

# Architectural Proposal: Automated Video-to-Notes Platform

## 1. Introduction: The Video Information Bottleneck

The modern digital enterprise and educational landscapes have undergone a seismic shift in information storage, moving from structured text documents to unstructured audio-visual assets. Organizations now routinely generate terabytes of long-form video content, ranging from three-hour technical workshops and quarterly business reviews to extended user research interviews and academic lectures. While video is an exceptional medium for capturing nuance, emotion, and demonstration, it suffers from a critical structural flaw regarding information retrieval: it is linear and opaque. Unlike a text document that can be scanned in seconds, a four-hour video file imposes a 1:1 consumption tax—to extract a specific insight, a user must often scrub through gigabytes of data or watch the content in its entirety. This phenomenon creates "dark data," where valuable institutional knowledge remains locked within large binary files, inaccessible to search engines and knowledge workers alike.

The objective of the "Video-to-Notes" initiative is to dismantle this accessibility barrier through the deployment of an automated, scalable pipeline. The requirement is to process a local repository of high-definition, long-duration (3–4 hours) video files, automatically generating a "Summary Package" for each. This package serves as a semantic index, transforming the linear video into a non-linear hypermedia document comprising a structured Markdown summary, precise highlight clips, and contextual screenshots. The target outcome is a system where a user can consume the core value of a multi-hour recording in under ten minutes, effectively compressing the time-to-insight by a factor of twenty.

This report provides an exhaustive technical analysis of three potential architectural pathways to achieve this goal: leveraging existing Online SaaS platforms, constructing a Hybrid Architecture utilizing local processing and Cloud AI APIs, or deploying a Fully Offline Open-Source pipeline. The analysis is governed by strict constraints: the handling of massive file sizes (200MB+ to several GBs), the necessity for batch processing without manual intervention, and the requirement for absolute temporal precision in asset generation to prevent "hallucinated" clips that misalign with their semantic descriptions.

### 1.1 The Physics of Data and Constraint Analysis

The specific constraints of this project—files located locally, large file sizes, and extended durations—dictate the architectural viability of any proposed solution. The fundamental physics of data transfer plays a defining role. A four-hour video encoded at a modest 5Mbps bitrate results in a file size of approximately 9GB. Processing a batch of 50 such videos involves managing nearly half a terabyte of data.

In a traditional cloud-centric workflow, this necessitates the upstream transfer of 500GB of data before any processing can occur. On a standard symmetric gigabit connection, this is manageable, but on typical asymmetric business connections (e.g., 50Mbps upload), the ingestion phase alone becomes a multi-day bottleneck, introducing latency that far exceeds the actual processing time. Furthermore, long-duration videos present a unique challenge to Artificial Intelligence models. A four-hour transcript contains between 30,000 and 45,000 tokens. Standard Large Language Models (LLMs) with 8k or 32k context windows cannot ingest this entire narrative in a single pass, necessitating "chunking" strategies that often sever the semantic links between the introduction of a concept and its conclusion hours later.<sup>1</sup>

Therefore, the successful architecture must solve two primary problems: the **bandwidth penalty** of moving large video files and the **context window saturation** inherent in summarizing long-form narratives.

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## 2. Comparative Architectural Analysis

We evaluated three distinct approaches against the core success criteria: clarity of architecture, handling of bulk constraints, and the precision of the output assets.

### 2.1 Approach 1: Online/Cloud-Based SaaS Solutions

*Market Segment: AI Video Repurposing Platforms (e.g., Pictory, Exemplary.ai, ScreenApp)*

The first approach examines the viability of "buying" rather than "building." The market has seen a proliferation of SaaS tools designed to "repurpose" long-form content into short-form clips, driven largely by the social media economy (TikTok, Reels, YouTube Shorts).<sup>2</sup> These platforms typically offer a web-based interface where users upload videos, and the system automatically generates transcripts, summaries, and clips.

#### 2.1.1 Architectural Limitations for Long-Form Archival

While these tools offer low initial friction, their underlying architecture is fundamentally misaligned with the "Video-to-Notes" requirements. The primary misalignment is the **Business Logic of Virality vs. Utility**. Platforms like Pictory and Exemplary.ai optimize their algorithms to find "engaging" or "viral" moments—segments with high audio energy, laughter, or rapid pacing—suitable for social media consumption.<sup>2</sup> The "Video-to-Notes" project, conversely, requires the extraction of "informational" highlights—technical diagrams, strategic decisions, or action items—which may be delivered in a monotone voice or during quiet deliberation. The "black box" nature of SaaS prompts means we cannot easily reprogram their AI to prioritize "database schema discussions" over "jokes."

#### 2.1.2 The Throughput and Duration Wall

The most fatal flaw for this specific use case is the **Duration Limit**. Most commercial SaaS video processors enforce hard caps on video length to manage their own GPU compute costs. ScreenApp, for example, limits Business Plan users to 3 hours per video.<sup>3</sup> A 3-hour and 15-minute lecture would trigger a processing failure or require the user to manually split the file using video editing software before upload. This manual intervention violates the "batch mode" constraint, transforming an automated pipeline into a labor-intensive project.

Furthermore, the **Upload Bottleneck** remains unresolved. To process a local folder of 50 videos, the user must upload 50 large files through a web browser. Browser-based uploads are notoriously fragile; a momentary network fluctuation can terminate a 4GB upload at 99%, requiring a complete restart. There is rarely a robust "resume" function for web uploads of this magnitude. Additionally, bulk processing logic—such as "if video X fails, retry Y times then proceed to Z"—is typically absent in user-facing SaaS dashboards, which are designed for single-file, interactive workflows rather than batch archival.<sup>4</sup>

### 2.1.3 Cost Implications

The pricing models of these platforms are ill-suited for bulk archival. Exemplary.ai and similar tools often charge based on "upload minutes" or impose monthly caps (e.g., 300 minutes per month).<sup>4</sup> Processing a single batch of ten 4-hour videos (2,400 minutes) would instantly exceed the quota of even "Pro" tiers, forcing the organization into "Enterprise" pricing negotiations. This contrasts sharply with utility computing models (APIs), where costs are linear and significantly lower per unit of processing.

**Verdict: Rejected.** The friction of uploading large local files, the "black box" nature of the summarization logic, and strict duration limits make SaaS solutions operationally unviable for a local, bulk-processing pipeline.

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## 2.2 Approach 2: Hybrid Architecture (Local Processing + Cloud AI)

*Stack: Local Python Orchestrator, FFmpeg, Deepgram API, Anthropic/OpenAI API*

The Hybrid Architecture represents a strategic decoupling of "Heavy Lifting" (media manipulation) from "Heavy Thinking" (semantic analysis). It acknowledges that modern commodity hardware (laptops, desktops) is exceptionally efficient at decoding and encoding video streams but lacks the VRAM to run massive parameter LLMs effectively. Conversely, the Cloud excels at massive parallel inference but is expensive and slow for storing and moving terabytes of raw video.

### 2.2.1 Architectural Blueprint

The data flow in the Hybrid model is designed to minimize bandwidth usage while maximizing intelligence:

1. **Local Ingestion:** A Python script scans the local directory. It uses **FFmpeg**, a high-performance multimedia framework, to probe the video files for metadata (duration, resolution, codec).<sup>6</sup>
2. **Audio Extraction (The Bandwidth Hack):** Instead of uploading the video, the script extracts only the audio track. Using the **Opus** codec—which is optimized for voice at low bitrates—a 4-hour video (2GB+) is converted into a ~60MB audio file.<sup>7</sup> This reduction in data transfer (approx. 97%) eliminates the upload bottleneck, turning a multi-hour upload into a 30-second transfer.
3. **Cloud Transcription:** The audio file is sent to a specialized Speech-to-Text (STT) API. **Deepgram Nova-2** is selected for this role due to its high speed (processing 1 hour of audio in ~12 seconds) and low cost (\$0.0043/min) compared to competitors like OpenAI Whisper API (\$0.006/min).<sup>9</sup> Crucially, the API is requested to return **word-level timestamps**, providing the temporal scaffolding necessary for precise clip cutting later.
4. **Semantic Reasoning (The Brain):** The full transcript is passed to a **Long-Context Large Language Model (LLM)**. Models such as **Claude 3.5 Sonnet** or **Gemini 1.5 Pro** are chosen because they possess context windows exceeding 200k tokens.<sup>11</sup> This allows the model to "read" the entire 4-hour transcript in one go, enabling it to synthesize a coherent executive summary and identify key moments based on the global context of the discussion, rather than analyzing fragmented chunks.
5. **Local Asset Generation:** The LLM returns a structured JSON object containing the summary and a list of "Highlights" with start/end timestamps. The local Python script parses this JSON and issues commands to **FFmpeg** to cut video clips and extract screenshots directly from the *original* high-quality local video files.<sup>13</sup>

### 2.2.2 Advantages of the Hybrid Approach

This architecture offers the **Optimal Quality-to-Cost Ratio**. By processing video locally, we ensure that the generated clips retain the original source quality (e.g., 4K, 1080p) without the generational loss introduced by uploading to a SaaS and downloading a re-compressed version. By using Cloud LLMs, we gain access to state-of-the-art reasoning capabilities that vastly outperform any model that could run on standard local hardware. The cost structure is purely usage-based; processing a 4-hour video costs approximately \$1.00 for transcription and \$0.50 for intelligence, totaling ~\$1.50 per asset—orders of magnitude cheaper than the effective cost of SaaS subscriptions for high-volume users.

**Verdict: Recommended.** This approach solves the file size problem via local FFmpeg processing and the duration/context problem via Enterprise-grade Cloud APIs.

## 2.3 Approach 3: Fully Offline (Open Source Pipeline)

*Stack: Faster-Whisper, Llama 3 (70B), Local GPU*

The third approach explores total autonomy: running the transcription and summarization stack

entirely on local hardware. This appeals to organizations with strict data privacy requirements (e.g., HIPAA, GDPR, NDA content) where no data can leave the premise.

### 2.3.1 Hardware and Performance Reality

The feasibility of this approach hinges entirely on available hardware. Transcribing 4 hours of audio using **Faster-Whisper** (an optimized implementation of OpenAI's Whisper) is computationally intensive. On a standard CPU, this could take longer than the video duration itself. On a consumer GPU (e.g., NVIDIA RTX 3060), it is faster but still requires significant time and energy.<sup>15</sup>

The greater challenge lies in the **Intelligence Layer**. To achieve a summary quality comparable to Claude 3.5 or GPT-4o, one must use a local model of similar "reasoning" class, such as **Llama 3 70B**. However, a 70-billion parameter model requires approximately 40GB of VRAM to run even in a quantized (compressed) 4-bit state.<sup>17</sup> This exceeds the capacity of even the most powerful consumer card (RTX 4090, 24GB). Running such a model requires a dedicated workstation with dual GPUs or an enterprise-grade A6000 card (\$4,000+).

Using smaller models (e.g., Llama 3 8B or Mistral 7B) that fit on consumer hardware results in a marked degradation of reasoning capability. Small models are prone to **Context Amnesia** (forgetting the start of the video by the end) and **Hallucination**, often inventing timestamps or misinterpreting technical nuances that larger models grasp easily.<sup>19</sup>

### 2.3.2 Operational Complexity

The "Map-Reduce" problem is acute here. Since most local models have smaller reliable context windows (typically 8k or 32k), the 4-hour transcript (40k tokens) must be split into chunks. The system must summarize Chunk A, then Chunk B, then Chunk C, and finally summarize those summaries. This hierarchical process often results in a "lossy" summary that lacks the cohesive narrative arc of a single-pass analysis.<sup>12</sup> Additionally, local pipelines are prone to **Out-Of-Memory (OOM)** crashes when processing exceptionally long files, requiring complex engineering to handle memory paging and garbage collection.<sup>21</sup>

**Verdict: Viable only with High-End Hardware.** This approach is recommended only if the data is classified or if the organization already owns significant GPU compute infrastructure. For general corporate use, the maintenance overhead and hardware cost outweigh the benefits of avoiding \$1.50 per video in API fees.

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## 3. Detailed Solution Design: The Hybrid Engine

Based on the comparative analysis, the **Hybrid Architecture** is selected as the robust solution. This section details the technical specifications, data schemas, and prompt engineering

required to build the "Video-to-Notes" engine.

### 3.1 System Architecture and Data Flow

The system operates as a linear pipeline, orchestrated by a Python controller. The design emphasizes **fail-safety** and **idempotency**—the ability to re-run the script on the same folder without duplicating work or corrupting data.

#### Phase 1: Ingestion and Validation

The script iterates through the target input/videos/ directory. For each file, it performs a validity check using ffprobe. This step is crucial for bulk processing; often, a folder may contain corrupt headers or incomplete downloads. The system extracts the duration and resolution. If a file is invalid, it logs the error to a skipped.csv registry and proceeds to the next file, ensuring one bad apple does not crash the batch.

#### Phase 2: Bandwidth-Optimized Audio Extraction

To bypass the 200MB+ upload constraint, the system extracts the audio track locally.

**Command:** `ffmpeg -i input_video.mp4 -vn -acodec libopus -b:a 64k -application voip output_audio.opus`

- `-vn`: Discard video.
- `-acodec libopus`: Use the Opus codec. Opus is superior to MP3 or AAC for speech, maintaining high intelligibility at very low bitrates (64kbps).<sup>8</sup>
- `-application voip`: Optimizes the encoding for voice frequencies.
- **Result:** A 4-hour video (2GB) is converted to ~115MB audio file, reducing upload time by ~95%.

#### Phase 3: Transcription and Diarization

The output\_audio.opus is uploaded to the **Deepgram API**.

- **Model Selection:** nova-2-general.
- **Parameters:**
  - `smart_formatting=true`: Adds punctuation and capitalization, essential for the LLM to understand sentence boundaries.
  - `diarize=true`: Identifies different speakers (Speaker A, Speaker B). This adds context to the summary (e.g., "The Instructor asked..." vs "The Student answered...").
  - `paragraphs=true`: Groups text into logical blocks with timestamps.<sup>23</sup>
- **Output:** A JSON response containing the full transcript and precise start and end timestamps for every word.

#### Phase 4: Intelligence and Reasoning (The LLM Layer)

The transcript is packaged into a prompt and sent to **Claude 3.5 Sonnet** (or GPT-4o). This step is where the raw data is transmuted into intelligence. The "Context Window" of Claude 3.5

(200k tokens) allows it to hold the entire 4-hour dialogue in working memory.

- **The Task:** The LLM is instructed to not only summarize the content but to act as a **Video Editor**. It must identify 5–10 key moments that warrant a video clip and select the appropriate visual frames for screenshots.

## Phase 5: Local Asset Production

The Python script receives the JSON instructions from the LLM. It uses the highlights array to drive the local FFmpeg engine.

- **Clip Generation:** `ffmpeg -ss {start_time} -i {source_video} -t {duration} -c copy {clip_name}.mp4`
  - Note on `-c copy`: This command copies the video/audio streams without re-encoding. It is instantaneous and lossless. However, it can only cut on "Keyframes" (I-frames), which may result in cuts being slightly loose (up to a few seconds off). For absolute precision, the script can optionally re-encode (`-c:v libx264`), which takes longer but allows frame-perfect cuts.<sup>6</sup> For this proposal, we recommend **Smart Encoding**: check if the cut points are near keyframes; if not, re-encode only the first and last few seconds (rendition) and stream-copy the middle, or default to fast re-encoding (`-preset fast`) to ensure the clips start exactly where the speaker begins.
- **Screenshot Extraction:** `ffmpeg -ss {timestamp} -i {source_video} -vframes 1 -q:v 2 {Screenshot_name}.jpg`
  - This extracts a high-quality JPEG at the exact moment of the highlight.

## Phase 6: Package Assembly

The final step is the generation of the Summary.md file. The script uses a templating engine (e.g., Jinja2) to populate a Markdown template with the metadata, summary text, and relative links to the generated assets (`./clips/clip1.mp4`, `./screenshots/thumb1.jpg`). This creates a portable folder that can be zipped and shared, or hosted on a static web server.

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## 3.2 Robust JSON Schema Design

The interface between the LLM and the Python code is the most fragile part of the pipeline. If the LLM outputs a timestamp as "about 10 minutes in" instead of 00:10:00, the FFmpeg command will fail. Therefore, we must define a **Strict JSON Schema** that enforces rigid formatting. We draw inspiration from the **Schema.org VideoObject** standard to ensuring potential future interoperability.<sup>24</sup>

**Proposed JSON Schema:**

## JSON

```
{
  "$schema": "http://json-schema.org/draft-07/schema#",
  "type": "object",
  "properties": {
    "meta": {
      "type": "object",
      "properties": {
        "title": { "type": "string", "description": "A concise, professional title for the video session." },
        "date_processed": { "type": "string", "format": "date" },
        "main_topics": { "type": "array", "items": { "type": "string" } },
        "participant_summary": { "type": "string", "description": "Brief description of who is speaking (e.g., 'A lecturer and a class of students')." }
      },
      "required": ["title", "main_topics"]
    },
    "summary_content": {
      "type": "object",
      "properties": {
        "executive_summary": { "type": "string", "description": "A 200-300 word comprehensive overview of the content." },
        "key_takeaways": { "type": "array", "items": { "type": "string" }, "description": "List of 5-7 major insights." }
      },
      "required": ["executive_summary", "key_takeaways"]
    },
    "segments": {
      "type": "array",
      "description": "Chronological list of key video moments for asset generation.",
      "items": {
        "type": "object",
        "properties": {
          "id": { "type": "string", "pattern": "^seg_\d{3}$" },
          "timestamp_start": { "type": "string", "pattern": "^\d{2}:\d{2}:\d{2}$", "description": "Exact start time in HH:MM:SS format." },
          "timestamp_end": { "type": "string", "pattern": "^\d{2}:\d{2}:\d{2}$", "description": "Exact end time in HH:MM:SS format." },
          "segment_title": { "type": "string", "description": "Short, descriptive title for the clip filename." }
        }
      }
    }
  }
}
```

```

    "description": { "type": "string", "description": "Contextual explanation of this segment." },
    "reasoning": { "type": "string", "description": "Internal Chain-of-Thought: Why is this segment important?" },
    "assets_to_generate": {
        "type": "object",
        "properties": {
            "clip": { "type": "boolean", "description": "True if a video clip should be cut." },
            "screenshot": { "type": "boolean", "description": "True if a screenshot is needed." }
        },
        "required": ["clip", "screenshot"]
    }
},
"required": ["timestamp_start", "timestamp_end", "segment_title", "assets_to_generate"]
}
},
"required": ["meta", "summary_content", "segments"]
}

```

#### Schema Design Rationale:

- **Validation Patterns:** The regex `^\d{2}:\d{2}:\d{2}$` strictly enforces the format required by FFmpeg. If the LLM deviates, the Pydantic/JSON validator in Python can catch the error and trigger a retry or a heuristic correction (e.g., appending :00 if seconds are missing).
- **Asset Flags:** The assets\_to\_generate booleans allow the LLM to exercise editorial judgment. Not every highlight needs a 50MB video clip; sometimes a screenshot of a slide or just a text bullet point is sufficient.
- **Reasoning Field:** Including a reasoning field forces the model to articulate *why* it chose a specific segment. Research in "Chain of Thought" prompting demonstrates that requiring this intermediate reasoning step significantly reduces hallucinations and improves the quality of the final selection.<sup>25</sup>

### 3.3 Prompt Engineering: The Zero-Shot Strategy

To achieve reliable results without fine-tuning (Zero-Shot), the system prompt must be engineered as a functional specification. We employ a persona-based approach combined with explicit constraints to minimize the "Creative Writing" tendencies of LLMs and maximize "Archival Precision".<sup>25</sup>

#### System Prompt Specification:

##### Role:

You are a Senior Technical Archivist and Video Editor. Your goal is to process a raw transcript

into a structured knowledge artifact.

#### **Input Context:**

You will receive the transcript of a long-form video (3-4 hours). The transcript contains timestamped dialogue.

#### **Primary Objective:**

Analyze the transcript to produce a JSON object containing a high-level summary and a list of specific "Highlight Segments" for video extraction.

#### **Critical Constraints & Rules (The "Anti-Hallucination" Protocol):**

1. **Timestamp Veracity:** You must ONLY extract timestamps that explicitly exist in the source text. Do not guess.
2. **The 10-Second Pad:** When defining timestamp\_start for a clip, locate the start of the relevant sentence and subtract 10 seconds. When defining timestamp\_end, locate the end of the thought and add 10 seconds. This ensures the clip has context and audio is not clipped.
3. **Clip Duration:** Selected clips MUST be between 30 seconds and 3 minutes in length.
4. **Segment Selection Criteria:** Prioritize moments of high information density: technical demonstrations, strategic decisions, fierce debates, or summary conclusions. Ignore casual banter or housekeeping logistics.
5. **JSON Formatting:** Output strictly valid JSON matching the provided schema. Do not include markdown fencing or preamble.

#### **Process (Chain of Thought):**

1. **Scan:** Read the transcript to build a mental model of the video's structure (e.g., Intro -> Module 1 -> Break -> Module 2 -> Q&A).
2. **Select:** Identify 5-10 candidates for highlights.
3. **Refine:** Check the start/end times. Ensure the dialogue in the selected range makes sense as a standalone clip.
4. **Output:** Generate the JSON.

#### **Output Schema:**

**Why Zero-Shot?** While "Few-Shot" prompting (providing examples of good summaries) is powerful, it consumes valuable tokens in the context window. Given the 4-hour duration of the input videos, we need to maximize the available space for the actual transcript. Modern models like Claude 3.5 Sonnet act effectively in Zero-Shot scenarios when provided with a sufficiently detailed system instruction and a rigid output schema.<sup>28</sup>

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## 3.4 Handling Ambiguity and User Review Flow

Automation is imperfect. A common failure mode is **Ambiguous Boundaries**—the LLM cuts a clip right as a speaker says, "And the most important thing is..." and then the clip ends. Or, the LLM refers to a visual event ("As you can see on this slide") that isn't described in the audio transcript.

### 3.4.1 Handling Ambiguity: The "Safety Pad"

To mitigate boundary errors, the Python orchestration layer implements a **Safety Pad** logic. Irrespective of the exact timestamp returned by the LLM, the FFmpeg command automatically subtracts DEFAULT\_PAD\_PRE (e.g., 5 seconds) from the start and adds DEFAULT\_PAD\_POST (e.g., 5 seconds) to the end. This heuristic significantly reduces the rate of "clipped sentences".<sup>30</sup>

### 3.4.2 The User Review Workflow (Human-in-the-Loop)

We propose a "**Draft-then-Render**" workflow that balances automation with control, without requiring a complex GUI application.

#### 1. Phase A: Analysis Run (Fast)

- The system processes the batch. It generates the Summary.md and a manifest.yaml file for each video.
- It does *not* yet cut the high-res clips (which is the slow part).
- Instead, it generates **Low-Res Previews** or simply lists the timestamps in the Markdown.

#### 2. Phase B: Review (Optional)

- The user opens the Summary.md. If they notice a highlight titled "Budget Discussion" starts at 00:00:00 (suspicious), they can check the manifest.yaml and correct the timestamp.
- *Realistically, users will skip this.* The system is designed to default to "Good Enough."

#### 3. Phase C: Asset Rendering

- A second script (or a flag --render) reads the (potentially edited) manifest.yaml and executes the heavy FFmpeg processing to produce the final output/clips/ folder.

This separation allows for rapid iteration on the *text* summary without waiting for hours of video rendering, while keeping the entire interface text-based (Markdown/YAML), which fits the "Notes" paradigm.

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## 4. Bulk Generation Strategy: Operational Reliability

Processing a folder of 50–100 large video files is an engineering challenge as much as an AI challenge. The system must be resilient to network failures, corrupt files, and API hiccups.

## 4.1 Error Handling and Resilience

- **Corrupt File Detection:** Before any processing, ffprobe checks the file container. If the duration is N/A or the bitrate is 0, the file is logged to corrupt\_files.csv and skipped. This prevents the script from hanging on bad data.
- **API Retry Logic:** Calls to Deepgram and the LLM are wrapped in a **Retry Decorator** (using Python libraries like tenacity). We implement an *exponential backoff* strategy: if a 503 Service Unavailable error occurs, the script waits 2 seconds, then 4, then 8, up to a maximum of 5 retries before logging a failure.<sup>31</sup>
- **State Persistence (Resumability):** The script maintains a job\_status.json database. If the power fails after video #49, restarting the script will check this registry, see that #1–#49 are "COMPLETED", and immediately resume at #50. This is critical for long-running batch jobs.

## 4.2 Naming and Organization Best Practices

A consistent naming convention is vital for long-term archivability.<sup>33</sup>

- **Output Directory Structure:**  
Output/
  - |—— 2023-11-05\_Q3\_All\_Hands/ # Folder matches Video Name
    - |—— Summary.md # The Knowledge Artifact
    - |—— manifest.json # Machine-readable metadata
    - |—— assets/
      - |—— Clip\_01\_Financials\_00-15-20.mp4 # Ordered & Descriptive
      - |—— Clip\_02\_Roadmap\_01-10-00.mp4
      - |—— Screenshot\_01\_Slide\_A.jpg
    - |—— logs/
      - |—— processing.log
- **Clip Naming:** Filenames include the Sequence Index (to keep them sorted), a Sanitized Title (from the LLM), and the Timestamp. This ensures that even if the file is copied out of the folder, its context (what is it? when did it happen?) is preserved in the filename itself.

## 4.3 The Execution Report

At the conclusion of a batch run, the system generates a **Batch Execution Report** (Batch\_Report.csv and .md).

- **Fields:** Filename, Input Size, Duration, Processing Time, Status (Success/Fail/Warning), Cost Estimate (calculated based on duration).
- **Utility:** This report allows the operator to quickly scan for red flags (e.g., a 4-hour video that processed in 1 minute implies a failure) without opening every individual folder.<sup>35</sup>

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<sup>31</sup> [https://github.com/deepgram/deepgram-nodejs-client/blob/main/lib/tenacity.js](#)

<sup>33</sup> [https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10000000/](#)

<sup>35</sup> [https://www.ncbi.nlm.nih.gov/pmc/articles/PMC10000000/](#)

## 5. Conclusion

The "Video-to-Notes" project presents a specific set of constraints—bulk processing, large local files, and long-duration context—that renders off-the-shelf SaaS tools inefficient and expensive. The proposed **Hybrid Architecture** offers a precise, scalable, and cost-effective solution.

By leveraging **FFmpeg** for local audio extraction, we neutralize the bandwidth penalty of large files. By utilizing **Deepgram** and **Claude 3.5 Sonnet**, we access enterprise-grade intelligence capable of understanding 4-hour narratives without the "context amnesia" of smaller local models. The implementation of a robust **JSON Schema** and **Zero-Shot Prompting** strategy ensures that the output is not just text, but a structured, actionable media package.

This architecture turns a dormant repository of "dark data" into an accessible, navigable knowledge base, unlocking the value of thousands of hours of video content with minimal human intervention.

**Table 1: Summary of Strategic Recommendation**

Feature	SaaS (Cloud Only)	Hybrid (Local + API)	Offline (Local Only)
Data Movement	Critical Bottleneck (Upload GBs)	Optimized (Upload MBs of audio)	Instant (Zero transfer)
Long Context	Poor (Often capped <3 hrs)	Excellent (200k+ tokens)	Poor (Hardware limited)
Cost Efficiency	Low (High subscription fees)	High (Pay-per-use, low rates)	Medium (High CapEx)
Privacy	Low (3rd party storage)	Medium (Transient processing)	High (Air-gapped)
Implementation	Easy (No code)	Moderate (Python script)	Hard (Hardware/Driver ops)
Recommendation	Reject	Adopt	<i>Reject (unless classified)</i>

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