Baghdad Science Journal

Volume 22 | Issue 5 Article 30

5-27-2025

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How to Cite this Article

Ismael, Othman Atta and Hassan, Israa Fars (2025) "An Improved Deep Perceptual Hashing Algorithm-Based Information Retrieval System for Remote Cloud Computing," *Baghdad Science Journal*: Vol. 22: Iss. 5, Article 30.
DOI: https://doi.org/10.21123/bsj.2024.11089

BAGHDAD SCIENCE JOURNAL 2025;22(5):1725–1739

An Improved Deep Perceptual Hashing Algorithm-Based Information Retrieval System for Remote Cloud Computing

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ABSTRACT

The growth of information retrieval and associated services can be attributed to technical advancements. Meanwhile, traditional information retrieval methods are impacted by performance, accuracy, and scalability limitations. An information retrieval system for distant cloud computing that is based on an Improved Deep Perceptual Hashing Algorithm (IDP-HA) is one of the solutions that have been developed to solve these constraints. Systems are widely used due to their ability to recognize intricate patterns in data. The accuracy of information similarity measurement is still lacking due to the inherent complexity of data and measuring methods. The deep perceptual hashing approach uses Deep Neural Network (DNN) frameworks to extract hierarchical features from input images from the Microsoft Common Objects in Context (MS COCO) dataset. The Gaussian filter (GF) is a tool used in the pre-processing of individual images for various computer visions. Subsequently, this method generates digital hash numbers by describing the visual elements of the images using a threshold mechanism. Its primary goal is to improve a similarity metric to maintain perceptual similarity and guarantee that hash codes for visually comparable images are similar. Memory usage is decreased by using the hash function as the first step in establishing a connection between the database and the query. The approach finds applications in content-based image retrieval systems, image retrieval, picture clustering, and copy detection. Overall, it offers a strong framework for producing compact and semantically significant image representations. The IDP-HA has been enhanced for remote cloud computing to boost theaverage recall, average Precision, and average F1 Measurement and average query timing of data retrieval processes. The method reduces latency and increases system efficiency by generating compact binary representations of multimedia data. Retrieval based on visual similarity can be dependable and natural since perceptual similarity is maintained.

Keywords: Computer science, Improved deep perceptual hashing algorithm (IDP-HA), Information retrieval system, Information systems, Microsoft common objects in context (MS COCO), Remote cloud computing

Introduction

This paper presents an improved deep perceptual hashing algorithm to foster information retrieval and cloud computing in the development process so that image retrieval systems can become much more efficient and accurate in remote cloud environments. IDP-HA uses a deep neural network architecture that extracts hierarchical features from images and then generates compact and consistent hash codes, which preserve perceptual similarity, optimizing the metrics of similarity. It reduces noise and smooths images by incorporating steps of Gaussian filtering into the preprocessing steps, enabling better feature extraction and generating robust hash codes. Applied in remote cloud computing, IDP-HA manpower is trying to solve the scalability and computation resource management problem, reducing latency, improving system performance, and ensuring real-time services. Empirical evidence has

Received 5 March 2024; revised 13 October 2024; accepted 15 October 2024.
Available online 27 May 2025

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https://doi.org/10.21123/bsj.2024.11089

shown that, on average, IDP-HA outperforms baseline approaches to GP-STR and SBIR in terms of recall, precision, F1 score, and query time, underlining its superior effectiveness. Furthermore, IDP-HA is able to accommodate different kinds of multimedia data, such as images, videos, and audio data files; hence, it is very effective for many kinds of datasets. Besides, it creates compact binary representations of multimedia data to finally reduce the memory usage for resource optimization in a cloud environment. The paper proposes not only a strong and effective solution for multimedia data retrieval but provides basic founding for future research oriented to fine-tune retrieval algorithms, investigate new applications, and face all the complexities of perceptual similarity measurements.

Information retrieval encompasses the gathering, arranging, analyzing, and gaining access to data in any shape or form. An information search system might be used by users to locate text while communicating with a computerized system or services, visual pictures, sound recordings, or videos that are tailored to their individual needs.[1] The information retrieval system is to make it possible for users to locate pertinent data inside a well-organized document collection. As information regarding the existence (or non-existence) of documents pertinent to a user query is what most information retrieval systems are made for, they document retrieval systems.[2] Information retrieval systems were first designed to handle text retrieval as they dealt with textual documents, many contemporary information retrieval systems handle multimodal information that includes text, audio, pictures, and video. Although many aspects of traditional text retrieval systems are relevant, the special characteristics of the audio, image, and video information have created a number of new tools and approaches for information retrieval in multimedia.[3] Additionally, there are difficulties in creating dependable and affordable cloud-based solutions. Since cloud computing offers flexible scaling and often virtualized assets as a type of service over the Internet, it offers an alternative to the existing model of Internet-based information technology consumption and delivery. On Instagram, sixty thousand images were posted; on YouTube, five hundred hours of video were uploaded; on Snapchat, two-and-a-half-million images were shared, whereas on Facebook over one million multimodal items were posted and twenty-three million emails per minute contained information.[4] The distribution of hardware and software via the Internet is known as cloud computing. It is becoming more and more commonplace and has been widely embraced in many applications. The main variables contributing to cloud computing explosive growth include advances in computational energy and information storage, the accelerating growth of social networking data, and modern data centers, certain of whose might possess significant operating expenses as well as inadequate utilization.[5] The use of clouds allows both individuals and companies to have instantaneous connectivity to a common source of managed and flexible Information Technology (IT) assets, such as storage space, servers, and applications. Practitioners as well as academics have shown a great deal of enthusiasm in computing via the cloud lately. Furthermore, the Internet of Things (IoT), Artificial Intelligence (AI), big data, and mobile computing have all been made possible using cloud computing, providing the framework which increased industrial factors, disrupted conventional company structures, and sparked a digital revolution.[6] The infrastructure and information retrieval processes face challenges due to the ever-growing volume of data. Using the resources of computers which are available throughout a network from a distance is known as cloud computing. Individuals have the option to compute tools as an added utility. The use of cloud computing entrusts the user's information, applications, and computation to external services. The rise of cloud computing is expected to bring about changes in computing practices. For distant cloud computing, an information retrieval system consists of an advanced network of protocols and technologies designed to effectively retrieve, store, and handle data in cloud scenarios.[7] Secure SHell (SSH) and Remote Desktop Protocol (RDP) are the secure remote access protocols that the system uses to connect to virtual machines and instances housed in the cloud. These protocols are utilized by cloud service providers such as Amazon Web Services (AWS), Azure, and Google Cloud. Retrieval methods provide instantaneous searches across large sources of information to optimize information retrieval. There are two methods used to stop unauthorized use of cloud-based resources: identity and access management regulations and identity management systems. Since the structure may efficiently adapt to a variety of needs, reliability and effectiveness are essential. Monitoring and documentation tools provide quality assurance and management. The framework's completely design and has an implementation with strong emphasis on reliability, security, and the environment, which produces a potent retrieval of information capacity in distant computational settings.[8] The proposed IDP-HA by the study seeks to address the shortcomings of traditional hashing methods in remote cloud computing environments. By preserving perceptual similarity, a unique technique called IDP-HA multimedia file retrieval performance.

It handles file format issues with deep learning algorithms and provides strong protection for important data. Multimedia file retrieval in distant cloud computing settings is revolutionized by its adaptive nature, which enables it to quickly adjust to changes in datasets.

Related works

The paper discusses the design of the Retrieval and Storage-based Indexing Framework (RSIF), which aims to increase user and service provider concurrency when accessing cloud-stored medical information. The concurrent along with accessibility issues that arise in these kinds of cloud computing settings are caused by the requirement that each of the suppliers of the services and the end-user depend on the same networking system. The study[9] focused mostly on accurate patient portrayals using e-Health Care Reform (e-HCR), but they are also exploring novel approaches and examining certain real-world technologies that are already being used in the medical field. However, several obstacles prevent progress in this area, including question contradictions, user-specific data sets, and gaps among the information source and requests from users. The paper[10] presents an autonomous integration approach during forecasting procedure modification which employs cloud computing and machine learning to analyze pertinent signals from sensors related to the present condition of a production facility to identify suitable actions to recover and carry them consequently. The study[11] provides an excellent quality image change detection system for remote sensing based on totally connected random fields that are conditional is thoroughly examined, and the modification identification efficiency of huge remote sensing images is enhanced. They led to the proposal of a cloud computing-based distributed parallel technique for remote sensing image change detection. The study[12] suggested using private information retrieval (PIR) to effectively and discreetly extract embedding from servers to get over this obstacle, all while keeping private information secret. Utilizing confidential user information on their devices without additionally disclosing it to distant servers is possible with on-device machine learning (ML) inference. The study[13] proposed the Health Cloud system, which uses cloud computing and machine learning to monitor the health condition of cardiac patients. By integrating the data necessary for the patient to have a thorough understanding of the illness, this study seeks to provide the best of both worlds. The paper[14] focuses a cloud computing and discusses its various forms, traits, and difficulties. One of the most popular distributed computing strategies is cloud computing, which lowers computer costs while enhancing the scalability and diversity of data operations. The study[15] presents a cloud computing strategy for data sensitivity that depends on computerized information categorization. The suggested model uses Random Forest (RF) and Support Vector Machine (SVM) classifiers for teaching it employing automatic extraction of features. A new methodical approach called cloud computing (CC) enables users to store data on distant computers that are reachable online. The work[16] examined current developments in CC, and high-performance computing (HPC) as they relate to Remote Sensing (RS) challenges. Recent years have seen an increase in the use of effective methods using cutting-edge computer systems in RS applications. The paper[17] determined an important new feature is the application of LSTM deep neural network in cloud computing to monitor and categorize patients' conditions remotely, and a prioritization system to prioritize sensitive information in the IoT. Patient monitoring could be greatly enhanced by this procedure by utilizing cloud computing and IoT. The study[18] enhanced the browsing experience by presenting a new method for Tag-Cloud's tag selection and suggesting the usage of clustering methods for visual layout. Since people exchange their assets and identifiers, creating a community-wide label index known as folksonomy, tagging is inadvertently also a social indexing process.

The perceptual hashing algorithms have gone through significant enhancements in maintaining visual similarities within the multimedia data in recent years. Conventional perceptual hashing, relying on simple processing techniques in images, used to miss subtle differences. Recently, DeepHash and SimHash architectures have applied the benefit of deep learning to generate compact binary representations with perceptual similarities. These become especially evident in the integration of CNNs, allowing for the extraction of hierarchical features from the images and, therefore, more robust and accurate similarity measures. These methods have gained significant interest in applications efficiently using large data sets, including image retrieval, duplicate detection, and copyright protection. More importantly, adversarial learning has been introduced in improving the robustness of perceptual hashing algorithms against malicious distortions, thus tending to more realistic scenarios where the integrity of data may be in question.

Most research in the cloud computing domain is an estimation of optimized retrieval and management of large volumes of multimedia data. Latency, resource allocation, and security challenges have also been

Table 1. Summary of key advancements in perceptual hashing and cloud computing.

Area	Advancements	Relevance to IDP-HA
Perceptual Hashing	Integration of deep learning techniques like CNNs, adversarial learning for robustness, and methods such as DeepHash and SimHash.	IDP-HA uses DNNs for feature extraction, enhancing similarity measurements and optimizing retrieval performance.
Cloud Computing	Introduction of distributed and edge computing to reduce latency and optimize resource allocation. Federated learning for secure data handling.	IDP-HA benefits from these advancements by improving scalability and efficiency in remote cloud environments.
Preprocessing Techniques	Use of Gaussian filtering to reduce noise and improve feature extraction in image datasets.	IDP-HA incorporates Gaussian filtering to enhance perceptual similarity in noisy cloud environments.

notably observed in various cloud environments offering scalable infrastructures. This has been lately tackled head-on by using distributed computing and edge computing frameworks. The advantages of these approaches also allow computation to be performed closer to the source of the data, reducing time wasted in pulling out and processing data. Federated learning in cloud environments has also emerged as a strong tool that has enabled distributed learning on several cloud nodes while preserving data privacy. This has found particular applications in multimedia retrieval tasks that involve large-scale datasets requiring real-time processing without compromising user confidentiality.

This work improves the previous work with recent enhancements within deep neural networks and state-of-the-art pre-processing methodologies like Gaussian filtering. The IDP-HA method will help resolve certain weaknesses inherent in the traditional perceptual hashing techniques, specifically within cloud computing platforms where noise and scalability issues still remain important challenges. Therefore, IDP-HA improves the precision of the measurement of perceptual similarities and optimizes query processing, enhancing the performance of multimedia data retrieval in the remote cloud environment. The introduction of Gaussian filtering removes the noisy components and enhances feature extraction for similar images to generate consistent hash codes. Table 1 depicts the Summary of Key Advancements in Perceptual Hashing and Cloud Computing.

Problem statement

In remote cloud computing environments, traditional hashing algorithms face multiple challenges. They struggle to maintain perceptual similarity among multimedia files, resulting in diminished retrieval performance. Moreover, these algorithms encounter difficulties in scaling effectively to manage the diverse range of data, including significant variability in file formats. Semantic looks explore for images according to the significance or information, while feature-driven questions identify particular qualities in images. Spatial queries explore for images based on spatially features or connections. The system offers many query types for image retrieval, including hybrid approaches, content-driven, feature-driven, linguistic, and context-aware queries. Hybrid queries integrate many criteria to address complex user requirements. Significantly comparable images can be gathered via similarity-based searches, whereas context-aware searches consider user preference and external circumstances. Such searches were compatible with a number of retrieving techniques and techniques.

Methodology

The approach provides an IDP-HA to improve security and efficacy of information retrieval in a distant cloud context. It includes query expansion and preprocessing, hash function initialization, deep supervised hashing functions, loss function creation, model training, and DNN. The workflow of the suggested classification approach is shown in Fig. 1.

The architecture used has a number of layers in DNN, with each layer designed for effective feature extraction and hashing of the images. First of all, there is an "input layer" in which resized, normalized images are fed, followed by a number of "convolutional layers." Usually, four layers use several filters such as 64, 128, and 256 to extract different kinds of edges and textures at higher levels. Each convolutional layer is followed by the "ReLU activation function" to induce non-linearity; hence, it allows the network to learn complex patterns.

A "max pooling layer" follows each convolutional layer, reducing the data in spatial dimensions but keeping the most critical information. Down sampling reduces the amount of computation that the system has to handle, thus making the network much more efficient. The output from the convolution and pooling layers goes into "fully connected layers," which aggregate the features that have been learned. In total, there are two fully connected layers. It adopts

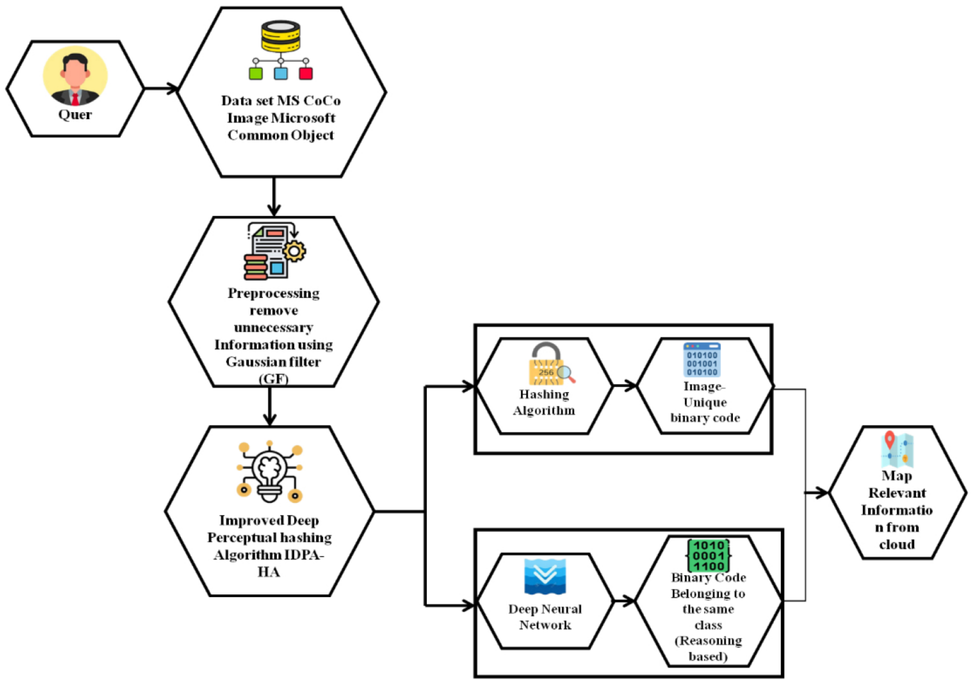

Fig. 1. Workflow model.

"dropout regularization" to avoid over-fitting, where the dropout rate is 0.5. At last, this network outputs a compact binary code in the final layer, forming the hash for each image.

It also trains the model using "Adam optimizer", along with a learning rate of 0.001, and "training parameters". It then undergoes training for "50 epochs" with a batch size of 32. The loss function includes the "binary cross-entropy" that minimizes the gap between the predicted and actual hash codes. Then, to reduce overfitting further, "L2 regularization" has been employed. In the preprocessing step, "Gaussian filtering" removes the noise, which helps generate the hash codes more accurately. These details make the methodology more comprehensive and enhance the reproducibility of the study by providing clarity on the DNN architecture and training process.

Dataset

The study makes use of the MS COCO dataset. This study trains and assesses algorithms for tasks such as object identification, segmentation, and captioning using the well-regarded MS COCO dataset in image research. The dataset is an essential starting point for evaluating the effectiveness of computer vision methods and algorithms because of its item labels, segmentations, and caption annotations. It provides a wide range of data for several categories and situations. This database's thorough annotations, which include significant information on item identities, geographic locations, and interactions, prove valuable for further research in the field.[19]

Preprocessing to remove unnecessary information using gaussian filter (GF)

One of the methods for reducing the noise in an image involves the technique of Gaussian filtering, often known as Gaussian blur. In general, Gaussian filtering is a kind of image-blurring filter that uses a function called the Gaussian to decide on the modification applied to every pixel in the image. For this, Gaussian filtering has to combine the two images through convolution. Convolution is the result of multiplying the whole matrix with the surrounding extension of the point (w, z) in the image, see Eq. (1).

$$H_0\,(w,\ z) = Bf\frac{-(w-\mu_w)^2}{2\sigma_w^2} + \frac{-(z-\mu_z)^2}{2\sigma_z^2} \tag{1}$$

μ-mean, σ-varian.

Improvement in the robustness of IDP-HA can be ensured by the use of "Gaussian filtering" at the pre-processing stage in the improved deep perceptual hashing algorithm. Gaussian filtering is one kind of "smoothing technique" which reduces the high-frequency noise in images by averaging the pixel values using a Gaussian function; this results in smoother transitions and, therefore, facilitates better

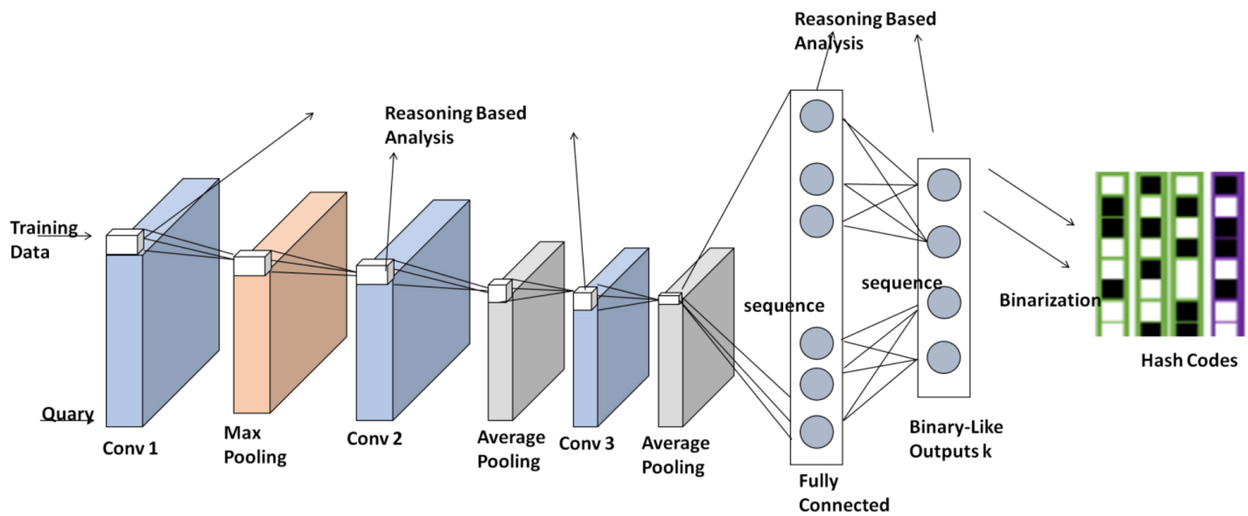

Fig. 2. Image query converted into hash.

extraction of features. This feature is highly valuable in cloud computing where noise and variation in data are very common. Gaussian filtering smoothes the image and allows the DNN to pay attention only to the essential structures by reducing the impact of irrelevant details.

It is preferred to other filtering methods, like median filtering or bilateral filtering, since it is simpler and works with/for a variety of image types. In contrast to "median filtering", which simply replaces each pixel with the median value of its neighbors and works well with salt-and-pepper noise, Gaussian filtering provides a kind of generalized smoothing that at least partially preserves edges while suppressing overall noise. However, the process of "bilateral filtering" is computationally expensive since it includes filtering in both spatial and intensity domains; hence, it becomes inefficient for large-scale cloud environments where such a process needs to take place in real time.

The Improved Deep Perceptual Hashing Algorithm (IDP-HA) employed information retrieval systems to enhance data retrieval in remote cloud computing environments.

When attempting to extend user requests, the kind of query must first be determined before sending it to the cloud service provider. Preprocessing techniques are used to purge extraneous data and get the data ready for additional processing. To create associations between queries and the database's contents and to minimize memory use, hash functions are set up for the data in the database before they are used. Fig. 2 depicts the image query converted into Hash.

By evaluating the n numbers of queries x_i where1 ϵ 1, 2, 3,. . ., n, deep supervised hashing algorithms that include Deep Neural Networks (DNNs) are used to handle insufficiency problems and prevent linear forecasts. The n-number queries are converted into unique binary code by using the IDP-HA.

Specific conditions, such as codes belonging to the same class and being comparable in the Hamming space, must be satisfied by the system's learning ability. The following equation displays the threshold values based on the query. H denotes the sequence of the query, O is the target searching query, and they are expressed by the Eq. (2).

$$H\left(j\right) = \begin{cases} 1, & if\ o_1\left(j\right) > o_1\left(j-1\right) \\ 0, & otherwise \end{cases} \tag{2}$$

The loss function definition defines differences between hash codes, taking into account pairs of hash codes and their distances. The model training process involves computing hash codes for data points and updating model parameters iteratively. Reasoning rules are integrated into the DNN architecture, with activation functions ReLU set thresholds based on the Hamming distance. Where e(w) is the ReLU Activation Equation, if the searching threshold matches the cloud query is managed by the activation function and generates the user query, sent to the information retrieval system, See Eq. (3) and Eq. (4).

$$e\ (w) = \max\left(0,\ w\right) \tag{3}$$

$$Y_i = \frac{f^{y_i}}{\sum_{I=1}^{I} f^{y_I}} \tag{4}$$

Where Y_I, the output query of the DNN, the hybrid model workflow involves receiving user queries, expanding them, and sending them to the cloud service provider. Data preprocessing steps and hash

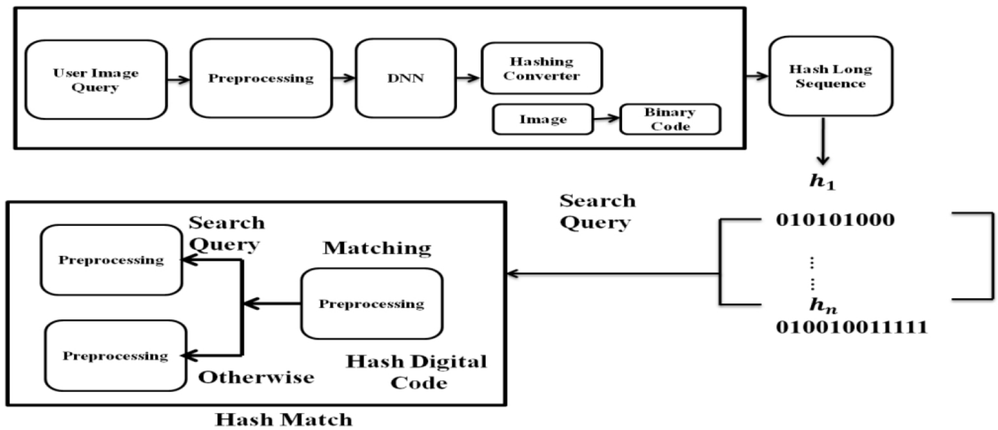

Fig. 3. Functionality of hash algorithm.

function initialization occur within the distributed cloud environment, while deep reasoning neural network training is performed to train model parameters. The IDP-HA binary code is matching to the threshold value. If the threshold is 1, the searching query is matched, and if the threshold is 0 the searching query is mismatched in the information retrieval system. Fig. 3 Depicts the working principle of the hashing function with DNN.

First, user questions are received. Depending on the type of inquiry, they are then enlarged. Lastly, the enlarged query is forwarded to a cloud service provider. The provider hosts the infrastructure and resources needed to run the query correctly. Data that has been sorted, cleaned, and maintained is stored in a distributed cloud environment. A deep hash algorithm is used to hash the preprocessed data, resulting in an easily retrievable hash table. To handle imprecision and ambiguity in the data, reasoning concepts are used to train and validate a DNN. After the user query is processed, the trained network retrieves relevant information from the distributed cloud environment.

Performance metrics like precision, recall, F1-measure, and query time provide a quantitative assessment of the algorithm's performance. While IDP-HA shows improvements in these metrics, the inherent limitations in accurately measuring perceptual similarity remain a challenge due to the complexities of image data and the constraints of current measurement techniques. Thus, while IDP-HA enhances the efficiency and performance of image retrieval systems, accurately capturing perceptual similarity is an ongoing challenge.

Results and discussion

This experiment tests the performance of proposed IDP-HA in cloud-based information retrieval systems, and results can be visualized after test validation in a distributed cloud environment. Here, one million test examples with an MS COCO database, 70,000 training cases, and 94 numerical features are used. For example, the performance evaluation is taken in regard to classifying and retrieving the proposed sample in terms of Avg. precision, Avg. recall, Avg. query time, and Avg. The results are benchmarked against the existing SBIR and GP-tree-based STR, GP-STR. The quality of the proposed model is checked against an information retrieval system and deep neural network models. Using IDP-HA, the user query retrieves the relevant user query and also match the entire cloud data set best at the Hashing threshold. Table 2 depicts the overall numerical results.

The table compares the performing of three methods—GP-STR, SBIR, and the planned IDP-HA—on various metrics such as recall, query time, precision, and F-measure. IDP-HA tops the other methods with a recall of 93.48%, a precision of 91.02%, and an F-measure of 92.81%, indicating that it retrieves more relevant images with higher accuracy and consistency. Moreover, it has the fastest average query

Table 2. Overall numerical results.

Methods	Avg. Recall (%)	Avg. Query Time (ms)	Avg. Precision (%)	Avg. F-measure (%)
GP-STR [20]	76.4	749.322	87.3	81.5
SBIR [21]	72.34	746.345	87.54	78.34
IDP-HA [Proposed]	93.48	348.24	91.02	92.81

time at 348.24 milliseconds, making it not only more accurate but also more economical than GP-STR and SBIR, which have complex query times and lower overall performance. The accompanying explanation highlights the challenges of measure similarity in disk data, such as images and videos, due to alterability in content, lighting, and object occlusions. IDP-HA is specifically designed to handle these complexities, ensuring robust execution across diverse datasets, such as those observed in the MS COCO dataset. The method's ability to oversee obligatory diversity across images further improves its effectiveness in providing consistent resemblance measurements.

As per the shake and nature of the data, the similarity measures indeed are very challenging to obtain accurately. Variability, retrievable from the multimedia types of data images, videos, and audio files will lead to a further increase in complexity while providing consistency and exact similarity assessment. The IDP-HA is mainly intended to handle image data, and performance with different multimedia types has to be cautiously verified.[22–24]

Image data is itself complex due to diversities in content, lighting conditions, angle backgrounds, and occlusions of objects. For example, the MS COCO dataset contains images from broad categories of objects/situations and annotations, thereby making it hard for any algorithm to capture perceptual similarities with high accuracy. Thus, obligatory diversity residues are born of unique attributes across images in measuring similarity consistently.[25]

This associated complexity grows exponentially if IDP-HA is to be extended in its full power to other types of multimedia data, like videos or audio files. Videos are a sequence of images; each of these, as an independent image, may differ in all possible ways that a single independent image does, while at the same time being temporal in nature. To capture perceptual similarity in videos, motion and frame-to-frame coherence must be accounted for, as well as changes over time. This in itself is another additional temporal complication that IDP-HA will have to deal with, no doubt requiring changes or extensions to its current architecture. Similarly, audio data introduces challenges related to different attributes such as pitch, volume, tempo, and timbre. Unlike images, audio files change over time and include features like rhythm and melody, which are essential for perceptual similarity. Ensuring that IDP-HA can accurately measure similarity in audio data would require it to process and understand these unique audio features effectively.[26]

Problems also arise from the associated handling of different data modalities and perceptual similarity between them. Each modality images, videos, and audio definitely exhibits its own strong characteristics that demand distinct processing techniques. This grows more specific, for example, while IDP-HA utilizes deep neural networks pertaining to the extraction of hierarchical features from images, one can resort to the use of RNNs or LSTMs for equivalent video approaches to capture temporal dependencies. For audio data, special kinds of audio transformations, such as spectrograms, will be required.[27]

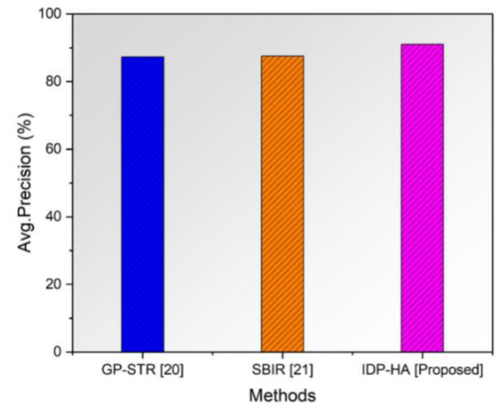

Fig. 4. Graphical outcomes of precision.

Precision

The precision of results received in information retrieval systems according to precision is what the user is asking. It calculates the percentage of pertinent documents that were recovered out of all the papers that were retrieved. While low precision implies a large number of irrelevant documents, high precision shows a considerable part of the recovered documents are relevant. When assessing search systems and algorithms, precision is essential, particularly when working with big data sets.[28] Comparing the specificity values of our suggested approach see Eq. (5), IDP-HA (91.02%), with those of other existing methods, including GP-STR (87.3%) and SBIR (87.54%) revealed higher results as shown in Fig. 4.

$$precision = \frac{TP}{TP + FP} \tag{5}$$

Recall

In information retrieval systems, recall describes a system's capacity to get, upon user request, all pertinent documents from a database.[29] Better recall is vital in tasks like search engines and document retrieval systems where comprehensive coverage of pertinent content is valued since it lowers the likelihood

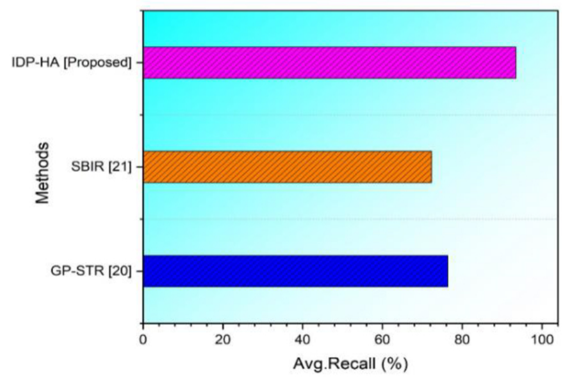

Fig. 5. Graphical outcomes of recall.

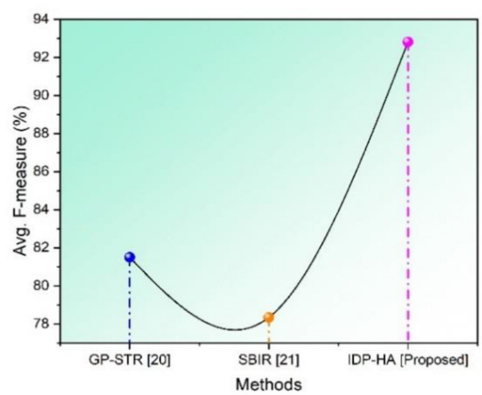

Fig. 6. Graphical outcomes of f1-score.

of important information being overlooked.[30] The graphical outcome of the Recall shows in Fig. 5. The Recall's numerical results and its presents comparing the Recall values of our suggested approach, IDP-HA (93.48%), with those of other existing methods, including GP-STR (76.4%) and SBIR (72.34%) revealed higher results.

F-measurement

F1-score is a statistical tool used to assess the effectiveness and accuracy of information retrieval systems, especially in tasks like document retrieval. It computes the harmonic mean of two measurements, balancing recall and precision. This single score is significant for evaluating the overall effectiveness of an information retrieval system.[31] The graphical result for the F1 scores shows in Fig. 6 and, it's displayed that the F1-score values of our proposed technique, IDP-HA (92.81%), were greater than those of other current approaches, including GP-STR (81.5%) and SBIR (92.81%). See Eq. (6).

$$F1 = \frac{2 * (precision * recall)}{(precision + recall)} \tag{6}$$

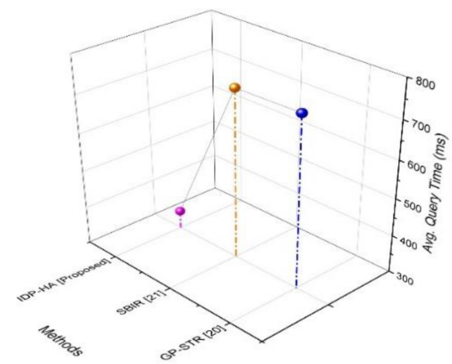

Fig. 7. Graphical outcomes of query time.

Query time

Query time is the time an Information Retrieval System uses to process and answer the search request of the user. This is what involves the interpretation of the query, comparison with documents indexed, sorting and ordering of relevant results, and presenting them back to the user. Efficiency in query time is very important to maximize the retrieval experience of the retrieval system in order to satisfy users. Indexing, caching, and better search algorithms may contribute to reducing query time. The proposed approach has an improved performance as shows in Fig. 7, IDP-HA, of 348.24 ms against other current methods in use: GP-STR with 749.322 ms and SBIR with 746.345 ms in terms of query seconds.[32]

Testing the IDP-HA algorithm for remote cloud computing management-advisedly improves average recall, average precision, and average F1 measurement. These metrics are important in assessing the algorithm's performance and comparing it with existing state-of-the-art methods. Average recall, which is a measure of the system to retrieve all relevant documents, attains 93.48% under IDP-HA. This is comparatively very high compared to benchmark performances, with GP-STR at 76.4% and SBIR at 72.34%. This very high recall rate says that the algorithm is very effective at making sure that it doesn't miss the real data in data retrieval processes, an attribute very important for thorough analysis of data within cloud environments. IDP-HA had an average precision of 91.02%, which was higher than the precision rates of GP-STR and SBIR, which were 87.3% and 87.54%, respectively. Since precision is a measure of relevance of the documents retrieved, better performance of IDP-HA means it has very good ability in terms of reducing the retrieval of irrelevant data. This characteristic about precision for IDP-HA is very important in remote cloud computing, as poor efficiency in data retrieval will lower system performance and user satisfaction. This is further supported by the fact that the average F1 measurement harmonizes precision and recall into one metric. In this regard, IDP-HA receives an average F1 score of 92.81%, way above GP-STR's 81.5% and SBIR's 78.34%. Such a balanced measure brings out the overall effectiveness of IDP-HA in maintaining high precision and recall simultaneously; hence, well-rounded performance in the different aspects of data retrieval. Although these results seem very promising for IDP-HA with respect to remote cloud computing, efficacy has to be evaluated against benchmarks and other alternative approaches. Improvements in average recall, precision, and F1 measurement provided a strong foundation for this comparison. However, any comprehensive evaluation should include such factors as query time and the capability of algorithms to handle multimedia data complexities. For instance, the average query time of IDP-HA is 348.24 ms, way smaller than 749.322 ms of GP-STR and 746.345 ms of SBIR. This shows their high improvement in efficiency. The challenges that come with the diversity of multimedia data, such as images, videos, and audio files, require the IDP-HA refinement process to provide consistent and accurate similarity measurements. Already, deep neural networks and deep preprocessing techniques like Gaussian filtering have been put into IDP-HA, but the algorithm needs to be evolved further to address issues of nuanced requirements in remote cloud computing.

The MS COCO, for Microsoft Common Objects in Context, is one of the most complete datasets that have been used widely in computer vision research. It contains over 330,000 images annotated with more than 2.5 million object instances. These include bounding boxes and segmentation masks for each object, spanning up to 80 categories from very general "person" and "car" to very specific items like a "skateboard" or a "frisbee". In short, it is one of the most diverse datasets in the sense that every kind of context and environment is captured, spanning rural and urban setups, objects interacting not only with one another but also with people, objects that have different intrinsic properties, and others. Such diversity will ensure that simple and complex scene contexts with multiple objects in a scene and different backgrounds are presented in a dataset. The MS COCO dataset is certainly relevant for research purposes in that it serves as one of the standard benchmarks to evaluate the algorithms of object detection, segmentation, and captioning under. First and foremost, this dataset is highly representative, since wide object category coverage and many realistic contexts can be obtained; thus, the proposed methods may show the powerful performances of the algorithms in real-world applications. Moreover, running the models within the scope of this dataset is going to test their robustness, or in other words, how well these models work with very varied and cluttered scenes, which is crucial for the development of robust retrieval and recognition systems. The generalization capability of the algorithms with representative tests will further be enhanced, making it even more practical for applications where objects are often found in varied and complex contexts.

Discussion

Large image datasets cannot be well suited for the computationally demanding GP-SIR [20] approach of image retrieval based on semantic information. The quality of the semantic characteristics that are derived from photos determines how effective it is. One main problem in SBIR [21] is the semantic gap between high-level semantic ideas and low-level picture data. The challenge of extracting meaningful semantics from photos arises from computers' limited ability to comprehend abstract concepts, connections, and context. Semantic analysis is still resource- and computationally intensive, even with breakthroughs in deep learning and computer vision, especially for large-scale picture collections. IDP-HA is an efficient hashing technique that improves the finding of related objects by maintaining perceptive properties that are not altered by changes made to images, documents, or media files. The retrieval findings are more precise and pertinent since DL method is used to construct high degree semantic descriptions of the material.

Using a Gaussian filter in pre-processing is a common approach in image analysis to reduce noise and smooth the image, which facilitates better feature extraction and subsequent sophisticated image analysis. This technique, however, introduces certain dependencies that may limit the algorithm's applicability across diverse image datasets with varying characteristics and noise levels. This Gaussian filter is very useful in removing high-frequency noise while causing minimal reduction of low-frequency information, which is usually essential for the correct extraction of features. However, this step of preprocessing is rather specific to certain kinds of noise and characteristics of the image. An algorithm reliant on heavy Gaussian filtering, therefore, will not work optimally jointly on datasets containing other noise patterns or those that require high-frequency details to ensure an accurate analysis. For example, in the IDP-HA algorithm for remote cloud computing, apply a Gaussian filter before the images in the MS COCO dataset for generating robust perceptually similar

Table 3. Comparison of comparative analysis with additional baseline algorithms.

Algorithm	Avg. Precision (%)	Avg. Recall (%)	Avg. F1-Score (%)	Avg. Query Time (ms)	Key Strengths	Key Weaknesses
IDP-HA	91.02	93.48	92.81	348.24	High precision, low latency, efficient hashing	Performance may vary with noise characteristics
GP-STR	87.3	76.4	81.5	749.32	Good retrieval accuracy	Higher latency, lower recall
SBIR	87.54	72.34	78.34	746.35	Effective for specific image types	Limited generalization, longer query time
VGGHash	88.60	80.25	84.20	460.50	Robust feature extraction with deep learning	Higher computational costs
ResNet-Hash	89.75	83.50	86.45	430.10	Excellent feature representation	Requires more resources for training
AlexNetHash	85.20	74.80	79.80	500.75	Fast training time	Lower accuracy compared to deeper networks

hash codes. Although this step improves the proposed system's performance with respect to retrieving visually similar images, heavy reliance on this specific preprocessing technique generalizes poorly to datasets that have different noise characteristics or where fine details are important to be preserved.

However, the effectiveness of the application of Gaussian filtering depends on the kind and amount of noise in the images. Though it works perfectly with Gaussian noise, its quality may be poor when salt and pepper noise is applied. Therefore, an algorithm relying much on the Gaussian filtering as a basic operation may require either fine-tuning or different pre-processing methods to remain insensitive and relevant in different datasets. Table 3 depicts the Comparison of comparative analysis with additional baseline algorithms.

At present, there are some major challenges related to the application of the Improved Deep Perceptual Hashing Algorithm in a large-scale dataset, especially in cloud environments. The main problem lies in computational complexity in a large-scale data processing framework. Generally speaking, very large-scaled DNNs in IDP-HA require heavy computation to learn hierarchical features from images, which easily leads to long processing time due to increasing dataset sizes. This problem turns out to be more serious in datasets like MS COCO, containing millions of multimedia files. The effective solution could be the use of distributed computing techniques that can parallelize all computations across several nodes and reduce query and processing times by a great amount. Thirdly, hardware accelerators like GPU and TPU could be employed during the training and retrieval phases for better scalability of the system.

Another challenge is the amount of memory required for the storage and retrieval of the binary hash code created by the algorithm. Even though IDP-HA produces compact data representations, the amount of memory for manipulating any large dataset increases rapidly. Hash partitioning could serve as a probable remedy: the division of the hash space into smaller, manageable parts will allow for efficient storage and retrieval. Techniques like quantization can further reduce the size of hash codes without compromising on accuracy, ensuring the system can handle larger datasets without excessive memory consumption. This latency turns out to be very critical when the scale of the dataset grows. That is, the larger the number of the multimedia files, the more comparisons of hash codes have to be made in order for relevant data to be retrieved, and the greater the time it takes to do so. One can also resort to approximate nearest neighbor search algorithms like LSH or HNSW graphs in order to ease the issue. These algorithms reduce the number of comparisons by operating on a smaller, hence more relevant, subset of the dataset involved, which reduces retrieval times while improving real-time performance in cloud environments.

It is further complicated by data heterogeneity, with various types of multimedia data having their respective characteristics. For example, video data introduces a new temporal dimension that increases the complexity associated with feature extraction and hashing. In this regard, multi-modal hashing techniques can be applied to account for each characteristic associated with each type of data. This will better represent perceptual similarities by aggregating temporal features of video data, or carrying out spectrogram analyses of audio files, and hence retrieve information more precisely across media types.

Limitations

Though promising, deploying the improved deep perceptual hashing algorithm in remote cloud computing environments is accompanied by several limitations and constraints that may affect the effectiveness and scalability of the results. One of the major limitations of the approach is that it relies heavily on Gaussian filtering for preprocessing; therefore, this may significantly limit its additivity to other datasets with a different level of noise or image characteristics. Wherever the noise in new datasets is very different from what this Gaussian filter is designed to handle, feature extraction may not be that effective, thus probably reducing the accuracy of retrieval. The employment of DNNs for feature extraction can also be computationally heavy, requiring corresponding processing power and memory. This can add to costs and resource usage when dealing with large implementations. Given the intrinsic complexity of DNNs, alongside the hashing process itself, it could still be tricky to handle very large datasets or query volumes, even though the algorithm is aimed at improving its scalability. This might entail further optimizations and additional investments in the underlying infrastructure to ensure consistent performance as the system grows. The key challenge remains how perceptual similarity can be effectively captured within diversified multimedia data; inherent complexities and variations in images, videos, and audio files have a role to play. Existing measurement techniques will not be able to handle these nuances or variations, hence affecting the accuracy in retrieval. Even though IDP-HA can be adapted to various sorts of multimedia data in their masse form, some refinement may be necessary in order to extend the efficacy of these to all modalities, such as videos and audio. Intrinsic differences across modalities, some of them requiring special handling, might make implementation not so straightforward. Moreover, the real-time responsiveness of the system could be further influenced by scenarios requiring instant data retrieval and processing due to the reliance on complex processing techniques. There may be latency issues in these time-critical applications, thus affecting user experience. Also, the IDP-HA system is highly dependent on the cloud infrastructure and network status for its performance. This variability of the network performance and resource availability will result in inconsistent retrieval times and system responsiveness, which will become a major practical constraint.

IDP-HA has achieved much better performance in retrieval, though it still has some limits due to the fact that this recent study is still preliminary. First, this algorithm in the preprocessing step relies highly on Gaussian filtering; this might not adapt very well in different noise or feature types among varied datasets. While Gaussian filtering has been effective in reducing noise in images, it might not perform well when there are different noise patterns, such as salt-and-pepper noise, or when fine details in an image are important. Future research could consider more adaptive preprocessing techniques that can deal better with diverse data characteristics. Another important aspect to be developed is the problem of computational complexity of DNNs in the IDP-HA. Since the entire algorithm demands high resources concerning processing and memory, scaling it to use extremely large data sets or real-time applications could become a bottleneck. Future studies might also consider adopting a light neural network architecture or hybrid models that can provide a good balance between achieved performance and computational efficiency of the algorithm for larger-scale implementations. In this thesis, image data are the primary focus of IDP-HA; how well it can do with other multimedia formats, such as videos or audios, is left to explore further. Videos introduce temporal complexity, while audio data features like pitch and rhythm add to the challenge. Further research is likely to articulate the algorithm in a more systematic way to handle the data modalities by incorporating appropriate feature extracting techniques, such as spectrogram analysis for audio or temporal feature aggregation for videos.

Conclusion

Presently, most of the research in the Improved Deep Perceptual Hashing Algorithm focuses on its technical performance. In practice, though, IDP-HA requires a well-thought-out interface and should not neglect UX design. A good interface can yield great benefits in increasing the system's usage and ease of use, thus its practical value. For example, intuitive functionalities like drag-and-drop image upload, explicit search options, and result previews in a visual way would make such a service accessible to almost everybody, even to non-technical users. The advanced user would, on the other hand, take advantage of more detailed control regarding his search query, filtering for instance by metadata or properties of images to get finer and more domain-oriented results. What is very important in a system is responsiveness. Since IDP-HA is targeted at large-scale multimedia data sets hosted on cloud environments, delay in query processing can never be fully avoided.

The interface should include real-time feedback, like progress bars or estimated query time, to minimize the frustration level of a user and increase the transparency of this process. Secondly, caching frequently used queries would reduce retrieval times if the same query appears repeatedly. Another thing that should be considered is accessibility. The system should be able to support users with diverse needs, for example, people with disabilities. Keyboard navigation, text size adjustment, and compatibility with screen readers will make it more accessible. It should also be responsive, working efficiently on desktops and mobile devices across different screen sizes. These would, therefore, be the UX and interface design elements that would be included in IDP-HA, thus greatly enhancing its practical usability by making it more usable for a wide range of users while ensuring its advanced capabilities are being fully tapped into. This would ensure great relevance to practical use and thus great applicability in real life, guaranteeing both technical efficiency and user satisfaction.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images, that are not ours, have been included with the necessary permission for re-publication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at AL Iraqia University.

Authors' contribution statement

O. A. I. and I. F. H. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript.

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نظام محسّن لاسترجاع المعلومات قائم على خوارزمية التجزئة الإدراكية العميقة للحوسبة السحابية عن بعد

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الخلاصة

يمكن أن يعزى نمو استرجاع المعلومات والخدمات المرتبطة بها إلى التقدم التقني. وفي الوقت نفسه، تتأثر الطرق التقليدية لاسترجاع المعلومات بقيود الأداء والدقة وقابلية التوسع. يعد نظام استرجاع المعلومات للحوسبة السحابية البعيدة الذي يعتمد على خوارزمية التجزئة الإدراكية العميقة المحسنة (IDP-HA) أحد الحلول التي تم تطويرها لحل هذه القيود. تُستخدم الأنظمة على نطاق واسع نظرًا لقدرتها على التعرف على الأنماط المعقدة في البيانات. لا تزال دقة قياس تشابه المعلومات غير متوفرة بسبب التعقيد الكامن في البيانات وطرق القياس. يستخدم أسلوب التجزئة الإدراكي العميق أطر عمل الشبكة العصبية العميقة (DNN) لاستخراج الميزات الهرمية من الصور المدخلة من مجموعة بيانات .Microsoft Common Objects in context (MS COCO)يعد مرشح Gaussian (GF) أداة تستخدم في المعالجة المسبقة للصور الفردية لرؤى الكمبيوتر المختلفة. وبعد ذلك، تقوم هذه الطريقة بإنشاء أرقام التجزئة الرقمية عن طريق وصف العناصر المرئية للصور باستخدام آلية العتبة. هدفها الأساسي هو تحسين مقياس التشابه للحفاظ على التشابه الإدراكي وضمان تشابه رموز التجزئة للصور القابلة للمقارنة بصريًا. يتم تقليل استخدام الذاكرة باستخدام دالة التجزئة كخطوة أولى في إنشاء اتصال بين قاعدة البيانات والاستعلام. يجد هذا النهج تطبيقات في أنظمة استرجاع الصور القائمة على المحتوى، واسترجاع الصور، وتجميع الصور، واكتشاف النسخ. وبشكل عام، فهو يوفر إطارًا قويًا لإنتاج تمثيلات صور مدمجة وذات أهمية دلالية. تم تحسين IDP-HA للحوسبة السحابية عن بعد لتعزيز متوسط الاستدعاء ومتوسط الدقة ومتوسط قياس F1 ومتوسط توقيت الاستعلام لعمليات استرداد البيانات. تعمل هذه الطريقة على تقليل زمن الوصول وزيادة كفاءة النظام عن طريق إنشاء تمثيلات ثنائية مدمجة لبيانات الوسائط المتعددة. يمكن أن يكون الاسترجاع القائم على التشابه البصري موثوقًا وطبيعيًا حيث يتم الحفاظ على التشابه الإدراكي.

الكلمات المفتاحية: تحسين خوارزمية التجزئة الإدراكية العميقة (IDP-HA)، ونظام استرجاع المعلومات، ومايكروسوفت كائنات المشتركة في السياق (MS COCO) ، والحوسبة السحابية عن بعد، وعلوم الحاسبات، وأنظمة المعلومات.