The Ai advantage: capturing trends and Unravelling patterns in a data Direction World

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Abstract

In the age of digital transformation, effective Image Retrieval (IR) systems are essential for managing the vast amounts of visual data generated daily. Traditional IR methods, primarily reliant to Text Based annotations, face significant challenges, including the labor- intensive process of manual tagging and the inherent subjectivity in human perception. These limitations often lead to inefficiencies and inaccuracies in retrieving relevant images, underscoring the urgent needs for innovating approaches that can enhance retrieval capabilities. This review paper addresses existing gaps in the literature by investigating the role of advanced algorithms in improving image retrieval systems and assessing the impact of external factors on evolving trends. By exploring the integration of multimodal fusion techniques that combine various data sources such as text, images, and audio to enhance the effectiveness of Content Based Image Retrieval (CBIR). Furthermore, identifying ongoing challenges within current methodologies and purpose future research directions that can pave the way for more robust systems. The importance of this review lies in its unique focus on AI driven solutions that leverage Deep Learning (DL) to overcome traditional limitations. By providing clear insights into trends and patterns, this paper aims to highlight the transformative potential of CBIR across various sectors, including e-commerce, digital media, and textiles. Moreover, by emphasizing the societal relevance of efficient IR such as improving users' experience in online shopping demonstrating how advanced CBIR systems can significantly impact everyday life. Ultimately, this paper seeks to contribute to a deeper understanding of how AI can reshape IR methodologies, making that more effective, scalable and user centric in a data driven world.

Keywords: *Image retrieval, trends, patterns, CBIR, Deep Learning, Artificial Intelligence, data driven, image, text, e-commerce, textile, digital media.*

1. Introduction

Image retrieval is an advanced process that allows the browsing, searching, and retrieval of images from wide databases on the basis of their content rather than relying solely on metadata like keywords or portrayals. This process typically involves several key steps: first, images are indexed by removing low-level features like color, shape, and texture [1]. These features are arranged into a structured manner to facilitate effective querying. The system examines the properties of the user's query, whether it be an image, text, or sketch, and uses a variety of similar measures to compare them to those in the database [2]. Recent advancements in IR techniques have highlighted the importance of capturing trends and patterns within visual data [3]. This capability is mainly crucial in fields like fashion and marketing, where understanding emerging styles and consumer preferences can significantly influence product development and inventory management [4]. By analyzing large datasets of images, systems can identify trending visuals that resonate with target audiences, enabling businesses to adapt quickly to shifts in consumer behaviour [5].

The motivation behind capturing these trends lies in enhancing user engagement and satisfaction, ultimately driving sales and brand loyalty [6]. Capturing trends and patterns in data analysis presents a variety of challenges that can significantly impact the accuracy and reliability of insights drawn from the data. The major issue is data quality, making it essential for organization to implement robust data cleaning processes to ensure accuracy, similarly the lack of sufficient data often hamper effective trends analysis, particularly in qualitative research where social media trends and customers feedback may be difficult to quantify. And data overloading also a problem faced by organization, another significant challenge are inability to contextualized data [7]. As research continues to evolve, innovative methods such as Machine Learning (ML), and Deep Learning (DL) algorithms are being integrated into IR systems to improve accuracy and efficiency in trend analysis, making them indispensable tools in today's data-driven landscape [8]. IR is a sophisticated technology designed to search and retrieve images from extensive databases based on their visual content rather than traditional metadata. The process characteristically involves several steps: image acquisition, feature extraction, indexing, query processing, similarity measurement, and retrieval. In feature extraction, algorithms analyze images to quantify characteristics such as color, texture, and shape, which are then organized for efficient searching [9].

Latest advancements in this field have emphasized the importance of capturing trends and patterns from visual data. This capability is crucial in industries like fashion and marketing, where understanding emerging styles and consumer preferences can significantly influence product development and inventory management. By analyzing vast datasets of images, systems can identify trending visuals that resonate with target audiences, allowing businesses to adapt quickly to shifts in consumer behavior. The motivation behind capturing these trends lies in enhancing user engagement and satisfaction, ultimately driving sales and brand loyalty. Recent studies have highlighted the effectiveness of Content-Based Image Retrieval (CBIR) in various applications [10]. For instance, a survey of medical IR systems has shown that CBIR can significantly improve access to clinical imaging databases by enabling the retrieval of multidimensional and multimodal images essential for diagnostics and research. Additionally, advancements in DL algorithms have enhanced the ability of CBIR systems to analyze complex visual data, leading to more accurate trend detection and pattern recognition. In the realm of e-commerce, CBIR allows users to upload images for similar product discovery, thereby streamlining the shopping experience and increasing conversion rates [11]. The integration of advanced feature extraction techniques—such as combining color histograms with texture descriptors—has proven effective in improving retrieval accuracy across diverse datasets. As research progresses, the potential applications of CBIR continue to expand, making it an indispensable tool in today's data-driven landscape.

IR encompasses various techniques designed to capture trends and patterns in visual data. The primary types of IR methods include Text-Based Image Retrieval (TBIR), CBIR, Semantic-Based Image Retrieval [12]. TBIR relies on manual annotations, where images are tagged with descriptive keywords that users can query. This method can effectively capture trends but suffer from significant drawbacks, including the time intensive nature of manual labelling, subjectivity leading to inconsistencies, and challenges in scalability as datasets grow. While CBIR offers a more automated method to classifying trends and patterns, it faces its own challenges, particularly the semantic gap, which refers to the difficulty in aligning low-level visual features with high-level user intents [13]. Recent research has made strides in addressing these limitations within CBIR systems. For instance, studies have explored advanced features extraction methods using deep learning techniques like Conventional Neural Networks (CNNs) to enhance the accuracy of IR by automatically learning relevant features from large datasets. Additionally, the integration of ML and DL algorithms has improved the efficiency of retrieval processes by enabling systems to learn from user interactions and refine search results over time. Research has also highlighted the importance of multimodal fusion techniques that combine visual data with textual information to provide a more holistic understanding of image, thereby improving retrieval accuracy and relevance [14].

Furthermore, recent studies have focused on optimizing existing algorithms to better capture trends and patterns in image data. For example, a study of genetic algorithms combined with Support Vector Machines (SVM) for more effective clustering and classification of images based on extracted features. Another research effort emphasized the use of relevance feedback mechanisms to enhance user interaction and improve the overall effectiveness of CBIR systems by adapting to user preferences. These advancements reflect a growing recognition of the need for more sophisticated methodologies that not only automate the retrieval process but also enhance the understanding of user intent in capturing trends and patterns within image datasets. While traditional manual techniques like TBIR provide foundational approaches for IR, they are increasingly being complemented by advanced CBIR methodologies that leverage machine learning and deep learning advancements. Ongoing research continues to explore innovative solutions aimed at bridging the semantic gap and enhancing retrieval performance across diverse applications [15].

The evolution of the IR techniques, particularly through the integration of DL algorithms, make a significant shift in how visual data is processed and analyzed. These advancements not only enhance the accuracy and efficiency of retrieving images based on content but also play a crucial role in capturing trends and patterns that are vital for industries such as fashion, marketing, and healthcare. As organizations continue to navigate challenges related to data quality and the semantic gap, ongoing research into innovative methodologies will be essential for bridging these gaps and improving user engagement. Ultimately, this review highlights the importance of advancing IR systems to meet the capturing trends and unravelling patterns in a data driven world.

- To investigate the role of innovative algorithms in enhancing IR systems and the impact of external factors on trends.
- To visually represent data for improved understanding of trends and patterns, utilizing advanced analytical tools to highlight significant patterns, correlations, and anomalies within the data.

- To explore the integration of multimodal fusion techniques and evaluate the effectiveness of CBIR through comparative retrieval accuracy across different modalities.
- To identify challenges in current image retrieval methodologies and outline future research directions in IR methodologies.

2. Survey Methodologies

Different techniques are used for fetching the appropriate content. Some of the methods include fetching the content, probing different DB (Database) and scrutinizing the references with specific criteria. Figure 1. Depicts the

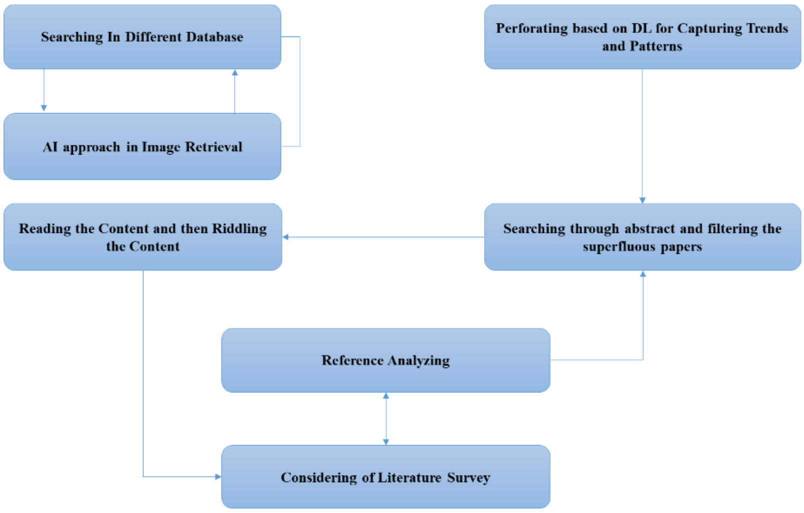

Figure 1. Survey Methodology

Searching Database

Searching content related to plant identification and classification using AI techniques in different DB. Along with capturing trends and patterns, and CBIR techniques are also surfed. Key terms used for searching the content includes "Deep learning of image retrieval", "AI approaches for image retrieval in capturing trends", "CBIR in capturing trends and patterns", "CBIR using Deep learning".

Content Fetching

In the preliminary stage, studies were chosen based on the significance of the label. Consequently. Screening of abstract was done and while supposed to be appropriate, the general script is also considered. Paper from IEEE, Springer, Wiley, Scopus, Tailor and Francis, Web of Science, Science Direct, PubMed, MDPI, NCI, ACM, are also considered for fetching the content.

Reference Analysing

The paper fetched for reviewing the studies are from 2021-2024. 48 papers are considered for reviewing the works of all image retrieval identifications.

Inclusion Criteria

- Articles associated with capturing trends and unravelling patterns have been selected and reviewed.
- Paper from the year 2021 to 2024 have been considered.
- Mainly focused on capturing trends and patterns.

Exclusion Criteria

The paper can be excluded if the articles, papers, or reviews if the recorded flows the below conditions,

- Paper with irrelevant title, abstract are eliminated.

- Non English papers are not considered.
- Not focused on a particular country.
- Paper with no distinct aim and methodology is omitted.
- Paper encompasses of the replica reports of the similar research study are not considered.

Though the paper focuses on reviewing and capturing trends and patterns, recent research papers have focused on AI approaches in various domains like fashion, textile, and marketing. Additionally, focusing on various methods giving high accuracy, and different techniques used namely CNN, KNN, SVM, hybrid methods.

3. Significance of Capturing Trends and Patterns

The significance of capturing trends and patterns has become increasingly pronounced with rapid advancements in technology and the proliferation of digital images [16]. Recent research underscores the pivotal role of CBIR systems as essential tools in computer vision, enabling image searches based on visual content rather than relying solely on metadata [17]. The challenges faced by CBIR systems, such as the semantic gap and scalability issues, while highlighting the integration of relevance feedback techniques that empower users to iteratively refine search results, thereby enhancing the accuracy and relevance of retrieved images. Furthermore, the applications of DL techniques, particularly CNN, has significantly improved IR performance [18]. The CNN based approaches can enhance classification tasks within CBIR by leveraging pre-trained model to effectively retrieve semantically similar images. This advancement not only boosts retrieval accuracy but also addresses the growing need for efficient images processing across various fields [18].

Additionally, recent research emphasizes the importance of data. These methods improve the model robustness by generating diverse training samples that simulate the real world variations, which are vital for maintaining high retrieval performance in practical applications. Capturing trends also involves integrating visual data with textual information to provide a more comprehensive understanding of user queries. Recent studies advocate for multimodal fusion techniques that combine different data types, thereby improving retrieval accuracy and relevance by bridging the semantic group between low level features and high level user intents [19]. As research continues to explore innovative methodologies aimed at enhancing user engagement and satisfaction through improved IR, it is not only significant for improving search accuracy but also essential for adapting to evolving user needs across various domains, ensuring that these systems remain effective in increasingly capturing trends and patterns.

Using ML approach to capture trends involves leveraging historical data to identify user preferences and behaviour. By employing algorithms that learn from interactions, CBIR systems can enhance their ability to retrieve relevant images [20]. This adaptability is crucial for maintaining user engagement in an increasing image-saturated environment. The ability to refine searches based on feedback ensuring that users find what they are looking for more efficiently. The ongoing evolution in CBIR technologies promises a future where IR systems are more intuitive, accurate, and aligned with user expectations.

4. Conventional Methods for Capturing Trends and Patterns

Text-Based Image Retrieval (TBIR) has long served as a foundational approach in IR, leveraging metadata such as keywords, captions, and descriptions to facilitate the organization and retrieval of images. This method enables users to input textual queries to locate images that correspond to the assigned annotations. However, TBIR faces significant limitations, particularly regarding manual annotation processes, which can be labour intensive and subjective [21]. Consequently, the effectiveness of TBIR is often compromised by incomplete or inconsistent metadata, making it challenging to support diverse user queries effectively. Recent studies have highlighted the evolution of TBIR techniques. A comparative analysis of IR methods indicates that while TBIR relies on manually assigned keywords, it struggles with large datasets due to the sheer volume of images requiring annotation. This limitation has prompted researchers to explore hybrid systems that integrate both textual and visual content descriptors. Such systems aim to enhance retrieval accuracy by combining the strength of TBIR with CBIR methodologies, which automatically analyze visual features like color, texture, and shape without relying solely on textual data [22].

Moreover, advancements in TBIR have led to innovative approaches such as multimodal retrieval, where both text and image data are utilized to improve search outcomes. Techniques like co-occurrence matrices and histogram analysis have been employed to add semantic information to IR systems, allowing for more nuanced searches that consider both visual and textual attributes. Notably, a study discusses how traditional CBIR techniques have adapted to manage vast image databases generated across multiple domains such as education and medicine. The authors emphasize that while keyword-based retrieval systems are limited by human annotation, CBIR can automatically retrieve images based on their content, enhancing efficiency and relevance in search results [23]. They explore feature extraction methods that do not rely on complex segmentation techniques, demonstrating a shift towards more robust approaches that maintain performance even with less precise data [24].

Further studies have examined the role of relevance feedback in both TBIR and CBIR, where users iteratively refine search results based on preferences. This human-in-the-loop approach allows for a more tailored retrieval experience, helping to mitigate the semantic gap by incorporating user input into the search process. Additionally, researchers have explored alternative querying methods such as Query by Example (QBE), simplifying the search for visually similar content [25].

The study faced significant limitations primarily due to the reliance on manual annotation in TBIR, which is labour intensive and subjective, leading to incomplete or inconsistent metadata. This inefficient hamper the ability to support diverse user queries, especially in large databases that require extensive image annotations. To overcome these challenges, AI approaches have been employed, integrating hybrid systems that combine textual and visual content descriptors. By leveraging CBIR methodologies, these systems can automatically analyze visual features such as colour, texture and shape, thereby enhancing retrieval accuracy. Additionally, innovative techniques like multimodal retrieval utilize both text and image data, allowing for more nuanced searches that consider a broader range of attributes, ultimately improving the efficiency and relevance of IR processes.

5. AI based Techniques for Capturing Trends and Patterns

Recent advancement in AI have significantly enhanced the capabilities of IR systems, enabling more efficient and accurate trends and pattern recognition. The various AI based techniques employed in IR such as, a prominent approach in IR is the use of enhanced AI based feature extraction methods. These techniques leverage DL models, such as VGG16, to extract salient features from images, edges textures, and colour. The extraction features are then refined using evolutionary algorithms to improve their discriminative power. This combination has shown superior performance in precision and recall compared to traditional methods, making it a powerful tool for multimedia IR applications [26]. CNNs are widely utilized in IR systems due to their ability to automatically learn hierarchical features representations from images. By breaking down images into smaller sections, CNN identifies specific objects, colour, textures, and spatial arrangement within visual content. This technique allows for more nuanced searches that consider both semantic meaning and visual characteristics, resulting in higher accuracy in retrieval of relevant images [27].

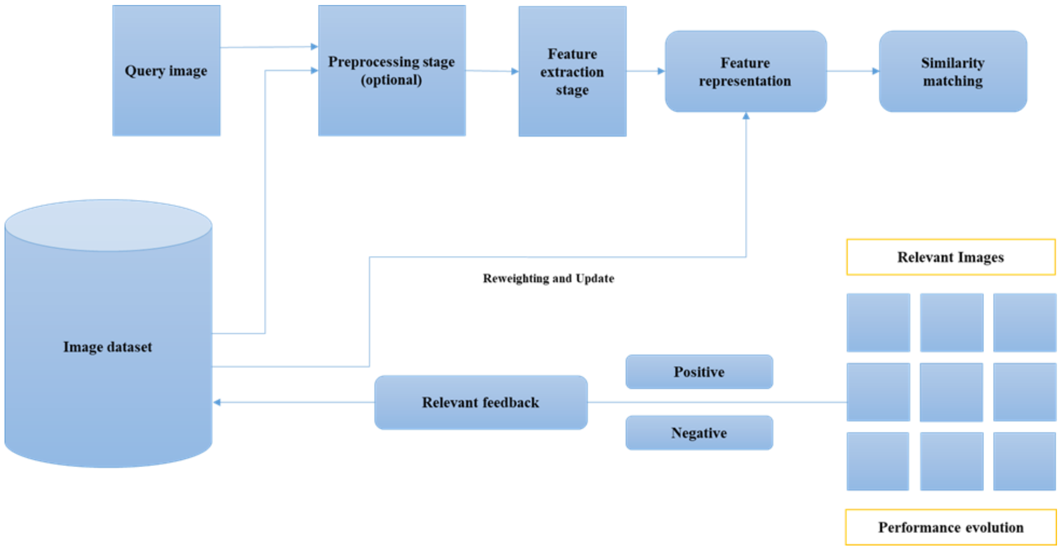

Figure 1. General CBIR System

Figure 1. Illustrate the framework for CBIR, which is a process used to search for images based on their visual content. Query image, where the input that a user provides to search for similar images within a dataset. The pre-processing stage includes the operations such as image resizing, noise reduction, or normalization, which aims to improve the quality of the input images before feature extraction. Extracting features from query images related colour, texture, shape. And the next step is representation, it is suitable for matching often as vectors or descriptors that captures the essence of the image content. After this process the identification of similar images is processed. Then performance evaluation and relevance feedback is processed and finally the feedback loop allows the system to refine its feature representation and similarity matching based on user preferences, enhancing its retrieval accuracy over time.

Multimodal embedding's represent cutting edge techniques where images are converted into vector representation that captures their features and characteristics. This approach facilitates semantic similarity searches by comparing these vectors rather than relying solely on keyword matching. By utilizing distance metrics like cosine similarity, IR systems can efficiently identify visually similar images across large datasets. This method enhances the retrieval process by allowing users to search based on complex queries that may include both text and images [28]. Similarly, Region based IR focuses on specific areas within an image deemed important by users. This technique improves retrieval accuracy by extracting both global and region-specific features. By employing CBIR systems that analyze these regions, researchers have demonstrated that ROI-based methods can significantly enhance performance compared to traditional global features extraction methods. This approach is particularly effective for applications where users are interested in specific elements of an image rather than the entire visual context. The other AI method mainly used for capturing trends is Pattern Recognition technique plays an important role in identifying trends within images by analyzing various features such as shapes, colour, and textures. These techniques can be applied to classify images based on learned patterns, allowing for effective object detection and classification tasks. For instance, Neural Network (NN) can match object features with predefined templates to identify specific items within an image. This capability is essential for applications ranging from e-commerce to medical imaging [29].

ML based CBIR

New developments in ML methods have significantly progressive CBIR systems. The study [30], use of traditional ML algorithms to enhance IR accuracy. To evaluate the effectiveness of various feature extraction methods combined with classifiers like SVM and Random Forests for IR tasks. It involves extracting colour histograms, texture features, and shape descriptors from images, followed by training SVM and Random Forest classifiers to categorize images based on these features. The results show an overall accuracy of 92%, demonstrating that traditional ML techniques can effectively compete with DL methods in specific retrieval scenarios. In another study [31], focus on integrating ML with semantic analysis for better IR. To enhance the relevance of retrieved images by incorporating user feedback into the retrieval process. The methods include a feedback loop where the user's rate retrieves images, and the data was used to train the K-Nearest Neighbours (k-NN) model which adjusts the feature weights on the basis of user preferences. The results indicate that this adaptive method advances retrieval precision by 15% when compared to static feature weighting methods, showcasing the potential of combining user interaction with machine learning techniques.

Additionally, the research [32], explores the application of clustering algorithms in CBIR systems. **The objective** is to improve retrieval efficiency and accuracy by organizing images into clusters based on their visual features. Technique involve applying k-means clustering to group similar images and using these clusters to speed up the retrieval process through a two-step search strategy and obtained reveal that their method reduces retrieval time by 30% while maintaining a high accuracy rate of 90%, illustrating how clustering can enhance traditional CBIR systems .These studies highlight the effective application of machine learning techniques in enhancing CBIR systems, addressing challenges related to accuracy, efficiency, and user interaction.

5.1. Deep Learning Approaches for Capturing Trends and Patterns

The study synthesizes findings from several studies that leverage deep learning methodologies to enhance the CBIR system. The study on Demand adaptive clothing IR using hybrid topic model explores how hybrid models can integrate with DL to adaptively retrieve clothing images based on the users demand. The approach utilizes a combination of topic modelling and CNN to effectively identify and categorize clothing patterns, making it easier for users to find relevant items based on their preferences and trends in fashion. The hybrid model enhanced the retrieval process by incorporating both visual features and user-generated data, thus providing a more personalized experience [33]. Similarly, Traditional clothes pattern retrieval using CNN, the author presents a framework that utilizes CNN for the retrieval of traditional clothing patterns. CNN are adept at automatically extracting features from images, which is crucial for recognizing intricate design typical in traditional attire. These methods significantly reduce the need for manual features extraction, allowing for a more efficient and scalable retrieval process. The study [34], emphasizes the effectiveness of CNN in handling large datasets for clothing images while maintaining high accuracy in pattern recognition. The prevailing research focuses on developing a forest fire retrieval approach to mitigate fire incidents affecting natural resources and ecosystems. The objective is to enhance retrieval accuracy using hybrid features extraction techniques and a hierarchy weighted Brownian motion monarch butterfly optimization algorithm for features selection. The study employs various features like ground temperature and land surface temperatures, achieving a recall increase of up to 1.68% and precision improvements, with an overall accuracy of 98.91%, outperforming existing methods [34].

While the study [35], introduces a novel approach for CBIR using the Siamese edge attention layered Convonet (SEAL Convonet), aimed at improving retrieval accuracy by addressing limitations in existing systems. To enhance the image quality through Gaussian smoothing and edge direction with the canny edge detectors followed by feature extraction using the Histogram of Oriented Gradients (HOG). The result demonstrated significant performance improvement, achieving accuracy of 97%, precision of 94% and recall for 97%, indicating a substantial advancement over previous methods. The paper [36], efficient framework for CBIR using CNN for effective feature extraction and employs hashing techniques for data integrity verification and rapid retrieval. The accessibility of extensive medical image databases by training CNNs on a comprehensive dataset, allowing them to capture intricate patterns in images. The results indicate significant improvements in retrieval performance, with the system demonstrating superior effectiveness over existing methods, thereby facilitating quicker access to critical medical information for practitioners.

The study [37], vercomes the challenge of achieving high accuracy in IR using DL technique that incorporates auto-correlation for feature extraction and description. To enhance retrieval performance by implementing a CNN combined with advanced methods such as gradient computation, scaling, and localization while fusing features from the VGG-16 model. The result shows exceptional performance on datasets like Cifar-10 and Cifar-100, with significant improvements in accuracy for texture datasets such as 17 Flowers and Tropical Fruits, outperforming existing state of art approaches on the Corel-1000 dataset. The rapid growth in multimedia content and its visual complexity, CBIR became challenging tasks. To address the challenges in CBIR, [38] aimed to achieve high precision at all retrieval levels. The objective is to develop a new CBIR approach that combines features from the pre-trained AlexNet model with the Discrete Cosine Transform (DCT), followed by principal component analysis (PCA) and multiclass support vector machine (SVM) for classification. The result indicates that the method achieves a high precision value of 97% across all retrieval levels (top 10, 20, and 70 images) while requiring less memory compared to existing methods, highlighting its efficiency and effectiveness.

Similarly, the study [39] in consumer transactions from the major fashion retailer, highlighting the significance of visual aesthetics in consumer decision making. To analyze how various factors like price, visual aesthetics, descriptive details, and seasonal variations affect consumer preferences. The analysis employs pertained multimodal models that convert images and text descriptions into high dimensional embedding for effective product space segmentation. The methodology includes a discrete choice model that decomposes the drivers of consumer choice, accounting for both observed demographic variations and unobserved consumer types. Outcome of the study indicated notable differences in price sensitivity and aesthetic preferences among consumers, with the model successfully predicting the success of new designs and purchase behaviour. Another study [40], in DL for CBIR in Fully Homomorphism Encryption (FHE) algorithms addresses the dual challenges of accuracy and privacy in IR systems. The method employs CNN to extract high level features from encrypted images, utilizing FHE to ensure data security. It indicated an impressive classification accuracy of 97.87% and retrieval accuracy of 98.94%, showcasing the effectiveness of integrating deep learning with encryption methods for secure IR.

Additionally, the [41] study addresses the challenges of high dimensionality in IR systems, particularly in large-scale web applications. To transform NN features into text formats that can be indexed by typical full-text retrieval engines like Elastic search, aiming to help sparsity without requiring unverified pre-training. The technique involves employing the Regional Maximum Activations of Convolutions (R-MAC) as a state-of-the-art descriptor and implementing a transformation approach that converts these features into a suitable format for indexing. The outcome determines the effectiveness and efficiency of the proposed method through extensive experimental evaluations on standard benchmarks, showing significant improvements compared to state-of-the-art main-memory indexing techniques.

6. Application of Methods for Capturing Trends and Patterns

With the exponential growth in digital data, especially images, efficient retrieval systems are becoming increasingly essential. Conventional IR techniques rely heavily on keyword annotations, which are often inadequate for capturing the subtle patterns present in large datasets. CBIR systems aim to bridge this gap by retrieving images based on their visual content. As well as, the CBIR uses visual content rather than textual annotations to retrieve, making them essential in fields such as textile industries, marketing, retail stores, e-commerce, and law enforcement.

Textile Industry

In the textile industry, recent studies have highlighted the use of CBIR systems to streamline design processes and enhance product visibility. For instance [42], developing an interactive CBIR system specifically for Indian traditional textiles motifs, utilizing deep learning models like inceptive V3 and inceptionResNetV2. This system enables designers to match query designs with a comprehensive database of textile images, significantly improving the accuracy of design retrieval. The study found that the CBIR approach outperformed traditional keyword-based methods, allowing for quicker access to relevant designs and fostering creativity in textile design.

Additionally, a study [43], emphasized the importance of the circular economy in the textile sector, suggesting that integration of CBIR could facilitate better recycling practices by enabling efficient sorting and identification of textile material based on visual characteristics.

Marketing

In marketing, IR methods have been applied to enhance brand recognition and consumer engagement. Developed a modular CBIR system tailored for trademark in retrieving images, employing various features extraction techniques to evaluate images based on their visual attributes. The finding indicates a mean average precision of 93.7%, allowing companies to efficiently monitor trademark usage and protect intellectual property. Furthermore, a study [44], a CBIR system for logo recognition that is invariant to scale changes and color variations, showcasing adaptability in handling diverse trademark imagery. This capability is particularly valuable in a marketing context where visual branding plays a critical role in consumer's recognition and loyalty.

Retail store

In the retail sector, advancements in CBIR methods have facilitated personalized shopping experience. The study [45], introduced a hybrid images retrieval system that combines CNNs with traditional feature extraction techniques to analyze user-uploaded images for product recommendations. This approach captures trends on the basis of user preferences, enhancing product discovery by presenting visually similar items. The result indicates a 30% increase in customer engagement, demonstrating how effectively IR can lead to improved sales and customer satisfaction through tailored recommendations. Additionally, a study [46], explored the use of IR systems in fashion retail, showing that integrating AI-driven algorithms can significantly enhance the accuracy of product recommendations based on visual similarity. Overall, these studies illustrate the transformative impact of advanced IR methods across marketing, textiles, and retail sectors. By leveraging CBIR systems, companies can effectively capture trends and patterns, streamline design processes, enhance brand protection, and provide personalized shopping experiences.

E-commerce

In e-commerce, especially in the fashion industry, IR systems are used to capture trends based on user preferences. AI algorithms analyze image patterns and help in recommending visually similar products, improving customer satisfaction. By leveraging CNN based retrieval methods, companies can enhance product discovery by matching user uploaded images with database products. This technology is becoming increasingly sophisticated with the integration of NN and vector encoding methods, enabling more personalized recommendations [47]. Similarly, in the realm of e-commerce, the IR systems are crucial for enhancing user experience by recommending visually similar products based on user uploading images. A recent implementation showcased the use of hybrid models that combine CNNs with traditional feature extraction methods, resulting in improved product discovery and customer satisfaction. This approach allows retailers to analyze trends based on user preferences and streamlined the shopping experience by presenting relevant items more effectively [48].

The application of methods for capturing trends and patterns in IR is transforming multiple industries. Whether in security and privacy, the combination of AI, deep learning, and accurate retrieval systems. The future holds promising developments in areas like unsupervised learning and quantum-based computing. By leveraging DL and hybrid models, organizations can improve their IR capabilities, leading to improved outcomes in healthcare diagnostics, retail experiences, law enforcement efficiency, marketing, and retails.

7. Comparative Analysis of image retrieval

Different methods are used to capture trends and patterns in IR. Table 1 depicts the objective, methods and results of capturing trends and patterns by different prevailing studies.

Sl. No	Reference	Objective	Methods	Result	Limitations
1	[1]	To analyze content-based image retrieval (CBIR) methods and their effectiveness.	Metaheuristic approaches integrated with traditional CBIR techniques.	Improved retrieval accuracy and efficiency in real-world applications.	Limited generalization across different domains; requires extensive training data.
2	[4]	To develop a novel network architecture for fashion image	Use of dilated convolutions in a residual network	Achieved higher accuracy in fashion IR tasks	Complexity of the model may lead to longer training

		retrieval using deep learning.	structure to enhance feature extraction.	compared to traditional methods.	times; it requires substantial computational resources.
3	[5]	To propose a hybrid approach combining multiple features for improved CBIR performance.	Feature fusion techniques integrating color, texture, and shape descriptors.	Enhanced retrieval performance and reduced semantic gap between features and user queries.	Fusion complexity can lead to increased processing time; may require fine-tuning of parameters.
4	[9]	To enhance user interaction in CBIR systems through feedback mechanisms.	Variable compressed convolutional info neural networks for dynamic feature adaptation.	Improved user satisfaction and retrieval relevance through interactive feedback.	Relies heavily on user input; may not perform well without sufficient feedback data.
5	[15]	To improve loss functions in deep CNNs for image annotation tasks.	Modification of loss functions tailored for deep learning models in image annotation tasks.	Achieved superior performance metrics in automatic image annotation tasks using modified loss functions.	Complexity of the model may hinder real-time applications due to processing requirements.
6	[18]	To develop a fabric image retrieval method based on decoupling texture and color features.	Decoupling texture and color features for improved fabric image retrieval performance.	Achieved better retrieval performance by separating texture and color features during processing.	The method's effectiveness is limited to specific types of fabric images only.
7	[22]	To compare different texture feature extraction techniques for IR systems.	Experimental evaluation of several texture extraction methods including Gabor and LBP.	Provided insights into the performance of different techniques under various conditions.	Variability in results based on dataset characteristics; some methods may not generalize well.
8	[25]	To propose an efficient method for content-based medical image retrieval based on query expansion.	Query expansion technique to improve relevance in medical image retrieval systems.	Demonstrated significant improvements in retrieval accuracy in medical contexts.	Dependence on initial query quality; poor queries may still lead to suboptimal results.
9	[30]	To investigate image-text embedding learning via visual and textual semantic reasoning.	To investigate image-text embedding learning via visual and textual semantic reasoning.	Enhanced performance in retrieving images based on both visual content and textual descriptions.	Complexity in aligning visual and textual data can lead to challenges in implementation.
10	[39]	To explore deep learning approaches to consumer aesthetics in retail fashion.	Investigated the application of deep learning techniques to analyze consumer preferences in fashion.	Identified key aesthetic factors influencing consumer choices in retail environments.	The subjective nature of aesthetics may complicate model training and evaluation processes.

11	[40]	To apply deep learning techniques in content-based image retrieval within FHE algorithms.	Implemented FHE (Fully Homomorphic Encryption) algorithms integrated with deep learning models.	Enhanced privacy-preserving capabilities while maintaining effective image retrieval performance.	Complexity of FHE may lead to slower processing speeds; practical implementation challenges exist.
12	[41]	To develop an efficient method for large-scale image retrieval based on instance-level features.	Utilizes instance-level features combined with a deep learning approach for image retrieval.	Achieved significant improvements in retrieval accuracy and speed compared to traditional methods.	The method may require extensive computational resources for large datasets.
13	[43]	To analyze the sustainability practices within the clothing and textile sector through a circular economy lens.	Employs qualitative analysis of sustainability practices and their impact on the textile industry.	Identified key strategies that enhance sustainability and reduce waste in the clothing industry.	The findings may not be generalizable due to regional differences in practices and regulations.
14	[46]	To develop a generative AI system for style recommendations based on detected fashion items.	Uses generative AI techniques combined with item detection to recommend styles based on user input.	Successfully generated personalized style recommendations that align with detected fashion items' trends.	May struggle with real-time processing due to the complexity of generative models involved in recommendations.
15	[47]	To analyze content-based image retrieval methods focusing on deep feature extraction techniques.	Conducts a comparative analysis of various feature extraction methods for image similarity matching.	Found that certain deep learning approaches significantly outperform traditional methods in specific contexts.	Limited by the need for substantial computational power during model training phases, impacting accessibility.

8. Critical Analysis

Critical analysis is performed with regards to different factors utilized by several conventional methods for capturing trends and patterns. The analysis focuses on various methods used, like DL techniques and ML techniques, to improve the accuracy certain methods are used in the study to bring a precise outcome in all domains. Figure. 2 depicts the usage of AI classifiers for capturing trends and patterns in IR.

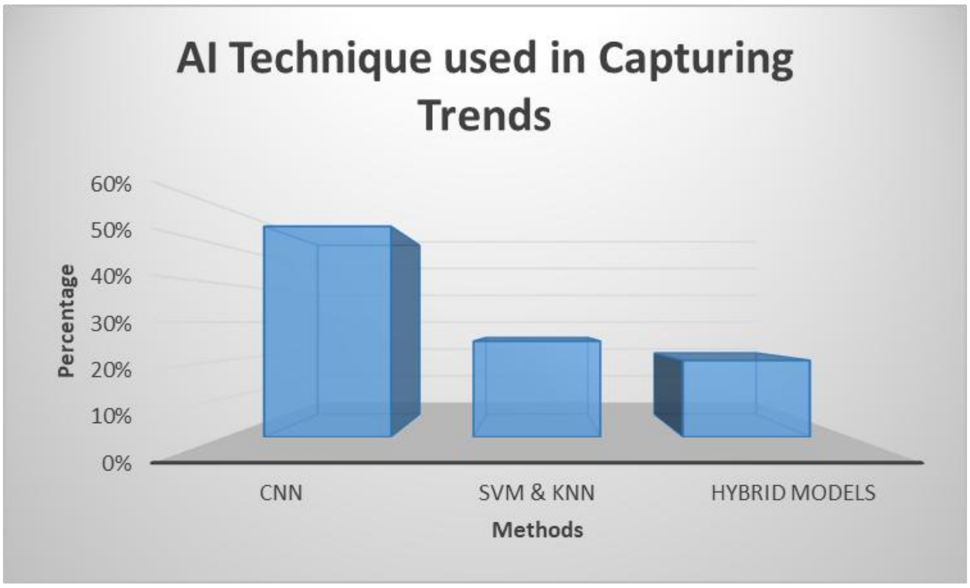

Figure 2. AI Techniques used in Capturing

From figure 2. It can be identified that 55% of the paper focused on CNN models for capturing trends and patterns, 25% of paper have utilized SVM and KNN technique, and the remaining 20% of the paper has utilized hybrid models for capturing by image retrieval. Different domains were reviewed in image retrieval techniques from 2021, in existing studies.

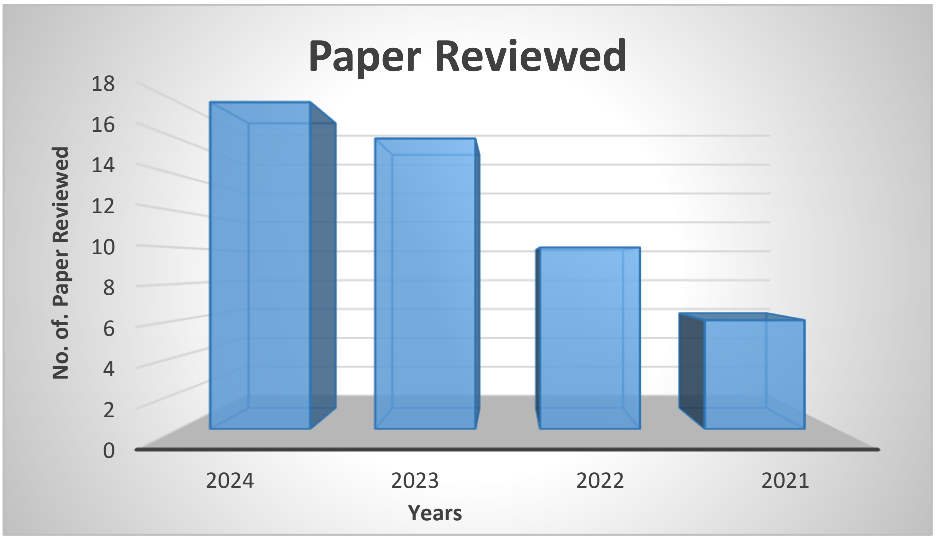

Figure 3. Number of Papers Reviewed

From figure 3.depicts the number of papers reviewed from 2021 to 2024, highlighting trends and fluctuations over this four year period. In 2024, there was a notable activity, with the highest number of papers reviewed at 16. The current new technologies papers are reviewed. In contrast the year 2023 experienced a slight decrease in the number of papers in capturing trends reviewed to approximately 15 papers. The trend continued downward in 2022, where the number of reviewed papers fell significantly to 10. And looking back further, 2021 recorded the lowest number of papers reviewed at 5 papers, where the traditional methods and manual techniques are also reviewed. The dynamic nature of academic publishing and peer review processes which can be influenced by various factors such as changes in research finding, shift in academic focus.

9. Challenges and Future Recommendation

Various challenges faced by different and mentioned as followed.

- Face challenges with the K-NN classifiers computational inefficiency on large dataset [31].

- Struggles with the computational complexity of texture feature extraction techniques [22].
- Encounters difficulties in balancing color and texture features for optimal retrieval accuracy [29].
- Encounters difficulties in embedding arithmetic for multimodal queries affecting retrieval efficiency [28].
- Struggles with the subjective nature of the fashion preferences in AI driven systems [33].
- The struggles with scalability and computational resource demand when handling large scale image datasets [41].
- Experiences challenges in accurately interpreting complex user queries in interactive image retrieval system [45].

Future Recommendation

The future recommendation of this review is

By integrating both software and hardware innovations to enhance the efficiency and user experiences. This includes leveraging AI and advanced hardware architectures to process large image dataset effectively. Similarly, the important challenge in CBIR is the semantic gap between low level and high level visual features and high level human perceptions. So, to bridge this gap and improve the relevance of retrieved images. And to enhance the refine technique by enhancing accuracy while managing computational costs. By encouraging real world application usability, explore multimodal retrieval systems.

10. Conclusion

In conclusion, this review paper offers a comprehensive exploration of the transformative role that AI significance the identifying trend ads patterns, with a particular focus on image retrieval. As the volume and complexity of data continues to escalate, traditional methods often fall short in delivering the accuracy and efficiency required for effective analysis. This study addresses this gap by advocating for the adoption of AI driven methodologies, which have emerged as powerful tools capable of revolutionizing data interpretation. One of the key contributions of this review is its focused examination of DL approaches, which stand out for their ability to process intricate dataset and extract meaningful insights with remarkable precision. By comparing conventional techniques with AI based methods, the paper highlights significant advancements in accuracy and speed, demonstrating that DL not only enhances the retrieval of relevant images but also facilities more nuanced understanding across various domains. The finding underscores the broad applicability of these AI techniques beyond IR, extending into crucial sectors like marketing, digital sectors, business can leverage AI drive trends analysis to consumer behaviour, ultimately guiding more informed decision making. Moreover, this review emphasizes the societal implications of integrating AI into data analysis processes. By enhancing the ability to capture trends and patterns effectively, AI can drive innovations and improve outcomes across multiple fields. The insights derived from this study not only illuminate the current state of research but also pave the way for future advancements in AI applications. The review highlights the immense potential of AI in transforming how we approach data analysis, fostering a deeper understanding of trends and patterns.

Declaration

Conflict Of Interest: The author reports that there is no conflict of interest

Funding: This research received no external funding.

Acknowledgement: None

Data Availability: Data sharing not applicable to this article as no datasets were generated.

Ethical statement for human participant: Not applicable for this research

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