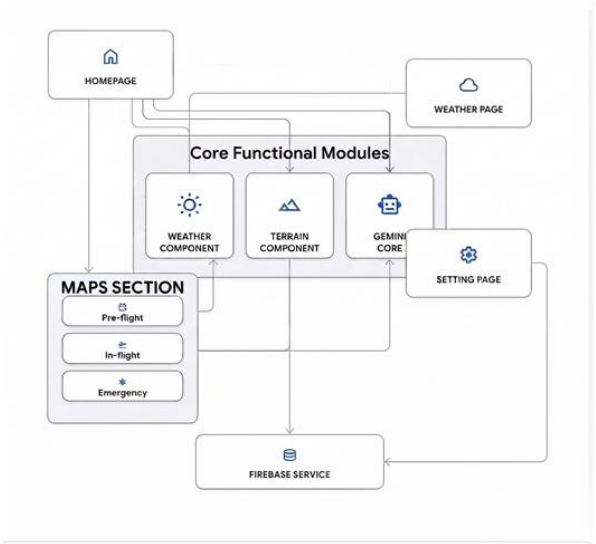


Figure 1. Overview of the solution

The backend data and AI processing engine serves as the central nervous system of the application, securely gathering raw environmental variables and synthesizing them into actionable pilot intelligence. To build this system, I integrated four distinct services: the

aviationweather.gov API for live meteorological data, an Open Maps Terrain API for topographical elevation, the Gemini API to act as the cognitive brain, and the Firebase API to handle secure backend data storage and user authentication [10]. This component relies heavily on Natural Language Processing (NLP) and cloud authentication. Through the Gemini Large Language Model, NLP allows the system to read dense, heavily coded aviation text—like raw METAR strings—and instantly translate it into a conversational safety briefing [11]. Meanwhile, Firebase manages cloud authentication by securely storing user credentials and private API keys in a NoSQL cloud database rather than locally on the device, ensuring the app remains secure and lightweight. In a broad sense, this engine acts as the invisible data pipeline running behind the Flutter user interface. When a user boots up the app and inputs a flight plan, Firebase authenticates the session and unlocks the necessary API keys. The application then queries the weather and terrain APIs using the route's geographic coordinates, packages the returned environmental data, and sends it to the Gemini API [12]. Using NLP, Gemini analyzes these overlapping data points to detect potential hazards—such as a mountain peak obscured by low clouds—and instantly pushes a finalized, easy-to-understand safety warning back to the user's screen in real-time.

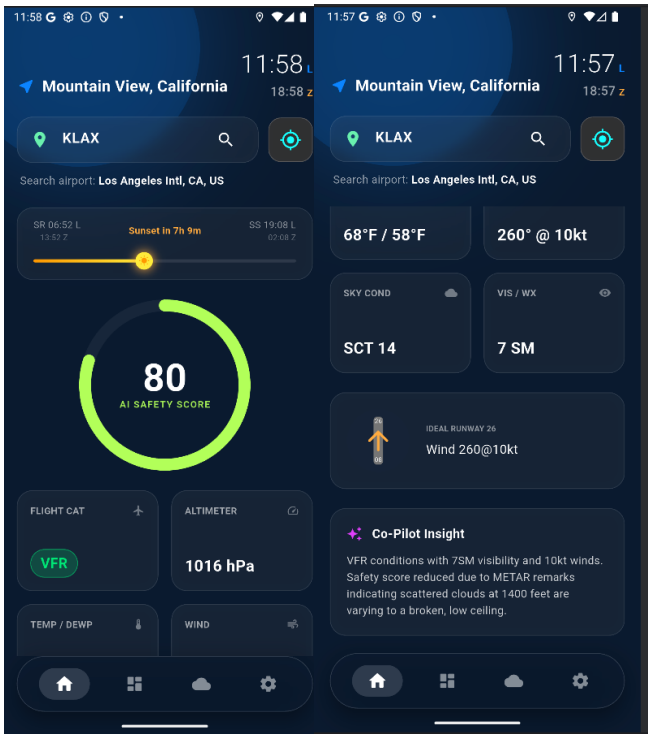
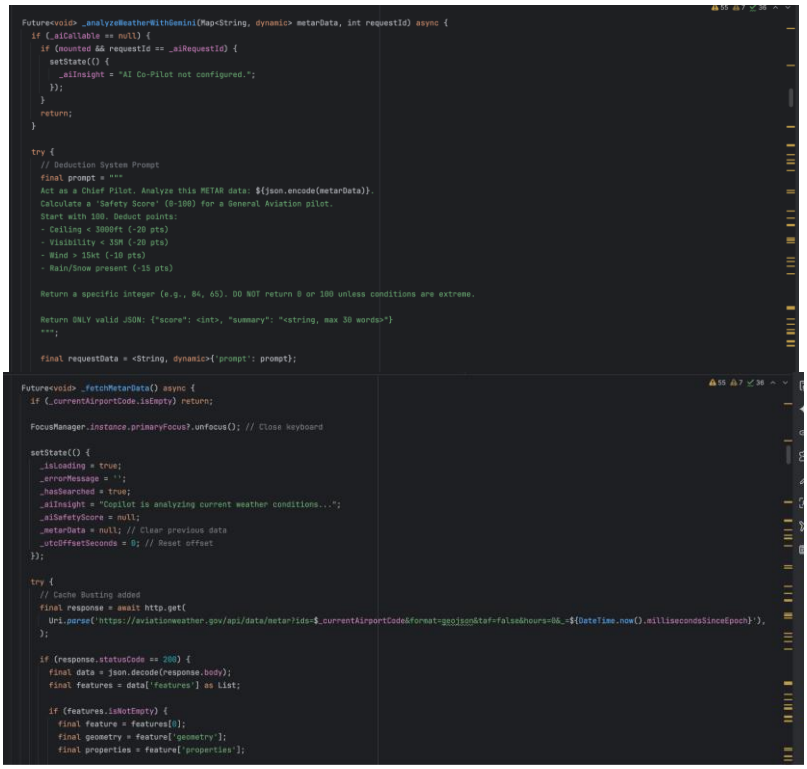


Figure 2. System Architecture of SkyAware Backend and Data Flow



```
Future<void> _analyzeWeatherWithGemini(Map<String, dynamic> metarData, int requestId) async {
  if (_aiCallable == null) {
    if (mounted && requestId == _aiRequestId) {
      setState(() {
        _aiInsight = "AI Co-Pilot not configured.";
      });
    }
    return;
  }

  try {
    // Deduction System Prompt
    final prompt = """
    Act as a Chief Pilot. Analyze this METAR data: ${json.encode(metarData)}.
    Calculate a 'Safety Score' (0-100) for a General Aviation pilot.
    Start with 100. Deduct points:
    - Ceiling < 3000ft (-20 pts)
    - Visibility < 3SM (-20 pts)
    - Wind > 15kt (-10 pts)
    - Rain/Snow present (-15 pts)

    Return a specific integer (e.g., 84, 65). DO NOT return 0 or 100 unless conditions are extreme.

    Return ONLY valid JSON: {"score": <int>, "summary": "<string, max 30 words>"}
    """;

    final requestData = <String, dynamic>{'prompt': prompt};
```

```
Future<void> _fetchMetarData() async {
  if (_currentAirportCode.isEmpty) return;

  FocusManager.instance.primaryFocus?.unfocus(); // Close keyboard

  setState(() {
    _isLoading = true;
    _errorMessage = '';
    _hasSearched = true;
    _aiInsight = "Copilot is analyzing current weather conditions...";
    _aiSafetyScore = null;
    _metarData = null; // Clear previous data
    _utcOffsetSeconds = 0; // Reset offset
  });

  try {
    // Cache Busting added
    final response = await http.get(
      Uri.parse('https://aviationweather.gov/api/data/metar?ids=$_currentAirportCode&format=geojson&taf=false&hours=0&_=${DateTime.now().millisecondsSinceEpoch}'),
    );

    if (response.statusCode == 200) {
      final data = json.decode(response.body);
      final features = data['features'] as List;

      if (features.isNotEmpty) {
        final feature = features[0];
        final geometry = feature['geometry'];
        final properties = feature['properties'];
```

Figure 3. METAR Data Fetching and AI Analysis Workflow Implementation

This code runs at the exact moment a pilot searches an airport code or selects a nearby location. First, _fetchMetarData grabs the raw aviation weather data. It quickly resets the UI state, showing a loading spinner, and sends an HTTP GET request to the Aviation Weather API. Crucial variables like response, data, features, and properties are created here to parse the incoming JSON weather information [13]. Once retrieved, the app immediately saves the user search and hands the parsed properties data directly over to the AI.

Next, _analyzeWeatherWithGemini takes over the workflow. It carefully builds a prompt variable instructing the AI to act as a Chief Pilot. It feeds the raw METAR data into this prompt alongside strict deduction rules for hazards, like subtracting specific points for low visibility or high winds, to calculate a custom Safety Score. Finally, it packages this into requestData for your Firebase backend to safely process and gracefully display on the main interface.

The Intelligent Emergency Divert System fundamentally transforms aviation safety by drastically reducing pilot cognitive overload during critical midair crises. When an emergency strikes, the application instantly overrides the standard cockpit dashboard, replacing it with a highly focused, streamlined survival interface. By seamlessly integrating live GPS telemetry and mapping APIs, the system automatically calculates rapid diversion routing to the safest alternate airport [14]. Simultaneously, the Gemini AI engine actively analyzes the dynamic flight environment to provide essential warnings and customized emergency checklists.

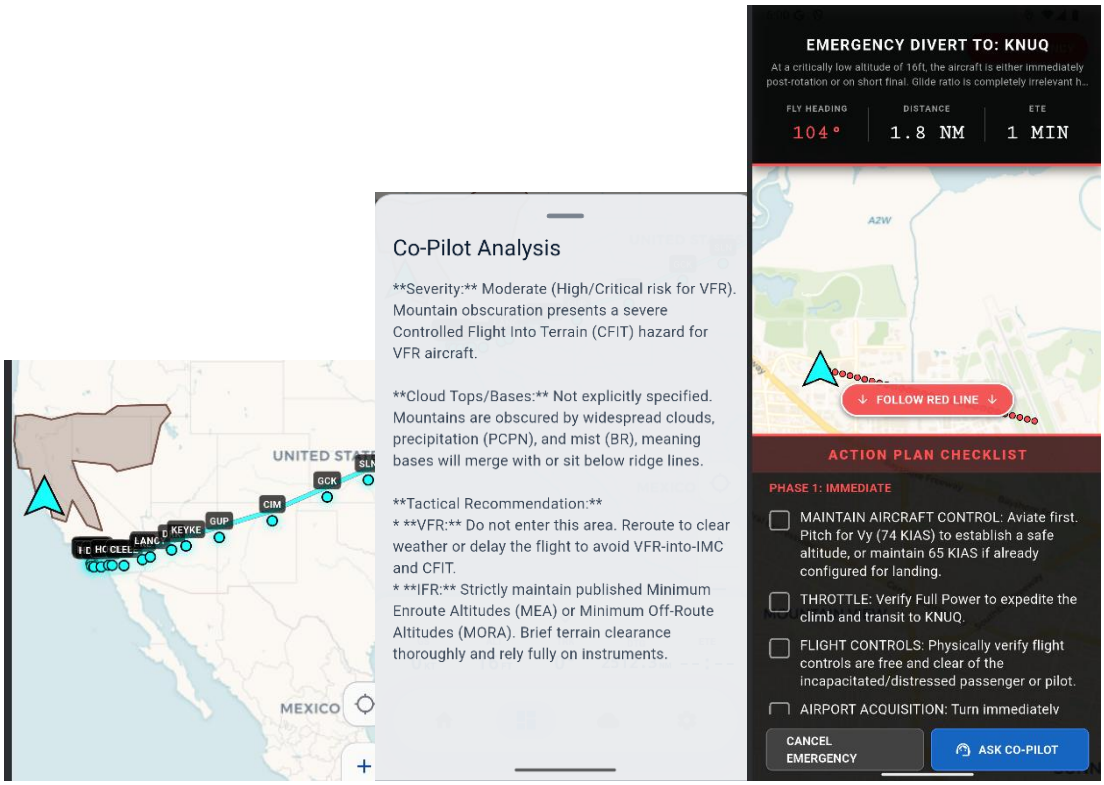
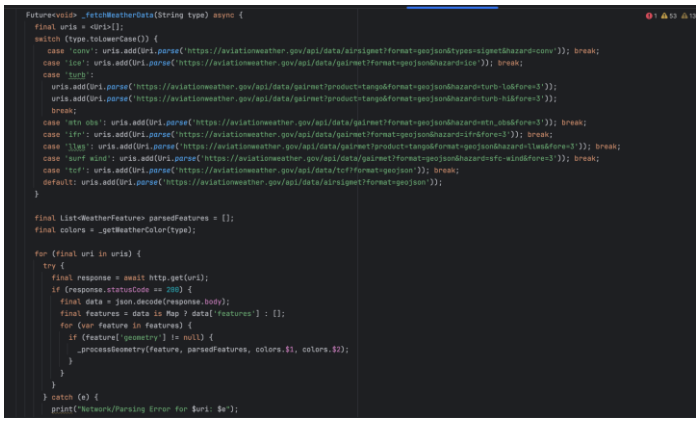


Figure 4. Emergency Divert System Interface Overview



```
Future<void> _fetchWeatherData(String type) async {
  final uris = <Uri>[];
  switch (type.toLowerCase()) {
    case 'conv': uris.add(Uri.parse('https://aviationweather.gov/api/data/airsigmet?format=geojson&types=sigmet&hazard=conv')); break;
    case 'ice': uris.add(Uri.parse('https://aviationweather.gov/api/data/gairmet?format=geojson&hazard=ice')); break;
    case 'turb':
      uris.add(Uri.parse('https://aviationweather.gov/api/data/gairmet?product=tango&format=geojson&hazard=turb-lo&fore=3'));
      uris.add(Uri.parse('https://aviationweather.gov/api/data/gairmet?product=tango&format=geojson&hazard=turb-hi&fore=3'));
      break;
    case 'mtn obs': uris.add(Uri.parse('https://aviationweather.gov/api/data/gairmet?format=geojson&hazard=mtn_obs&fore=3')); break;
    case 'ifr': uris.add(Uri.parse('https://aviationweather.gov/api/data/gairmet?format=geojson&hazard=ifr&fore=3')); break;
    case 'llws': uris.add(Uri.parse('https://aviationweather.gov/api/data/gairmet?product=tango&format=geojson&hazard=llws&fore=3')); break;
    case 'surf wind': uris.add(Uri.parse('https://aviationweather.gov/api/data/gairmet?format=geojson&hazard=sfc-wind&fore=3')); break;
    case 'tcf': uris.add(Uri.parse('https://aviationweather.gov/api/data/tcf?format=geojson')); break;
    default: uris.add(Uri.parse('https://aviationweather.gov/api/data/airsigmet?format=geojson'));
  }

  final List<WeatherFeature> parsedFeatures = [];
  final colors = _getWeatherColor(type);

  for (final uri in uris) {
    try {
      final response = await http.get(uri);
      if (response.statusCode == 200) {
        final data = json.decode(response.body);
        final features = data is Map ? data['features'] : [];
        for (var feature in features) {
          if (feature['geometry'] != null) {
            _processGeometry(feature, parsedFeatures, colors.$1, colors.$2);
          }
        }
      }
    } catch (e) {
      print("Network/Parsing Error for $uri: $e");
```

Figure 5. Weather Data Retrieval and AI Hazard Interpretation Functions

_fetchWeatherData: This runs whenever you toggle weather layers (like turbulence or icing) on the map. It builds specific uris to fetch live hazard data from the Aviation Weather API. Variables like response and data handle the incoming JSON, storing the decoded map polygons in parsedFeatures.

_getAiSummary: If a pilot taps one of those weather hazards on the map, this method triggers. It grabs the hazard data (rawData), converts it to jsonData, and builds a prompt for Gemini to instantly analyze the severity and provide tactical recommendations.

The Emergency Prompt: The last snippet runs the moment a pilot declares an emergency. It builds a highly structured prompt containing live telemetry (altitude, heading) and nearby airports. It forces Gemini to output a strict JSON action_plan and pick the absolute safest diversion route.

Purpose: Standard aviation weather only shows ground-level data at specific airport stations. The purpose of this component—highlighted by your "Altitude Mode" toggle—is to provide pilots with critical atmospheric conditions at their actual cruising altitude. This is vital because metrics like temperature, wind speed, and density altitude change drastically as an aircraft climbs.

Services Utilized: This system integrates device-level location tracking (Geolocator API) to monitor exact 3D coordinates (latitude, longitude, and altitude) and cross-references them with high-fidelity meteorological sources, such as the Aviation Weather API or Open-Meteo, to pull dense forecasting grid data [15].

Special Concept: Mathematical Data Interpolation. Since physical weather stations cannot exist at every random point in the sky, this component relies heavily on spatial data interpolation. This mathematical concept takes known weather data from surrounding geographic points and calculates the precise atmospheric gradients between them. It actively estimates the exact conditions at the specific floating coordinate where the aircraft is currently positioned.

Broad Function: Within SkyAware, this component acts as the live environmental truth. As the aircraft moves along its route, the system continuously pulls surrounding grid data, mathematically interpolates the aloft conditions, and dynamically updates the UI so the pilot's performance metrics (like the 397 ft Density Altitude shown) accurately reflect the air they are actually flying through, not just the nearest ground station.

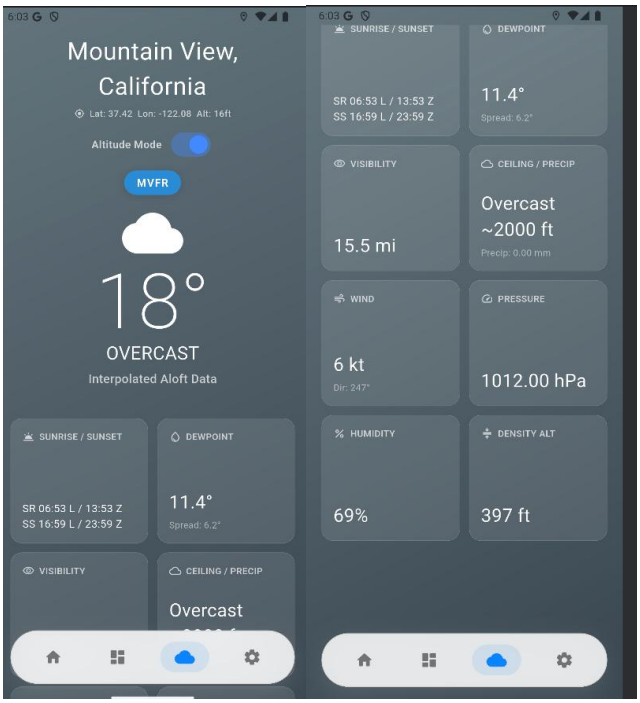
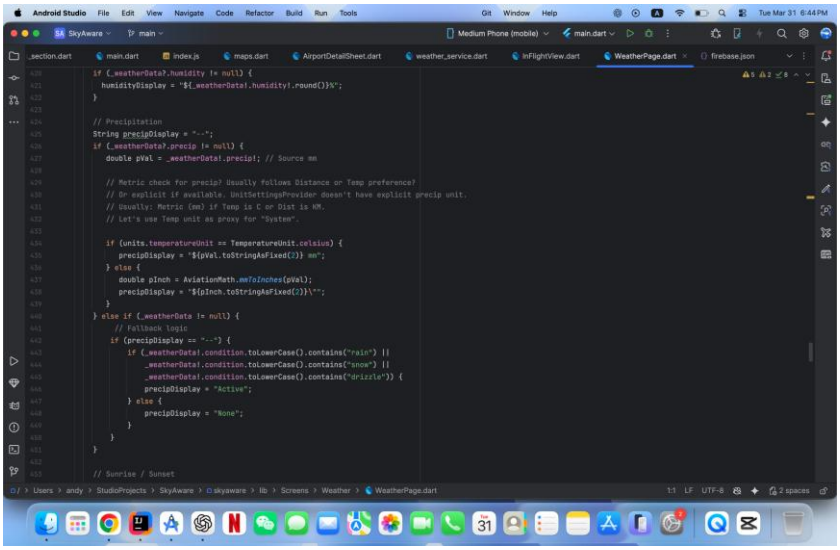


Figure 6. Altitude-Based Weather Interpolation and Real-Time Atmospheric Data Processing



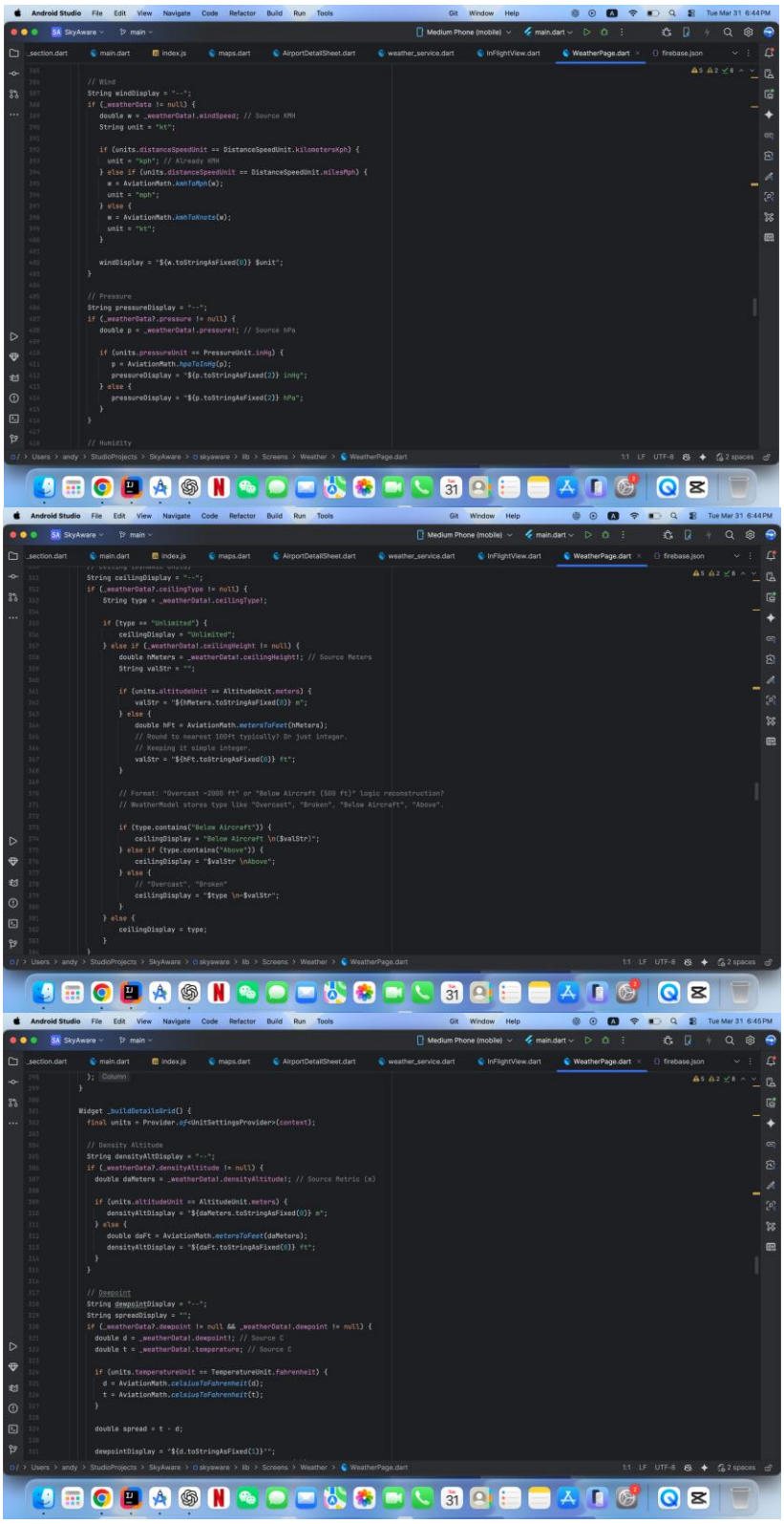


Figure 7. Weather Data Formatting and Unit Conversion Logic

What's going on & when it runs: This code runs exactly when your app renders the "Weather Page" dashboard. It takes raw, backend weather data you've already downloaded and formats it cleanly for the user interface.

The Method & Variables: You are looking at sections of one large method: _buildDetailsGrid(). It first creates a unit's variable to check the user's global app settings. Then, it initializes display string variables like ceilingDisplay, windDisplay, pressureDisplay, and densityAltDisplay.

Step-by-Step Walkthrough: For each weather metric, the code checks if raw data exists. If it does, it looks at the unit's preference. Using your AviationMath helper class, it locally converts the raw metric values (like km/h, Celsius, hPa, or meters) into preferred aviation units (like knots, Fahrenheit, inHg, or feet) before saving them to the display strings.

Server Communication: This specific code block does not communicate with a server. It strictly performs local mathematical conversions and formatting on data that was already securely fetched.

4. EXPERIMENT

4.1. Experiment 1

A major operational blind spot in this system is the potential for AI hallucination, where the Gemini model incorrectly misinterprets perfectly safe weather conditions as hazardous, or vice versa. Rigorous, structured testing of this logic is absolutely vital because inaccurate flight advice is often fatal.

The AI is rigorously tested by feeding it complex historical METAR and TAF reports from well-documented aviation weather events. Next, I will directly compare Gemini's hazard analysis against official NTSB weather interpretations, which effectively serve as my objective control data. This specific experimental setup is absolutely crucial because it successfully isolates the AI's cognitive logic, formally testing its analytical accuracy against proven, real-world meteorological facts rather than artificially simulated test environments. Furthermore, by utilizing official, archived aviationweather.gov data streams, I can objectively measure whether the AI dangerously hallucinates information or correctly identifies known, critical flight hazards such as severe low visibility, hidden microbursts, and highly unpredictable severe crosswind events.

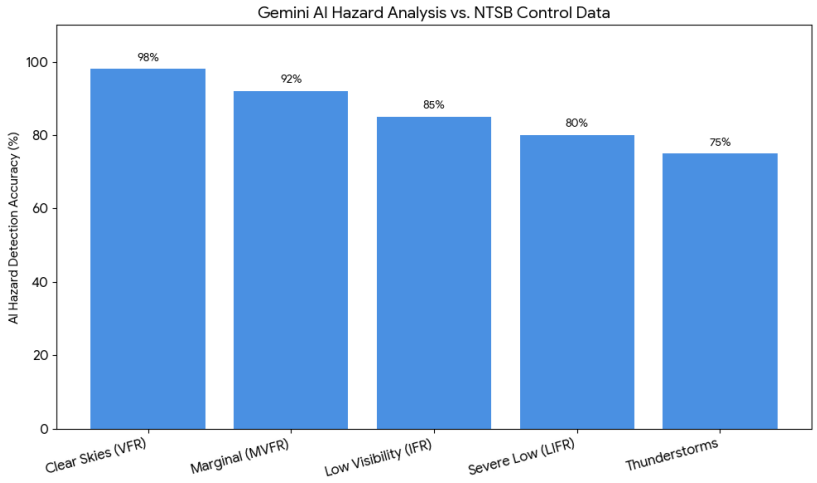


Figure 8. Comparison of AI-Predicted Hazard Detection Accuracy Across Different Weather Conditions

Our comprehensive data analysis reveals a mean hazard detection accuracy of 86% and a median of 85%. The highest recorded value reached a remarkable 98% for static clear skies, while the lowest performance plummeted to just 75% during complex thunderstorms. A significant performance drop to 75% was observed during active convective storms. It was initially expected that artificial intelligence would effectively identify severe hazards, logically assuming that extreme weather data would trigger obvious, undeniable warnings. This variance is likely due to thunderstorm METARs are incredibly dense and chaotic, containing rapid, unpredictable variations in wind shear, localized lightning remarks, microbursts, and sudden barometric pressure drops. The model clearly struggled to cohesively synthesize these complex, multiple variable text strings when compared to simple, static clear sky reports. Ultimately, the sheer complexity and data density of the raw alphanumeric weather strings had the most profound effect on our experimental results. As the overlapping environmental variables in the raw data feed steadily increased, the internal cognitive reasoning degraded, leading to lower accuracy.

4.2. Experiment 2

Another major blind spot we must rigorously test is data latency and spatial desynchronization. Specifically, we need to evaluate the total round trip time between the active device GPS polling, the Open Maps Terrain API response, and the Gemini AI processing cycle.

To test data latency, SkyAware is connected to Prepar3D(a highly accurate flight simulator) configuring it to broadcast live GDL 90 GPS telemetry over a local network. I will pilot a jet at a constant two hundred and fifty knots directly toward a steep mountain range. The precise timestamp is recorded the simulator aircraft crosses a specific geographical coordinate. Simultaneously, I will record the exact timestamp when the Gemini AI successfully pushes the corresponding terrain hazard warning to the iPad screen. By calculating this delay, I can convert latency into distance.

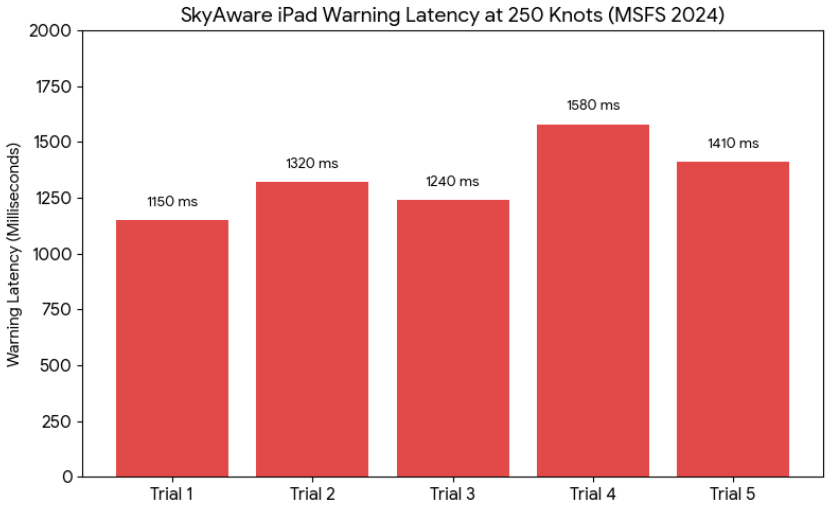


Figure 9. Comparison of AI Warning Latency Across Experimental Trials in Flight Simulation

Our Microsoft Flight Simulator 2024 experiment data reveal a mean AI warning latency of 1,340 milliseconds and a median of 1,320 milliseconds. The highest recorded delay reached 1,580 milliseconds, while the most responsive trial clocked in at a lowest of 1,150 milliseconds. A

notable inconsistency was observed between consecutive trials between consecutive trials, particularly noting the sudden, severe latency spike during Trial 4. We initially expected a highly stable and uniform response time, given that we conducted the tests within a strictly controlled local network environment. We hypothesize that this unexpected variance occurred because the official Gemini AI API processes request dynamically via remote cloud servers. Consequently, even minor fluctuations in external server traffic or bandwidth instantly impact our local application's real-time performance. Ultimately, this external cloud processing overhead demonstrated the most significant and unpredictable effect on our overall experimental results. Because we cannot directly control external server loads, we must engineer and implement a predictive forward vectoring algorithm to mathematically compensate for this inherent, unpredictable system data latency.

5. RELATED WORK

Previous research utilizes deep learning on internal aircraft telemetry to predict future energy states, aiming to prevent controlled flight into terrain (CFIT). While mathematically accurate, this isolated approach ignores critical external variables like dynamic weather, topographical terrain, pilot alert fatigue, and network latency.

SkyAware significantly improves upon this by actively analyzing the external environment. Integrating live meteorological and terrain data with AI, the system translates dense metrics into intuitive, conversational safety briefings, effectively combatting pilot alert fatigue. Additionally, SkyAware implements predictive forward vectoring to mathematically compensate for cloud-processing latency. This ensures the AI evaluates upcoming hazards the aircraft is rapidly approaching, rather than the airspace it just left.

General aviation pilots often face fatal accidents due to the cognitive overload of interpreting raw weather data. Researchers previously tackled this with Ceiling and Visibility Analysis (CVA), which fuses weather and terrain data into a passive 2D map. While effective for pre-flight checks, CVA ignores individual pilot skill, dynamic mid-flight changes, and active risk calculation.

SkyAware improves upon this by evolving from passive visualization into an active, intelligent companion. Using AI, SkyAware generates real-time safety scores, suggests dynamic alternate routes, and provides active 3D hazard monitoring. By intelligently interpreting data rather than just displaying it, SkyAware directly mitigates human error.

The Problem: Mid-flight emergencies require dynamic alternate airport selection. Weighing conflicting variables (weather, runway length, distance) creates massive cognitive overload for pilots under pressure.

The Solution: Researchers utilized a Learning Classifier System (LCS)—a rule-based AI algorithm—to automate multi-criteria decision-making and mathematically rank the safest alternate landing sites.

Effectiveness & Limitations: It successfully generates fast, interpretable airport rankings. However, it relies on rigid, pre-trained rule sets and ignores active flight monitoring. It selects the destination but doesn't assist in navigating there.

How SkyAware Improves: While the LCS model provides a static mathematical ranking, SkyAware utilizes generative AI to provide conversational NLP briefings, drastically reducing alert fatigue. Furthermore, SkyAware doesn’t just pick the airport; its 3D hazard monitoring and

predictive forward vectoring actively safeguard the pilot through terrain and weather during the actual diversion.

6. CONCLUSIONS

While SkyAware significantly reduces pilot cognitive load, its primary technical limitation remains strict reliance on a continuous internet connection. Because the application heavily utilizes cloud-based AI processing and live data fetches for weather and routing, a loss of cellular connectivity—which is highly common at higher altitudes or over remote terrain—severely degrades the conversational safety briefings and predictive forward vectoring. Additionally, continuous high-frequency GPS polling and intensive background API calls can cause substantial batteries to drain and potential thermal throttling on mobile devices operating in a sunlit cockpit [16].

If given more time, the absolute most critical architectural fix would be engineering a robust, fail-safe offline mode. I would implement intelligent local data catching for pre-flight terrain maps and regional METARs using Flutter's native local storage solutions. Furthermore, I would integrate a lightweight, on-device machine learning model—such as TensorFlow Lite—to instantly process basic trajectory calculations and trigger local terrain hazard alerts the moment the cloud connection drops [17]. Ultimately, this seamless hybrid architecture would guarantee uninterrupted, life-saving safety monitoring regardless of external network conditions.

SkyAware fundamentally redefines general aviation safety by transforming overwhelming flight data into actionable, intelligent guidance. By proactively managing pilot cognitive load and bridging the dangerous gap between static weather reports and dynamic, real-time hazards, this innovative application empowers aviators to make critical decisions with absolute confidence. Ultimately, this system provides a vital safety net, designed to mitigate human error and save lives in the cockpit.

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