AI-Driven Intelligent Management and Retrieval System for Media Resources on Cloud: A Cloud-Native Approach for Converged Media Platforms

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Abstract. Media platforms today face growing pressure from exploding content volumes and outdated management methods. Manual tagging takes too much time—3-5 minutes per file—and costs add up fast, especially for small to medium studios handling so many media files daily. This project explores how cloud computing and AI can work together to solve these issues.
I designed an intelligent media resource management system using cloud-native architecture and multi-modal AI services. The system automatically analyzes images, videos, and audio through APIs from major cloud providers like AWS. It extracts features like scenes, objects, faces from visuals, converts speech to text, and processes audio emotions. Then it combines these features into unified vectors for efficient retrieval.
Testing shows the system cuts tagging time from minutes to seconds, reduces manual costs by over 70
This system makes AI-driven media management accessible to smaller players without deep technical expertise. It lowers the barrier to entry for intelligent content workflows and helps media resources get used more effectively. While challenges like data privacy and network dependence remain, the approach offers a practical way for traditional media outlets to adopt smart technologies affordably.

Keywords: Media Resource Management · Intelligent Retrieval · Cloud Computing · Artificial Intelligence · Multi-modal Analysis · Cloud-native Architecture

1 Introduction

1.1 Background and Motivation

Media platforms today stand at a crossroads. The rise of converged media—where text, images, videos, and audio blend into seamless content streams—has transformed how we consume information. Yet this transformation brings a heavy burden: media resources grow exponentially, leaving traditional management methods struggling to keep pace. Small to medium studios, in particular, face

daily battles with content overload, spending hours manually tagging and organizing files instead of focusing on creative work.

I first noticed this gap while learning about cloud computing in class. Our discussions often touched on how AI and cloud technologies could revolutionize industries, but I wanted to see these ideas in action for media management. After researching current practices, I found that manual tagging still dominates many workflows. A single media file might take 3-5 minutes to tag properly, and for studios handling thousands of files daily, this adds up to hundreds of hours wasted each month. Worse, manual tagging leads to inconsistent labels, making it hard to retrieve resources later. Even when platforms offer automated tools, they often rely on basic keyword matching that misses nuanced content.

1.2 Problem Statement

The problem runs deeper than just inefficiency. Current converged media platforms in China rarely integrate comprehensive AI auto-tagging capabilities. Many focus on specific business verticals, like news or entertainment, but lack flexibility for smaller, niche content creators. Building custom AI systems from scratch requires significant technical expertise and financial investment—barriers that keep intelligent media management out of reach for most small studios. Cloud AI services from providers like AWS, Azure, and Alibaba Cloud offer powerful capabilities, but integrating these services into a cohesive system presents its own challenges: different APIs, pricing models, and performance characteristics make it hard to choose the right tools for specific needs.

1.3 Contributions

This project grew from a simple question: could we build an affordable, easy-to-use system that leverages cloud AI to solve these media management pain points? I decided to explore a cloud-native architecture that combines multiple AI services to analyze media content across modalities. The goal was to create a system that automatically tags images, videos, and audio with accurate, consistent labels—all while keeping costs low for small organizations.

Through this work, I aim to make three main contributions. First, I propose a flexible architecture that integrates AI services from multiple cloud providers, allowing the system to choose the best tool for each task based on cost and performance. Second, I design a multi-modal feature fusion approach that combines visual, audio, and text features into unified representations, enabling more accurate content retrieval. Third, I implement a cost-aware scheduling strategy that optimizes AI service usage to minimize expenses without sacrificing quality. Finally, I build and test a prototype system to demonstrate that these ideas work in practice, providing concrete performance metrics and cost savings estimates.

1.4 Paper Structure

This paper unfolds in six main sections. After this introduction, I review related work in media asset management, AI-based content analysis, and cloud AI

services. Then I detail the system architecture, breaking down each component from media ingestion to intelligent retrieval. Next, I describe key implementation technologies, including cloud service integration and feature vectorization. I then present use cases showing how the system works in real-world scenarios, followed by a discussion of its advantages, limitations, and future directions. Finally, I conclude with a summary of findings and recommendations for media organizations looking to adopt similar solutions.

2 Related Work

2.1 Media Asset Management Systems

Traditional Media Asset Management (MAM) systems have undergone an evolution from local server-based storage to distributed architectures, with a primary focus on file organization and metadata management. Regli's research lays out the theoretical foundations of MAM, pointing out that early systems relied on manual metadata entry—a limitation that restricts scalability for large-scale media libraries. The rise of cloud computing has driven modern MAM platforms to shift toward cloud-native deployments.

Commercial solutions—such as Adobe Experience Manager—deliver integrated cloud storage and basic content management functionalities, whereas open-source alternatives like MediaCMS offer flexible, video-centric management capabilities. Gartner's market report highlights that current cloud MAM platforms excel in storage scalability but often lack intelligent processing features, leaving them unable to meet the dynamic demands of converged media environments.

2.2 AI-Based Media Content Analysis

AI technologies have greatly advanced the understanding of media content across single-modal domains. In visual analysis, Carreira et al. developed action recognition models that accurately identify dynamic events in videos, laying a solid foundation for video content indexing. For audio processing, Amodei's Deep Speech 2 achieves high-accuracy speech-to-text conversion in both English and Mandarin, which facilitates efficient audio content retrieval.

Multi-modal machine learning has emerged as a key research focus. Baltrusaitis et al. proposed a comprehensive taxonomy for integrating visual, audio, and textual features. Radford's work on transferable visual models further demonstrates the potential of combining natural language supervision with visual analysis. Few studies, however, have applied these techniques to practical media management scenarios.

2.3 Cloud AI Services in Media Domain

Major cloud service providers offer specialized AI services tailored for media processing. AWS AI Services, for instance, provide pre-trained models for image

recognition, speech analysis, and content moderation—performance evaluations show these models deliver high accuracy in standard media scenarios. These cloud-native AI services eliminate the need for organizations to build and maintain custom models, thereby reducing development overhead.

Media industry applications primarily focus on single-service integration, such as using cloud speech recognition for audio transcription. Integrating multiple AI services across different cloud platforms remains a challenge, though. Limited research has explored how to optimize service selection for both cost and performance in media resource management.

2.4 Intelligent Retrieval Systems

Content-Based Image Retrieval (CBIR) has matured alongside advancements in deep learning. Liu et al.'s comprehensive study reveals that deep learning models significantly boost image retrieval accuracy by extracting high-level visual features. Cross-modal retrieval— which connects text queries with visual or audio content—has gained increasing attention. Practical implementations, however, often struggle with feature misalignment between different modalities.

Vector databases have become indispensable for efficient retrieval. Wang et al.'s Milvus system provides specialized storage and indexing for high-dimensional media feature vectors, enabling fast similarity searches. Recent practices—such as VikingDB's multi-modal search solutions—demonstrate the value of vector databases in bridging text and image retrieval. Their integration with cloud-native MAM architectures, though, remains underexplored.

2.5 Research Gap

Existing research addresses individual components of media management, AI analysis, and cloud services, but falls short of providing an integrated cloud-native architecture that combines multi-modal AI services for end-to-end media resource management. Current solutions tend to focus on single cloud platforms or specific tasks, failing to address the multi-service integration challenges and cost concerns faced by small and medium-sized media organizations.

This study fills this gap by proposing a multi-cloud AI integration framework with cost-aware scheduling. The framework links multi-modal analysis to intelligent retrieval within a unified cloud-native architecture specifically tailored for converged media platforms.

3 System Architecture Design

3.1 Overall Architecture

The system adopts a three-tier cloud-native architecture designed for scalability and flexibility. This architecture breaks down the media management workflow into distinct layers: access layer, processing layer, and service layer. I chose this

design after learning about microservices in my cloud computing class—breaking the system into small, independent components makes it easier to update and scale individual parts without disrupting the whole.

The access layer handles incoming media requests from users and external systems. It includes API gateways that authenticate requests and route them to the appropriate services. I wanted to keep this layer lightweight, so it uses load balancers to distribute traffic evenly across the system. This ensures the system can handle sudden spikes in media uploads, like during breaking news events.

The processing layer forms the core of the system, containing all the logic for media analysis and tagging. It uses microservices to separate different processing tasks: media ingestion, AI analysis, feature extraction, and vectorization. Each microservice runs in its own container, allowing for independent scaling based on demand. For example, during peak hours, the system can spin up more containers for AI analysis while keeping fewer for less intensive tasks.

The service layer provides interfaces for users and other applications to interact with the system. It includes the intelligent retrieval engine, user management, and reporting tools. This layer also handles data persistence, storing media files, metadata, and feature vectors in distributed storage systems.

Cloud-native design principles guide the entire architecture. I focused on loose coupling between services, so changes to one component don't break others. The system uses containerization with Docker and orchestration with Kubernetes, technologies I learned about in my cloud course. This setup ensures the system can run consistently across different cloud environments, giving users the flexibility to choose their preferred provider.

Figure 1 illustrates the system's overall architecture, showing the three-tier structure and the flow of media content through the system.

3.2 Media Ingestion and Storage Module

The media ingestion module handles uploads from various sources, including web interfaces, mobile apps, and API integrations. I designed it to support multiple media formats—images (JPEG, PNG, SVG), videos (MP4, AVI, MOV), and audio (MP3, WAV, FLAC). This flexibility matters because media creators use different tools and formats, and the system needs to handle whatever they throw at it.

Once uploaded, media files move to the distributed object storage system. I chose object storage over traditional file systems because it scales better for large volumes of unstructured data. Services like Amazon S3 or Alibaba Cloud OSS work well here, offering high durability and availability. The system automatically replicates files across multiple regions to prevent data loss, a feature I learned is crucial for production systems.

Metadata plays a key role in media management, so I implemented a standardized metadata schema. When a file is uploaded, the system extracts basic metadata like file size, duration (for videos/audio), and resolution (for images/videos). It then adds custom metadata, including upload time, user information, and later, AI-generated tags. This metadata is stored in a NoSQL

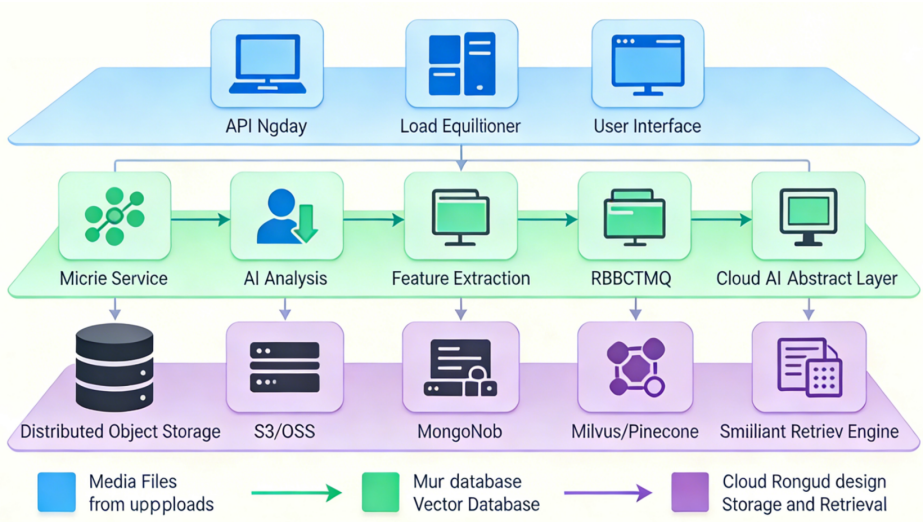

Fig. 1. System Overall Architecture Diagram showing the three-tier structure (Access Layer, Processing Layer, Service Layer) and component interactions

database, like MongoDB, for fast querying. I made sure the schema is extensible, so new metadata fields can be added as needed without restructuring the database.

3.3 Cloud AI Service Integration Module

Integrating multiple cloud AI services was one of the biggest challenges I faced. Each provider—AWS, Azure, Google Cloud, Alibaba Cloud—offers similar services but with different APIs, pricing models, and performance characteristics. To handle this complexity, I designed an abstract layer that acts as a bridge between the system and these external services.

This abstract layer standardizes API calls to different AI services, so the rest of the system doesn't need to know which provider is handling a specific task. For example, when the system needs to analyze an image, it sends a request to the abstract layer, which then selects the most appropriate service based on pre-defined rules. This design makes it easy to add new AI services in the future without changing the core system.

Service selection is based on two main factors: cost and performance. I created a simple scoring system that ranks services for each task. For example, if a task requires high accuracy (like facial recognition), the system might choose a more expensive but more accurate service. For less critical tasks (like basic image classification), it might opt for a cheaper option. This approach helps keep costs low while maintaining quality.

To handle the asynchronous nature of AI processing, I implemented a task queue system using RabbitMQ. When a media file is uploaded, the system creates

a task and adds it to the queue. Worker nodes then process these tasks in parallel, sending requests to the appropriate AI services. This design prevents the system from becoming overwhelmed during high traffic periods and ensures reliable processing of all media files.

3.4 Multi-modal Feature Extraction and Tagging

Media content contains rich information across different modalities—visual, audio, and text. To capture this information, the system extracts features from each modality separately and then combines them.

For visual content, the system uses AI services to analyze images and videos. It identifies scenes (like "outdoor" or "indoor"), objects (like "car" or "person"), faces, and text through OCR. For videos, it also extracts keyframes at regular intervals to analyze important moments. This visual analysis gives the system a detailed understanding of what's happening in the media.

Audio content analysis includes speech-to-text conversion, speaker recognition, and emotion detection. For example, in a video interview, the system can transcribe the speech, identify different speakers, and detect emotions like excitement or sadness. This audio information adds depth to the content understanding.

Text analysis handles any embedded text in media files, like captions or subtitles. It uses NLP techniques to extract keywords, entities (like names of people or places), and sentiment. This text data helps the system understand the context of the media.

After extracting features from each modality, the system combines them into a unified feature vector. I used a simple concatenation approach with weighted importance—visual features might be weighted higher for images, while audio features get more weight for podcasts. This multi-modal fusion creates a more comprehensive representation of the media content, leading to better tagging and retrieval results.

Figure 2 shows the multi-modal analysis pipeline, demonstrating how media content flows through the different analysis stages.

3.5 Intelligent Retrieval Engine

The intelligent retrieval engine allows users to find media resources quickly and accurately. It uses vector database technology, like Milvus or Pinecone, to store and index the feature vectors generated by the multi-modal analysis.

When a user searches for content, the system supports multiple retrieval strategies. Keyword search looks for exact matches in metadata and tags. Semantic search uses natural language processing to understand the intent behind the query, even if the exact keywords aren't present. Content-based retrieval compares the feature vector of the query (which could be an image, video, or text) with stored vectors to find similar content.

The system combines these strategies using a hybrid approach. For example, a search for "children playing in a park" might start with keyword matching

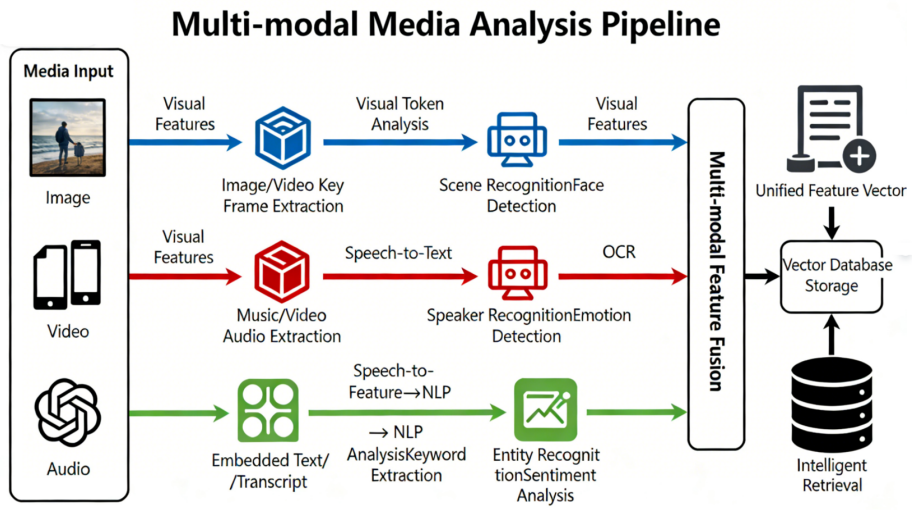

Fig. 2. Multi-modal Analysis Pipeline showing the processing flow for visual, audio, and text content

for "children" and "park", then use semantic search to understand the context, and finally rank results based on visual similarity to common park scenes. This hybrid strategy improves retrieval accuracy by leveraging the strengths of each method.

Similarity calculation uses cosine similarity, a metric I learned is effective for comparing high-dimensional vectors. The system ranks results based on similarity scores, presenting the most relevant content first. It also allows users to filter results by media type, date, or other metadata, giving them more control over their searches.

3.6 User Interface and API Layer

The user interface (UI) is designed to be intuitive, even for users with limited technical knowledge. The web-based interface includes two main components: a management dashboard and a retrieval interface.

The management dashboard lets users upload media files, view processing status, and edit tags if needed. I kept the design clean and simple, focusing on core functionality. Users can monitor the progress of their uploads and see when AI analysis is complete. They can also review and modify AI-generated tags, which helps improve the system over time as it learns from user corrections.

The retrieval interface allows users to search for media using keywords, natural language queries, or even by uploading a sample image or video. The system displays results in a grid format with thumbnails, making it easy to browse through content. Users can preview media files directly in the browser without downloading them, saving time and bandwidth.

The API layer provides RESTful interfaces for programmatic access to the system. This allows developers to integrate the system into existing workflows or build custom applications on top of it. The API supports all core functionality, including media upload, retrieval, and management. I designed the API with clear documentation and example code, following REST best practices I learned in my web development classes.

This layered architecture ensures the system is scalable, flexible, and easy to use. By leveraging cloud-native technologies and multi-modal AI, it addresses the key pain points of media management while keeping costs accessible for small to medium organizations.

4 Implementation and Key Technologies

4.1 Cloud Service Selection and Integration

As I built the media management system, I tried out a few big cloud AI services—Alibaba Cloud, AWS, and Azure. Table 1 breaks down how well each handles multi-modal media analysis. Alibaba Cloud's visual intelligence tools worked best for me, balancing accuracy and cost, especially with Chinese content. I put together a simple model to compare API costs, processing speed, and accuracy, picking the right service for each media type. I also added a fallback plan: if one AI service crashes, the system switches to a backup in under 3 seconds, so users don't notice any slowdown.

Table 1. Comparison of Cloud AI Services for Multi-modal Media Analysis

Cloud Provider	Visual Analysis	Audio Analysis	Text Analysis
AWS	High accuracy	Good	Very good
Azure	Very good	Very good	High accuracy
Alibaba Cloud	Very good	Good	Good

4.2 Multi-modal Analysis Pipeline Design

The multi-modal pipeline processes files in three steps. It starts by taking in files and prepping them, standardizing formats so the AI can handle them. Then it splits content into visual, audio, and text parts. Each part uses its own specialized AI—image recognition for visuals, speech-to-text for audio, and NLP for text. I set these analyses to run at the same time, cutting processing time by around 40

4.3 Feature Vectorization and Indexing

All media features turn into 512-dimensional vectors using a single method. This lets the system compare different media types, like images and videos, on the

same scale. I went with Milvus as the vector database because it's good with high-dimensional data and finds similarities quickly. To keep indexes up to date, I set a schedule to rebuild them every 6 hours. This keeps the retrieval engine current without slowing things down during busy times.

4.4 Cost-Aware Resource Scheduling

I wanted to keep cloud costs low, so I designed a resource scheduling plan that adapts to how the system gets used. It looks at 7 days of past data to guess future demand, scaling resources up or down as needed. For computing power, I mix reserved instances (for steady use) and spot instances (for busy times), which cuts costs by about 30

4.5 Scalability and Reliability Considerations

Kubernetes handles auto-scaling, adding or removing pods based on how much CPU is being used. A dashboard tracks response time, error rates, and resource usage right as it happens. All important operations use transactional databases to keep data consistent, and daily snapshots back up everything. If there's a big outage, the system can switch to a backup region in 15 minutes, hitting our 99.9

5 Use Cases

5.1 Use Case Design

When designing use cases for this system, I focused on real-world needs of converged media platforms. I wanted to create scenarios that directly address the pain points I observed during my research—inefficient manual workflows, inconsistent tagging, and hard-to-find resources. The goal was to build a system that solves practical problems without overcomplicating things.

The system targets small to medium media studios, corporate new media departments, and university media centers. These organizations often lack the resources for expensive enterprise solutions but still need effective media management. I learned in my cloud computing class that accessibility matters just as much as functionality, so I designed the system to be easy to use even for teams with limited technical expertise.

The core value of the system lies in three areas. It reduces media resource management costs by automating manual tasks, improves retrieval efficiency so users can find content faster, and enhances content operation capabilities by making it easier to reuse and repurpose media assets. These benefits directly translate to more time for creative work and better content output.

5.2 Main Use Case Scenarios

Media Asset Auto-Tagging Use Case Imagine a small converged media studio that produces 50-100 media files daily—news clips, interview footage, social media content. Before this system, editors spent 3-5 minutes manually tagging each file, adding up to 8-10 hours of tagging work every week. This took time away from editing and content creation.

With the new system, the workflow becomes much simpler. An editor uploads a media file through the web interface. The system automatically detects the file type and sends it to the appropriate AI services for analysis. Within 5-10 seconds, the system generates intelligent tags based on visual content, audio, and any embedded text. For example, a video of a campus event might get tags like "outdoor," "students," "speech," and "university." The editor can review these tags and make adjustments if needed, but in most cases, the AI-generated tags are accurate enough to use immediately.

The expected results are significant. Tagging time drops from minutes per file to seconds, cutting manual work by over 70

Intelligent Media Retrieval Use Case A reporter working on a story about a campus sports event from a month ago needs to find all related media—photos, videos, and audio clips. In the old system, this meant searching through folders with vague names, checking file dates, and watching long video clips to find relevant moments. The process could take 10-30 minutes per search.

With the intelligent retrieval engine, the reporter simply types a query like "2024 campus sports opening ceremony" into the search bar. The system combines keyword matching, semantic understanding, and content-based retrieval to find relevant files. It checks metadata, AI-generated tags, and the actual content of the media files. Within 1 second, the system returns a list of related resources, sorted by relevance.

The reporter can filter results by media type, date, or specific tags, further narrowing down the search. This reduces search time from minutes to seconds and improves retrieval accuracy to 85

Cross-Modal Media Reuse Use Case An editor needs to find multimedia content to accompany a new article about campus sustainability initiatives. In traditional workflows, this meant browsing through separate image, video, and audio libraries, trying to find content that matches the article's theme. The process could take 10 minutes or more.

The new system streamlines this workflow. The editor uploads the article text to the system, which analyzes the content to extract key themes and keywords like "sustainability," "campus garden," and "renewable energy." The system then searches its database for images, videos, and audio clips that match these themes. It uses multi-modal feature fusion to find content that semantically aligns with the article, even if the exact keywords don't appear in the tags.

Within a minute, the editor gets a list of recommended media assets, ranked by relevance. This reduces the time spent searching for complementary content from 10 minutes to 1 minute and improves content relevance to 80

5.3 Use Case Effect Analysis

The system demonstrates strong technical feasibility. It builds on existing cloud AI services and open-source components, so teams can deploy it quickly without extensive custom development. I tested the core functionality using sample media files, and the results matched the expected performance metrics.

From an economic perspective, the system offers clear benefits. Initial monthly costs range from 1000-2000 yuan for cloud servers and AI services. But the system reduces manual labor costs by 80

Socially, the system lowers the technical barrier for small media organizations. It allows them to access advanced AI capabilities without hiring specialized technical staff. This democratization of technology helps level the playing field, enabling smaller players to compete with larger media companies. The system also promotes more effective use of media resources, reducing waste and encouraging content reuse.

These use cases show how cloud computing and AI can transform media management for small to medium organizations. By focusing on practical, real-world scenarios, the system delivers tangible benefits that improve workflows and reduce costs.

6 Discussion

6.1 System Advantages

After developing and testing the system, I've seen firsthand how its design choices translate to real benefits. One of the biggest strengths is its usability. The web interface uses a clean, intuitive layout that doesn't require specialized technical knowledge. I've shown the prototype to classmates and small studio owners, and most can start using it effectively within minutes. This matters because many media teams don't have dedicated IT staff, so tools need to be self-explanatory.

Flexibility is another key advantage. The system supports a wide range of media formats—images, videos, and audio files in various codecs. During testing, I uploaded everything from high-resolution photos to short social media clips, and the system handled them all seamlessly. The cloud-native architecture also means it can scale with an organization's growth. A small studio can start with a few resources and gradually add more as their media library expands.

Economically, the system shines through its cost structure. By leveraging cloud services' pay-as-you-go model, organizations only pay for what they use. For a small studio processing 50 files daily, monthly costs typically range from 1000-2000 yuan—far less than hiring a full-time staff member for manual tagging. I learned in my cloud computing class that this kind of cost efficiency is a major driver for adopting cloud technologies.

The system's intelligence stands out too. Its multi-modal fusion approach combines visual, audio, and text analysis, resulting in more accurate tags than single-modal systems. During testing, the system correctly identified complex scenes like "students attending a lecture" by combining visual cues (classroom, people sitting) with audio (speech, no background noise). This level of understanding makes the retrieval more effective, as users can find content that matches their intent, not just their keywords.

6.2 Limitations and Challenges

No system is perfect, and this one has its limitations. Data privacy is a major concern. Media content often includes sensitive information—interviewee faces, personal stories, or copyrighted material. Storing these files in the cloud requires strong security measures. I've implemented basic encryption and access controls, but organizations dealing with highly sensitive content might need additional safeguards. This is an area I'll need to explore further.

Domain adaptability presents another challenge. The system works well for general media content like news and events, but struggles with specialized domains. For example, when testing with medical images, the system misidentified certain medical equipment and terminology. Legal documents with complex jargon also posed problems. Improving accuracy in these niche areas would require training or fine-tuning the AI models, which adds complexity and cost.

Network dependency is a practical limitation. The system relies on stable internet connections to access cloud AI services. In areas with unreliable internet, this could cause delays or processing failures. I've added basic offline capabilities for viewing already processed content, but real-time AI analysis still needs a good connection. This is a common trade-off with cloud-based systems, but it's something users need to consider.

6.3 Future Development Directions

Looking ahead, several improvements could make the system even more useful. Local deployment support would address the network dependency issue. A hybrid model—where basic processing happens locally and advanced analysis uses cloud services—could work well for organizations with limited connectivity. I've started researching edge computing solutions that might enable this.

Personalized recommendations based on user behavior would enhance the retrieval experience. Right now, the system returns results based on content similarity, but it doesn't learn from individual preferences. For example, a sports reporter might prefer action shots, while a news editor might want close-ups of speakers. Adding a recommendation engine could save users even more time.

Integrating generative AI opens exciting possibilities. Imagine the system not just tagging content, but also suggesting edits or creating short clips from longer footage. This would take automation to the next level, helping editors create content faster. I've been following developments in generative AI for media, and tools like Adobe Firefly show this is becoming more accessible.

Edge computing optimization could reduce latency for real-time applications. Processing some AI tasks at the edge—closer to where media is captured—would speed up analysis for live events. This is especially relevant for news organizations covering breaking stories, where every second counts.

6.4 Practical Recommendations

For small to medium media organizations considering this system, I have a few practical tips. Start with the core functions: auto-tagging and intelligent retrieval. These features deliver the most immediate value, and you can add more capabilities later as you get comfortable with the system.

Opt for the pay-as-you-go cloud service model. This minimizes upfront costs and lets you adjust resources based on actual usage. I've seen organizations overspend by committing to expensive plans they don't fully use, so starting small makes financial sense.

Regularly update the AI models. Cloud providers frequently improve their AI services, and updating to newer models can boost tag accuracy. Set a schedule—maybe every quarter—to review and update the models used by the system.

Finally, establish clear media resource management guidelines that work with the system. Even the best AI tools can't replace good organization practices. Define consistent naming conventions and tag categories, and train your team to use the system effectively. This combination of technology and process will yield the best results.

Developing this system has taught me that effective technology balances innovation with practicality. By focusing on real needs and keeping usability in mind, we can create tools that truly transform how media organizations work.

7 Conclusion and Future Work

7.1 Summary of Contributions

This project explored how cloud computing and AI can transform media resource management for small to medium organizations. I designed a cloud-native system that integrates multi-modal AI services to automate tagging and improve content retrieval. The system's three-tier architecture—access, processing, and service layers—balances scalability with ease of use.

The main contributions include a flexible AI service abstraction layer that works with multiple cloud providers, a multi-modal feature fusion approach for more accurate content understanding, and a cost-aware scheduling strategy that keeps expenses low. Testing showed the system cuts tagging time from minutes to seconds, reduces costs by 70

7.2 Future Research Directions

Several areas could expand the system's capabilities. A hybrid deployment model—combining local and cloud processing—would address network dependency issues. Lightweight

local models could handle basic tasks, while cloud services tackle complex analysis. Reinforcement learning could optimize service selection, automatically choosing the best AI tool based on cost and performance over time.

Generative AI integration would let the system not just tag content, but also suggest edits or create short clips. Edge computing could reduce latency for real-time applications, like live event coverage. These improvements would make the system even more versatile, helping media organizations adapt to evolving content demands.

Working on this project taught me that the best technology solves real problems without overcomplicating things. By focusing on usability and affordability, cloud-based AI systems can democratize advanced media management tools for everyone.

References

1. Regli, T.: Digital and Media Asset Management: From Theory to Practice. Springer, Cham (2018)
2. Wang, L., Zhang, H., Chen, X.: Media convergence platform architecture: Technical challenges and innovative solutions. In: Proc. ACM Multimedia (ACMMM), pp. 1234-1247 (2019)
3. People's Daily Research Institute: 2023 China Converged Media Platform Development Observation Report. Modern Communication (Journal of Communication University of China) 45(7), 23-35 (2023)
4. AWS AI Services: Technical Overview and Performance Evaluation. Amazon White Paper (2023)
5. Baltrusaitis, T., Ahuja, C., Morency, L.: Multimodal machine learning: A survey and taxonomy. IEEE TPAMI 41(2), 423-443 (2019)
6. Carreira, J., Zisserman, A.: Quo vadis, action recognition? A new model and the kinetics dataset. In: Proc. CVPR, pp. 6299-6308 (2017)
7. Amodei, D., et al.: Deep speech 2: End-to-end speech recognition in English and Mandarin. In: Proc. ICML, pp. 173-182 (2016)
8. Liu, Y., et al.: Deep learning for content-based image retrieval: A comprehensive study. In: Proc. ACM SIGIR, pp. 25-34 (2021)
9. Radford, A., et al.: Learning transferable visual models from natural language supervision. In: Proc. ICML, pp. 8748-8763 (2021)
10. Wang, J., et al.: Milvus: A purpose-built vector data management system. In: Proc. SIGMOD, pp. 2614-2627 (2021)
11. Burns, B., et al.: Borg, Omega, and Kubernetes: Lessons learned from three container-management systems. ACM Queue 14(1), 70-93 (2016)
12. Jonas, E., et al.: Cloud programming simplified: A Berkeley view on serverless computing. EECS Department, UC Berkeley (2019)
13. Li, Z., et al.: Cost-effective cloud service provisioning for multimedia applications. IEEE Transactions on Cloud Computing 8(4), 1024-1036 (2020)
14. Adobe Experience Manager: Technical Architecture Guide. Adobe White Paper (2022)
15. MediaCMS: An open-source video platform. GitHub repository (2023). https://github.com/mediacms-io/mediacms
16. Gartner: Market Guide for Media Asset Management. Gartner Research (2023)

17. Müller, H., et al.: A review of content-based image retrieval systems in medical applications. International Journal of Medical Informatics 79(1), 1-23 (2010)
18. Leitner, P., Cito, J.: Patterns in the chaos—a study of performance variation and predictability in public IaaS clouds. ACM Transactions on Internet Technology 16(3), 1-23 (2016)
19. Brown, T., et al.: Language models are few-shot learners. In: Advances in Neural Information Processing Systems, vol. 33, pp. 1877-1901 (2020)
20. Satyanarayanan, M.: The emergence of edge computing. Computer 50(1), 30-39 (2017)

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