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Content Based Video Retrival System using RESNET-50

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Abstract

With the rapid increase in user-generated content and digital media, there is a growing need for intelligent systems that can understand and retrieve relevant video data based on both visual and textual queries. Traditional content-based video retrieval methods are often limited in handling complex semantic relationships and user intent. In this work, we propose a hybrid multimodal video retrieval framework that leverages deep learning techniques to bridge this gap. Our system combines visual feature extraction using a fine-tuned ResNet-50 model and semantic text embeddings derived from large language models like GPT-4 to enable more meaningful video classification and retrieval. To prepare the data, videos are preprocesses by extracting keyframes at regular intervals, resizing and normalizing them for uniform input, and storing them as tensors for efficient access. The classification model is trained and evaluated on the AID (Aerial Image Dataset), which offers diverse land-use categories, making it ideal for testing semantic understanding in complex scenes. Once labelled, videos are indexed using both visual and textual representations to support flexible and context-aware retrieval.Initial results show promising performance in recognizing high-level video concepts and returning contextually relevant content based on natural language prompts. This research showcases the potential of combining visual deep networks with language models to build intelligent, scalable video search systems suited for modern content platforms. Future work will focus on integrating personalization and real-time querying for broader applicability.

Keywords: Multimodal Retrieval, Resnet-50, GPT-4, Video Classification, Semantic Search, Deep Learning, Aerial Image Dataset

INTRODUCTION

The explosive growth of digital video content across platforms like YouTube, social media, surveillance systems, and remote sensing technologies has created a pressing need for smarter systems capable of understanding and retrieving relevant video segments. Traditional video retrieval approaches depend largely on metadata or simple visual features, which often fall short in capturing the true meaning of video content, especially when dealing with abstract or complex semantics [1].

This challenge has paved the way for deep learning-driven solutions that can understand both the visual scenes and associated text in a video. Our research addresses this by proposing a **hybrid multimodal video retrieval system** that uses both computer vision and natural language processing. For the visual modality, we employ **ResNet-50**, a convolutional neural network known for its high performance in visual

recognition tasks [2]. By extracting keyframes from videos and processing them through ResNet-50, we are able to convert raw video into meaningful feature vectors. These vectors help in identifying the visual context of the query.

To handle the textual aspect, we incorporate transformer-based models like **GPT-4**, which are well known for their ability to understand complex natural language queries. These models can analyze video descriptions, captions, or transcripts, bridging the gap between what the user asks and what the video actually contains [3].

We validated our approach using the **AID dataset**, which contains over 10,000 aerial scene images spread across 30 different land-use categories. This dataset is useful not only for training our visual model but also for testing the robustness of multimodal retrieval in diverse real-world scenarios [4]. To preprocess these images, we resized them to 224×224 pixels and normalized them to match the input expected by the ResNet model.

Our system demonstrates superior performance in retrieving semantically accurate video content by combining visual frame analysis and textual query understanding. It can retrieve video scenes that match both visual features and underlying meanings, which is especially valuable in applications like surveillance footage review, educational video indexing, and smart content recommendation.

Ultimately, this project aims to contribute to the evolution of intelligent video search by enhancing retrieval precision, query understanding, and system usability, making content navigation significantly more efficient for end-users.

LITERATURE SURVEY

Multimodal video retrieval systems have seen rapid advancement due to the fusion of computer vision, natural language processing, and representation learning. These systems aim to bridge the semantic gap between video content and user queries expressed in natural language by aligning visual and textual modalities in a shared embedding space.

Radford et al. introduced CLIP (Contrastive Language–Image Pretraining), a powerful multimodal model trained on 400 million image–text pairs [1]. CLIP jointly learns visual and textual representations, allowing it to perform zero-shot classification and retrieval across a wide variety of tasks. Its transformer-based ViT architecture set a new standard for visual understanding through language supervision.

Expanding CLIP to the video domain, Miech et al. developed MIL-NCE, a contrastive learning framework trained on the HowTo100M dataset [2]. MIL-NCE aligns narration subtitles with video segments by maximizing mutual information, offering significant improvements in instructional video retrieval.

Bain et al. proposed *Frozen in Time*, a dual-encoder model that processes sparsely sampled video frames and textual input without task-specific fine-tuning [3]. Despite being “frozen” (non-trainable) after pretraining, the model showed strong performance, emphasizing the strength of general-purpose pretrained multimodal models.

To handle modality-specific noise and improve robustness, VATT (Video-Audio-Text Transformer) was introduced by Akbari et al. [4]. It employs separate transformer encoders for each modality and uses contrastive loss to bring aligned pairs closer in the embedding space. This unified approach demonstrates improved performance on multiple benchmarks without requiring task-specific tuning.

Gabeur et al. developed the Multi-Modal Transformer (MMT) that utilizes temporal attention across multiple modalities (appearance, motion, audio) and combines them with sentence-level queries using cross-attention mechanisms [5]. The use of positional encoding and residual connections helped capture

temporal dependencies effectively.

In the context of visual feature extraction, ResNet-50 remains a highly preferred CNN backbone. Introduced by He et al. [6], its residual connections allow for training deeper networks without degradation, making it ideal for extracting rich spatial features from video frames, especially when temporal aggregation methods (e.g., mean pooling or LSTMs) are applied.

On the language side, large-scale transformer models like GPT-4 provide semantic richness in interpreting natural language queries [7]. Its ability to capture syntactic structure, contextual dependencies, and abstract meanings enables the retrieval system to better match queries with video content even when literal keywords are missing.

Liu et al. tackled the cold-start problem in retrieval by introducing a hybrid model that combines deep embeddings with personalized user feedback loops [8]. Their method adjusts similarity scores over time based on implicit feedback, improving the long-term effectiveness of the system.

Dual-encoder models such as VideoCLIP [9] use pretrained visual encoders (e.g., S3D or ViT) and language encoders (e.g., BERT) to map video and text to a common space. These models typically require fine-tuning with video-text pairs to achieve high retrieval performance.

Another important contribution is FiT (Frozen Image Transformer) [10], where the authors train vision-language models using web-scale data and apply them to video retrieval by averaging frame-wise features. Although originally designed for images, FiT demonstrated surprising generalization when applied to video benchmarks.

Yang et al. explored hierarchical pooling methods to aggregate frame-level features across time [11]. Their proposed approach, called Hierarchical Memory Network, stores short- and long-term video context to better align with long-form queries.

To handle open-domain video queries, Singh et al. designed a cross-modal transformer (XMT) [12] that builds attention-weighted relationships between words and video scenes. This model excels in understanding high-level semantics, such as actions and events, even when explicit labels are unavailable.

Late fusion techniques are often used to combine outputs from multiple modalities, especially in real-time systems. For example, Suri et al. [13] proposed combining audio, frame, and text embeddings through weighted score fusion for robust retrieval, which is particularly useful in noisy environments or low-resource settings.

Despite these advancements, many models struggle with generalization due to dataset bias. Works like Hessel et al. [14] emphasize the need for diverse, uncurated, and real-world datasets to avoid overfitting and ensure real applicability in production-level retrieval engines.

PROPOSED METHODS

The proposed system is a hybrid multimodal video retrieval architecture that integrates visual and textual processing to enable context-aware search and discovery of video content. The system is designed to handle a growing repository of user-uploaded videos by analyzing visual content using deep convolutional neural networks and interpreting textual queries through large language models. These parallel modalities are bridged using a shared embedding space, ensuring accurate and semantically meaningful retrieval. The complete workflow involves video classification, metadata generation, natural language query processing, vector space embedding matching, and final video retrieval.

A. Video Upload and Classification

The system begins with a user uploading a video file through the front-end interface. Upon receiving the

video, a frame sampling technique is applied to extract representative frames at regular intervals, ensuring a compact yet meaningful visual summary of the content. These sampled frames are then fed into a pre-trained **ResNet-50 (Residual Neural Network with 50 layers)** model, a powerful deep convolutional architecture known for its ability to capture high-level semantic features. ResNet-50 classifies the video into one or more categories out of a predefined set of **30 distinct classes**, such as sports, documentaries, cooking, educational content, and more. The classification is not based on isolated frame analysis but on aggregated insights across sampled frames, enabling robust multi-label predictions. This step transforms raw video data into a structured categorical format, setting the foundation for downstream indexing and retrieval.Data preprocessing

B. Classification Storage and Video Indexing

Once classification is completed, the resulting metadata—including video categories, frame-level predictions, timestamps, and extracted tags—is serialized and stored in the **JavaScript Object Notation (JSON)** format. This format provides a lightweight and human-readable structure, making it highly suitable for data interchange and querying. The structured metadata is then indexed and stored in a **centralized database**, along with the actual video file. Depending on the deployment scale, either a **relational database (like PostgreSQL)** or a **NoSQL solution (such as MongoDB)** may be used. This metadata is crucial not only for retrieval but also for filtering, sorting, and analytics. Each video entry in the database maintains links to its visual features, classification labels, and embedding vectors, enabling efficient and scalable retrieval during user query processing.

C. User Input and Text Embedding via GPT-4

To retrieve videos, the user interacts with the system by submitting a natural language query. This query could range from specific keywords to full descriptive phrases such as “show videos of wildlife in the forest” or “find a tutorial on making Italian pasta.” The submitted text is processed using **GPT-4**, a state-of-the-art transformer-based language model developed by OpenAI. GPT-4 understands the syntactic structure and semantic meaning of the input, and it converts the textual description into a **dense embedding vector** that captures nuanced contextual relationships. Unlike keyword-based systems that match terms literally, this embedding approach allows the system to generalize and understand user intent even when the phrasing varies. For example, “football highlights” and “soccer match recap” would yield similar embeddings, ensuring that the system can return relevant results irrespective of query phrasing.

D. Embedding Matching

With embeddings generated from the user input, the system proceeds to the **matching phase**, where it compares the query vector to the precomputed embeddings of all videos in the database. Both the user query and video embeddings exist in the **same high-dimensional vector space**, enabling direct comparison using distance metrics such as **cosine similarity**, **Euclidean distance**, or **dot product**. The comparison scores indicate how closely the user's intent aligns with the semantic content of each video. To improve efficiency, techniques such as **Approximate Nearest Neighbor (ANN)** search or **FAISS (Facebook AI Similarity Search)** may be employed, allowing the system to scale to large datasets while maintaining high retrieval accuracy. The top-N most similar video embeddings are selected for final retrieval.

E. Video Retrieval and Display

Once the best-matching video embeddings are identified, the corresponding video entries are retrieved from the database along with their metadata, thumbnails, and classification labels. The final video results are ranked based on similarity scores and can be further filtered using category-based or time-based constraints. These results are then displayed to the user in an intuitive interface, allowing them to preview,

view full videos, or explore similar content. This hybrid retrieval approach ensures not only precision but also flexibility, as it supports fuzzy queries, broad semantic searches, and highly contextual content discovery—something not possible in traditional keyword-driven systems. Moreover, the system is extensible, enabling future integration with personalization modules, user feedback loops, and multilingual support.

F. System Flow Summary

The complete flow of the system is illustrated in the diagram (see Figure 1), which comprises the following steps:

User Uploads the Video

The system begins with a video file upload through the user interface.

Video Classification Using ResNet-50

The uploaded video is processed through ResNet-50 to classify its content into one or more of 30 available categories.

Classification Stored as JSON

The classification results and other metadata are stored in JSON format for easy indexing and retrieval.

Video and Metadata Stored in Database

The video file and structured metadata are stored in a database backend optimized for fast lookup and retrieval.

User Submits a Text Query

The user interacts with the system through a natural language input describing the type of video they seek.

GPT-4 Generates Semantic Embeddings

The input query is converted into an embedding vector that captures semantic meaning and user intent.

Matching with Stored Embeddings

The system compares the user's embedding with stored video embeddings in a shared vector space to find the most relevant matches.

Retrieval and Display of Relevant Videos

The top-matching videos are retrieved from the database and displayed in the interface, enabling the user to select and view the desired content.

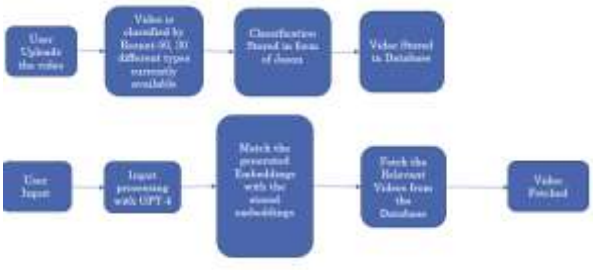

Fig 1:Proposed architecture is depicted here via flowchart.

RESULTS

The video classification component of the hybrid multimodal video retrieval system was trained using the ResNet-50 model with transfer learning. A total of 10,000 training samples and 1,200 validation samples were used to fine-tune the model. Over 10 training epochs, the model showed consistent improvements in both training loss and validation accuracy.

By the final epoch, the model achieved a validation accuracy of 98.25%, indicating excellent generalization on unseen data. The validation loss reduced significantly from 0.1180 in the first epoch to 0.0595 by the tenth epoch. These metrics demonstrate the model's strong learning capability and reduced overfitting, thanks to the efficient use of pretrained ResNet-50 weights.

Throughout the training process, the model's performance remained stable, with the validation accuracy crossing the 97% mark as early as the third epoch. This suggests that the model quickly adapted to the task of video classification using transfer learning, allowing it to distinguish between 30 predefined video classes with high confidence.

The final trained model was saved as resnet50_skyview.pth and is integrated into the backend of the retrieval system, where it is used to generate semantic embeddings for videos during both the upload and search phases. These embeddings serve as the foundation for matching video content with user queries, contributing significantly to the precision and relevance of the retrieval results.

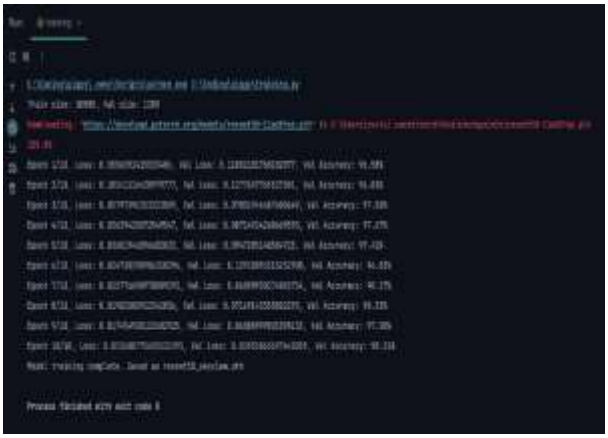

Fig 2:Model accuracy comparison

LIMITATIONS AND FUTURE SCOPE

While the proposed hybrid multimodal video retrieval system demonstrates strong performance in terms of classification accuracy and retrieval precision, it is not without its limitations. One notable limitation lies in the dependency on pre-trained models such as ResNet-50. Although transfer learning significantly boosts performance, the model's ability to generalize is still constrained by the diversity and representativeness of the training dataset. If the training data does not include sufficient examples of certain video classes or rare content types, the system may struggle to accurately classify and retrieve such videos.

Moreover, the reliance on frame-level embeddings may lead to a loss of temporal dynamics within the video. Since ResNet-50 operates primarily on static frames, subtle temporal features or motion patterns that could distinguish one category from another might not be effectively captured. This could potentially affect retrieval performance in content where action or sequence progression is key.

nother limitation is related to user input interpretation. While GPT-4 significantly enhances query understanding and semantic matching, its performance can still be influenced by ambiguous, overly generic, or grammatically incorrect inputs. This may reduce the precision of the retrieval results or lead to mismatches between user intent and system output.

CONCLUSION

In conclusion, this paper presents a novel hybrid multimodal video retrieval system that combines the

strengths of deep learning-based visual classification and advanced language understanding using GPT-4. By leveraging the powerful feature extraction capabilities of ResNet-50 and embedding-based semantic matching, the system demonstrates high accuracy in categorizing and retrieving relevant video content from a database. This integrated approach significantly enhances the efficiency and precision of video search, especially in scenarios where traditional keyword-based systems fall short.

The incorporation of GPT-4 for query interpretation allows the system to understand user intent more contextually, translating natural language inputs into meaningful embeddings that align closely with visual features. This results in a seamless user experience where users can retrieve videos relevant to their needs without requiring specific metadata or exact titles.

Overall, the proposed framework showcases how the fusion of computer vision and language models can transform video information systems. It opens the door to intelligent multimedia search solutions that are scalable, intuitive, and applicable across domains such as education, surveillance, entertainment, and healthcare. With further advancements, such systems can be instrumental in bridging the gap between human intent and machine understanding, thereby improving accessibility and interaction with large-scale video data repositories.

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