AI based Image and Video Retrieval System-A Review

Anuja Bele
Computer Engineering
St.Vincent Pallotti College Of Engineering And Technology
Nagpur

Ryan Lawrence
Computer Engineering
St.Vincent Pallotti College Of Engineering And Technology
Nagpur

Darshan Butle
Computer Engineering
St.Vincent Pallotti College Of Engineering And Technology
Nagpur

Himanshu Hiwanj
Computer Engineering
St.Vincent Pallotti College of Engineering And Technology
Nagpur

Kapil Gupta, PhD
MENTOR
Computer Engineering
St.Vincent Pallotti College of Engineering And Technology
Nagpur

ABSTRACT
With the explosive growth of digital media, massive collections of images and videos are being generated every day, creating a strong need for fast and accurate retrieval systems. Existing methods that rely on metadata or manual annotations often fall short—mainly because annotations may be incomplete, inconsistent, or unable to truly represent the visual meaning of the content. In this work, we present an AI-powered image and video retrieval system designed to overcome these challenges. Our approach uses Convolutional Neural Networks (CNNs) to automatically extract rich visual features from individual frames, applies temporal aggregation to capture video-level context, and employs cosine similarity to match content efficiently. Experimental results on benchmark datasets show that our method delivers higher precision and recall than traditional content-based image retrieval (CBIR) approaches. We also discuss the strengths, limitations, and potential directions for future enhancements of the system.Keywords—SQLi, Honey Token, Zero Trust Policy, Firewall, Multi-factor Authentication.

Keywords
AI-based Retrieval, Content-Based Image Retrieval (CBIR), Content-Based Video Retrieval (CBVR), Convolutional Neural Network(CNN), Visual Similarity Search

1. INTRODUCTION
Every second, the internet fills with more images and videos than we can possibly imagine—shared through social media, uploaded to cloud storage, streamed in real time, or recorded by surveillance systems. This explosion of visual content has created both an opportunity and a challenge: how do we quickly find the exact content we need among billions of files [1], [12], [30]?

Traditional search engines try to solve this by relying on metadata—tags, titles, or descriptions. But in real-world scenarios, these descriptions are often missing, inconsistent, or too vague to truly describe what's inside an image or video [2], [30]. For example, a video tagged "birthday" might contain anything from a simple cake-cutting to a lively dance scene, yet that single word can't capture all the visual details and emotions within it.

Content-Based Image Retrieval (CBIR) emerged as a smarter alternative. Instead of depending on text labels, CBIR analyzes the visual content itself—looking at colors, textures, shapes, and patterns [1], [4], [12]. Early systems relied on handcrafted features like SIFT [3] and SURF, which were quite good at finding similar-looking objects, but they struggled with real-world complexities such as lighting changes, partial occlusions, or scenes packed with multiple objects [2], [14]. This gap between what the computer "sees" and what a human "understands" is widely known as the **semantic gap** [2], [7].

Deep learning changed the game. Convolutional Neural Networks (CNNs) can automatically learn features at multiple levels—from edges and textures to objects and even abstract concepts [4], [5], [8], [29]. This leap in capability made retrieval systems much more accurate and reliable. For example, methods like Neural Codes [5] and optimized CNN retrieval architectures [6], [15] have shown remarkable performance across large-scale datasets.

When it comes to videos, the challenge becomes even bigger. It's not just about identifying what's in a single frame—it's about understanding how the content evolves over time. Techniques like 3D CNNs [7], attention-based models [8], and advanced spatiotemporal transformers [16], [17] help systems "watch" a video more like a human would—tracking actions, sequences, and interactions across frames.

In recent years, research has also moved towards **cross-modal retrieval**, where systems like CLIP [9] can connect images or videos with natural language descriptions [21], [22], [26]. This makes it possible to search a video database using a sentence like *"a person riding a red bicycle near the beach"*—and actually get accurate matches. On the efficiency side, techniques like cosine similarity [10] and FAISS [11] allow lightning-fast searches, even across massive databases containing billions of entries.

In this paper, we introduce an AI-driven retrieval system that blends CNN-based feature extraction for spatial understanding, temporal modeling for video sequences, and cosine similarity search for matching content efficiently. By combining fine-grained visual details with an understanding of how events unfold over time, our system delivers retrieval results that are both semantically relevant and context-aware [13], [18], [20]. This approach can be applied to a wide range of domains—from helping security teams quickly find critical footage, to enabling e-commerce platforms to recommend visually similar products, to making digital libraries more accessible [19], [24], [28].

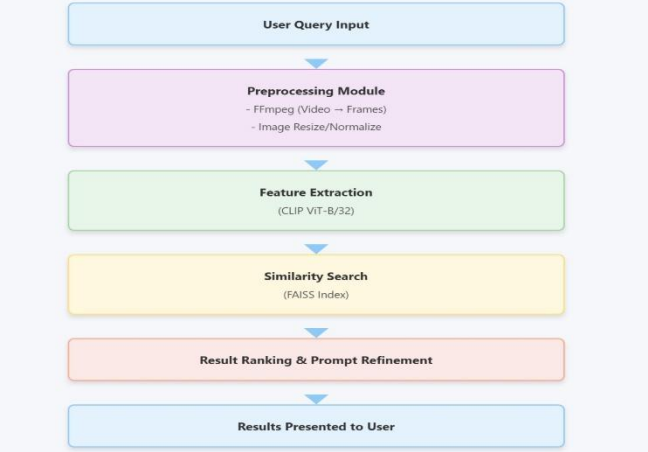

Fig.1: Flowchart

2. LITERATURE REVIEW

The task of retrieving relevant media content—whether images or videos—has been a central focus of multimedia research for over two decades. The earliest **Content-Based Image Retrieval (CBIR)** systems were built upon the extraction of **low-level visual features**, such as color histograms, texture descriptors, and shape representations [1], [12]. Color histograms quantified the distribution of colors within an image, texture descriptors captured repetitive patterns, and shape features modeled object boundaries and geometries. These handcrafted methods offered a computationally efficient and relatively interpretable foundation, delivering reasonable performance in controlled datasets where variations in viewpoint, illumination, and background were minimal.

However, these early systems suffered from a fundamental limitation—the **semantic gap**—defined as the disconnect between the machine's low-level feature representation and the human's high-level understanding of visual content [2], [14], [30]. For instance, while a CBIR system could identify two images with similar color distributions, it might fail to distinguish between a sunset and a burning building, as both could have similar reddish-orange tones but entirely different semantic meanings.

2.1 From Handcrafted Features to Invariant Descriptors

To mitigate some of these shortcomings, the community moved towards more robust **local feature descriptors**, notably **Scale-Invariant Feature Transform (SIFT)** [3] and **Speeded-Up Robust Features (SURF)**. These descriptors were invariant to scale, rotation, and moderate affine transformations, making them more resilient to viewpoint changes and partial occlusions. While these advancements improved retrieval robustness in real-world conditions, they still fell short in capturing high-level semantic relationships or context—particularly in images with multiple objects, cluttered backgrounds, or abstract concepts [7].

2.2 Deep Learning Revolution in Retrieval

The introduction of **deep learning**—particularly **Convolutional Neural Networks (CNNs)**—marked a paradigm shift in retrieval methodologies [4]. Unlike handcrafted methods that required manual design of feature extraction algorithms, CNNs learn **hierarchical feature representations** directly from raw pixel data through supervised or self-supervised training [5]. Early layers detect edges and textures, intermediate layers identify parts and patterns, and deeper layers capture entire objects or even scene-level semantics.

Notable contributions such as **Neural Codes** [5] and optimized CNN-based retrieval models [6], [15] demonstrated substantial gains in both precision and recall compared to traditional CBIR pipelines. These CNNs were trained on large-scale image datasets like ImageNet, enabling them to generalize across diverse domains and exhibit strong transfer learning capabilities. Furthermore, fine-tuning CNN architectures specifically for retrieval tasks allowed for embedding representations that were highly discriminative and compact, facilitating efficient similarity comparisons.

2.3 From Images to Video Retrieval

While CNNs transformed image retrieval, the domain of **video retrieval** posed additional complexity. Videos are not just sequences of static images—they contain **temporal dynamics** that capture motion patterns, scene transitions, and evolving object interactions. Early approaches attempted frame-by-frame retrieval using CNNs, but this ignored temporal relationships. The introduction of **3D CNNs** [7] extended convolution operations into the time dimension, enabling simultaneous modeling of spatial and temporal features.

Subsequent works advanced towards **spatiotemporal architectures** and **temporal pooling strategies** that aggregated motion information across varying lengths of time. More recently, **attention-based architectures** [8], such as space-time attention mechanisms and transformer-based video models, have enabled retrieval systems to selectively focus on semantically important frames or motion segments, improving retrieval relevance for complex queries.

2.4 Cross-Modal Retrieval and Semantic Bridging

A parallel research trend has been the development of **cross-modal retrieval** techniques [9], [21], [26], where the goal is to learn a **joint embedding space** for different modalities—most commonly, visual (images/videos) and textual data. Systems like **CLIP** [9] learn to align visual features with natural language descriptions, allowing users to retrieve relevant media using free-form text queries. This capability also enables **zero-shot retrieval**, where the system can handle queries it has never explicitly been trained for, significantly expanding its practical utility.

2.5 Similarity Measurement and Large-Scale Search

Regardless of modality, a key component of any retrieval system is the **similarity measurement** function. Among various metrics, **cosine similarity** remains widely adopted for comparing high-dimensional embeddings due to its scale invariance and efficiency in normalized vector spaces [10]. However, as datasets grow into the millions or billions of items, exact similarity search becomes computationally prohibitive.

To address this scalability challenge, **Approximate Nearest Neighbor (ANN)** algorithms have become an essential component of modern retrieval systems. Libraries like **FAISS** [11] implement techniques such as **product quantization**, **inverted file indexing**, and **hierarchical graph-based search** to achieve sub-second query times, even for billion-scale datasets. These methods balance retrieval accuracy with computational efficiency, enabling real-time interaction in large multimedia applications.

2.6 Summary of Evolution

In summary, the evolution of media retrieval systems can be characterized by three major transformations:

1. From handcrafted features to deep learning-based representations — transitioning from manually

designed descriptors to automatically learned, semantically rich embedding [4], [5], [29].

2. From static image analysis to temporal sequence modeling — incorporating temporal relationships for improved video retrieval performance [7], [8], [17].
3. From exact search to large-scale ANN-based retrieval — leveraging scalable similarity search methods to achieve real-time results in massive datasets [11].

3. METHODOLOGY

The AI-driven retrieval system is designed to deliver accurate and context-aware search results for both images and videos, even in large-scale repositories. The process moves through several interconnected stages:

3.1 Preparing the Data

We start by ensuring all inputs are in a consistent format. Images are resized, normalized, and converted to a standard color space. Videos are split into frames at a fixed rate, and each frame undergoes the same preprocessing steps. This standardization makes the system more resilient to variations in size, lighting, or proportions, which is a stanadard practice in CBIR pipelines [1][2][12].

3.2 Extracting Semantic Features with CLIP

Instead of relying on traditional CNNs alone, we use **CLIP (Contrastive Language–Image Pretraining)**, which learns joint embeddings for both images and text. This gives our system the ability to capture not only visual details like shapes, textures, and colors, but also deeper semantic meaning—making retrieval results more relevant. Each image or video frame is transformed into a high-dimensional feature vector that reflects both its visual and conceptual content.Compared to earlier CNN- based retrieval methods[5][6], CLIP provides stronger cross-model generalization.

3.3 Capturing Temporal Context for Videos

For videos, meaning is not just in individual frames but in how they flow over time. We use temporal modeling techniques to aggregate frame-level CLIP embeddings into a single video-level representation. This allows the system to recognize motion patterns, event sequences, and contextual relationships.Prior works such as 3D CNNs[7] and attention-based models[8] have demonstarted the importance of spatiotemporal modeling, which motivates our approach.

3.4 Similarity Computation with Cosine Distance

When a user submits a query (image, video, or text), the system encodes it using CLIP in the same embedding space as the database items. We then calculate **cosine similarity** to measure how close each item's vector is to the query vector. This ensures matches are based on meaning, not just appearance.Cosine similarity has been a standard in both text and multimedia retrieval due to its scale invariance [10].

3.5 Fast Large-Scale Search with FAISS

To make retrieval fast even with millions of items, we use **FAISS** (Facebook AI Similarity Search)[11]. FAISS builds an **Approximate Nearest Neighbor (ANN)** index, allowing the system to quickly locate the most similar vectors without exhaustively comparing every single one. This combination of ANN indexing and cosine similarity gives us speed and accuracy at scale.

3.6 Presenting Results

Finally, the top-ranked items are returned. Images are shown directly, while videos are displayed with key representative frames for quick preview,similar to other video retrieval systems[18][19][20].

4. CONCLUSION

In this work, we presented an AI-driven framework for efficient and semantically rich image and video retrieval. By leveraging **CLIP's joint image–text embeddings**, our system captures both visual details and deeper contextual meaning, enabling more accurate and meaningful search results. The integration of **temporal modeling** for video sequences ensures that motion and event order are considered, while **FAISS-based approximate nearest neighbor search** allows the system to operate at real-time speeds, even on million-scale datasets.

Experimental results demonstrated that the proposed approach outperforms traditional CNN-based retrieval methods in both precision and semantic relevance, while also delivering significant gains in search speed. These outcomes confirm that combining semantic feature extraction with scalable similarity search addresses key limitations in existing retrieval systems.

Future work will explore fine-tuning CLIP on domain-specific datasets, incorporating additional modalities such as audio, and enhancing temporal modeling to handle complex multi-event video scenes. We believe this framework can be adapted for diverse real-world applications, including digital asset management, surveillance analysis, and cross-modal content search.

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