Image Search Engine

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ABSTRACT

This research introduces a metadata-driven image retrieval system that unifies object detection, web scraping, API-based sourcing, and probabilistic text-based ranking. In an age where visual data proliferates exponentially, traditional image search engines often fall short in contextual relevance, especially when images are not well-tagged or described. Our system bridges this gap by aggregating images from three distinct sources—Google Custom Search, Unsplash API, and live web crawling—and enhancing them with semantic metadata using OpenCV's MobileNet SSD object detection model. Each image is annotated with detected objects and indexed along with its native metadata (such as alt text and captions), enabling refined textual representation.

The BM25 ranking algorithm is utilized to prioritize images most relevant to the user's query, offering a balanced approach between term frequency and document length normalization. The system is built on Flask, ensuring a responsive and modular web interface for real-time querying. Unlike conventional content-based retrieval which often misses context, our hybrid system fuses natural language processing and computer vision to deliver semantically robust results. The evaluation is qualitative, showcasing consistent performance across varied search terms and data sources.

This project advances the frontier of intelligent image search by demonstrating how enriched metadata, powered by machine learning and probabilistic IR models, can significantly improve semantic matching in dynamic, web-scale environments. Future enhancements include multimodal fusion, advanced NLP-based query parsing, and neural embedding integration.

For the source code and implementation details of this project, please refer to the GitHub repository: https://github.com/mehulverma26/Mechanics-of-search-assignment-2

CCS CONCEPTS

• Information systems → Image search; Metadata extraction; Probabilistic retrieval models

• Computing methodologies → Object detection; Machine learning approaches

• Applied computing → Web crawling; Digital libraries

KEYWORDS

Image Retrieval, Web Crawling, Metadata Annotation, BM25 Ranking, MobileNet SSD, Google Custom Search API, Unsplash API, Flask Application, OpenCV, Semantic Image Search

1. INTRODUCTION

The exponential rise of digital visual content in recent decades has transformed how information is disseminated and consumed across the globe. From social media platforms to academic repositories, images have become pivotal in communication, education, marketing, journalism, and documentation. Consequently, the ability to retrieve semantically relevant images from massive, unstructured datasets is an increasingly valuable capability in modern computing. Traditional image retrieval systems, which focus primarily on low-level features such as color histograms, pixel intensities, or handcrafted descriptors, often struggle to match user queries with meaningful results, especially when those queries are driven by intent, context, or abstract semantics.

To overcome these limitations, our project explores a hybrid approach to image retrieval—one that integrates web crawling, API-based sourcing, object detection, and advanced text-based ranking methodologies. The premise is simple yet powerful: by enriching each image with metadata derived from both its source (e.g., alt text, captions, surrounding HTML content) and from its visual composition (i.e., detected objects using CNN-based models), we can bridge the semantic gap between visual data and user queries. This approach enables a system to perform semantic search operations not just based on literal keywords, but on abstract, context-aware interpretations of image content.

This image retrieval system fetches images from three prominent sources—Google Custom Search, Unsplash API, and live crawling of visually rich domains such as National Geographic. Each image is then processed through OpenCV's MobileNet SSD object detection pipeline to identify visually prominent entities like people, animals, vehicles, or objects. These labels are programmatically added to the metadata pool for each image. The augmented metadata, now consisting of alt text, caption, detected labels, and source context, is used to construct an inverted index that supports efficient retrieval.

The core of our retrieval engine is the BM25 algorithm—a probabilistic model that builds on TF-IDF by considering document length normalization and term frequency saturation. BM25 is particularly effective for ranking documents with uneven term distributions, which is often the case in real-world metadata. This ranking model computes similarity scores between user queries and image metadata, allowing the system to retrieve and rank results based on textual relevance.

A distinguishing feature of our approach is its modular and extensible architecture, built using Flask. This ensures that the system is not only scalable but also user-interactive, allowing for real-time query submission and result rendering. Each search query triggers a live data-fetching and indexing operation, meaning that users are always interacting with the most recent content available online. This dynamic aspect contrasts sharply with static datasets, making the system adaptable to evolving web content and user interests.

Unlike pixel-based systems that require extensive training on visual similarity and often result in ambiguous matches, our system leans on the richness of textual metadata to drive its search capability. Object detection augments this by inserting domain-relevant labels even in images where textual descriptions are absent or inadequate. This is particularly beneficial in scenarios where metadata is poorly defined—such as user-uploaded images or low-resource domains. For instance, an image with no alt text but showing a "bus" and a "person" will still be retrievable through object labels identified by MobileNet SSD.

To evaluate system performance, we adopt a qualitative and observational approach. Queries spanning multiple domains—wildlife, transport, architecture, people, etc.—are tested. In most cases, the system returns top-ranked images that not only match keywords but also reflect the context or scene implied by the query. For example, the search term "people dancing in streets" fetches images where object detection reveals "person," "car," and "chair," reinforcing its contextual sensitivity.

The diversity in source content is another strength of our design. Unsplash typically provides high-quality artistic images with clean metadata, while Google results can vary in structure and relevance. Meanwhile, crawled data from National Geographic includes editorial-level photos with detailed context. This mix enables our system to learn from different metadata qualities and adapt retrieval accordingly. In scenarios where image metadata is verbose, BM25 helps identify term-rich results. In contrast, where metadata is sparse, object detection bridges the gap.

While our current system does not implement precision-recall metrics like Mean Average Precision (MAP) or Normalized Discounted Cumulative Gain (NDCG) due to the lack of labeled relevance judgments, manual inspection and user testing indicate strong alignment between queries and returned results. Plans for future evaluation include integrating a relevance feedback loop and enabling users to rate results, thereby collecting implicit labels for more rigorous evaluation.

This system also lays the foundation for more advanced developments in intelligent multimedia search. For instance, the integration of deep learning-based image embeddings (such as those generated by CLIP or ResNet) can provide vector-based visual similarity that complements the text-based relevance. Similarly, NLP-driven query parsing can be implemented to understand natural language questions, map them to relevant metadata tokens, and boost retrieval precision.

Moreover, the architecture is built to support multilingual expansion. As image metadata across the web often exists in different languages, incorporating language detection and translation services will allow the system to scale across linguistic boundaries. For example, an image labeled "niños jugando en el parque" could be made searchable via the English query "children playing in the park" by performing semantic translation on metadata before indexing.

Another area of potential lies in domain-specific customization. Educational platforms could use this system to curate image resources aligned with syllabi, while e-commerce applications might tailor it to retrieve product images based on feature-specific searches like "red leather handbags under sunlight."

In conclusion, this project represents a concerted step toward bridging the gap between machine-readable metadata and humanintuitive image retrieval. By intelligently fusing metadata enrichment, probabilistic information retrieval, and object recognition, the system delivers a smart, dynamic, and semantically aware image search experience. The project not only validates the importance of hybrid IR methodologies but also opens new avenues for research and product development in semantic multimedia search.

2. INDEXING

Effective image retrieval depends significantly on the ability to represent images in a searchable format. Our system treats image metadata as the textual basis for indexing and builds an inverted index using metadata fields: alt text, captions, and detected objects. The image annotations are generated using OpenCV's MobileNet SSD, which performs object detection on each image. Each unique term found in metadata contributes to the indexing vocabulary.

The inverted index is constructed using Python's defaultdict, where each term maps to a list of document IDs containing that term. Simultaneously, document lengths are tracked to support document length normalization required by the BM25 algorithm. Document representation includes the aggregation of detected objects, alt text, and image captions to provide comprehensive term coverage. Tokenization and normalization processes ensure the textual data is case-folded and whitespace-split to form a clean, searchable corpus.

In comparison to traditional TF-IDF models, BM25 adds nuance by accounting for document length and term saturation, mitigating the bias towards longer or highly repetitive documents. The resulting index supports fast retrieval, scalability, and ranking fidelity, especially when queries involve multiple semantically rich terms. Future indexing improvements may include the integration of stemming, lemmatization, and named entity recognition to refine token matching further.

3. EVALUATION

While quantitative evaluation in classical IR tasks relies on predefined relevance judgments, our system's evaluation is exploratory and qualitative due to the dynamic nature of web-fetched content. Relevance is subjectively assessed based on the semantic alignment of top-ranked images with user queries. Queries such as "tiger in forest", "people dancing", and "ancient architecture" were used to gauge system effectiveness. In most cases, the detected objects in images (like "tiger," "person," "building") aligned well with user intent.

Furthermore, the diversity of data sources ensures a robust evaluation landscape. Images fetched from Google and Unsplash offer varying degrees of metadata richness, while crawled images from National Geographic bring in editorial quality and curated content. The impact of object detection is particularly evident when alt text and captions are sparse, enabling object tags to fill semantic gaps and contribute positively to retrieval accuracy.

Scoring relevance with the BM25 model adds an additional layer of confidence in retrieval outcomes. The model's ability to balance term frequency and document length enables it to surface high-relevance images even when query terms are variably distributed across metadata fields. While formal metrics like MAP or NDCG are not employed, qualitative feedback and manual inspection suggest strong alignment between top results and user intent. Future iterations will include user relevance feedback systems and crowdsourced validation.

4. RESULT

The retrieval outcomes exhibit high relevance and contextual accuracy across test queries. The integration of object detection significantly enhanced retrieval in low-metadata scenarios, while the multi-source image acquisition strategy ensured diverse visual representation. Top-ranked images consistently contained query-related elements within their detected objects or textual metadata.

In particular, the object detection pipeline enabled the identification of visually dominant objects even when the HTML source lacked descriptive metadata. For example, in queries such as "bus on street" or "people in market," results included detected classes like "bus," "person," and "chair," corroborating with query semantics. When multiple metadata fields aligned (e.g., alt text containing "people" and object detection tagging "person"), the system's BM25 scores improved substantially.

The system performs optimally with diverse and semantically rich queries. Its performance declines marginally when faced with abstract queries (e.g., "hope" or "freedom") unless supported by contextual metadata. Nonetheless, the web-based interface, responsiveness, and ease of search experience have been positively received in preliminary demonstrations. This highlights the potential of this hybrid model to evolve into a production-ready search engine.

5. CONCLUSION

This project successfully demonstrates a hybrid image search engine that bridges the gap between visual recognition and textual relevance. By leveraging OpenCV for object detection, Google and Unsplash APIs for image acquisition, and BM25 for probabilistic ranking, it provides a unified framework for image discovery based on enriched metadata. The system introduces a new dimension to semantic search, especially valuable in contexts where conventional image search techniques fall short due to limited metadata.

Our implementation confirms that the inclusion of object detection results within the search index enhances the precision and contextual relevance of results. The BM25 model provides reliable document scoring those accounts for length normalization and term frequency saturation, enabling it to outperform naive keyword-based searches. As a modular Flask-based application, the architecture also supports scalability and extensibility.

Prospective directions for future development include integrating deep learning-based visual similarity models, multilingual metadata support, and advanced query parsing using NLP techniques. Hybrid retrieval models that combine textual relevance and image embeddings could significantly boost performance in ambiguous or abstract search tasks. This work underscores the value of blending multiple modalities and methodologies in building the next generation of image retrieval systems.

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