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Integrating CNN and KNN for Enhanced Image Content Algorithm

Gagandeep Kaur*[1], Satish Saini[2]

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Abstract: Multimedia content analysis is critical for visual data processing, particularly given the prevalence of digital visuals. Retrieving appropriate photos from networks such as Twitter and Instagram is a difficult research problem in computer vision. Traditional text-based search engines are inadequate to handle the volume and variety of visual data. To solve this, we present a novel hybrid CBIR model that combines CNN and KNN. This methodology enhances retrieval efficiency by closing the gap between picture attributes and human visual perception. We investigate a variety of retrieval techniques, including standard feature extraction and deep learning approaches. Our hybrid model for Query by Image Content Retrieval combines CNN feature extraction with KNN classification. By combining the two, we improve the effectiveness and efficiency of CBIR.

Keywords: *CBIR, CNN, QBIC, Hybrid Algorithm, Image retrieval, KNN, Machine Learning*

1. Introduction

With the latest advancements in technological era, the utilization of digital cameras, smartphones, and the Internet has significantly been escalated. As a result, the proliferation of shared and stored digital media data has led to a significant increase, presenting a complex research challenge in effectively searching and retrieving relevant images from vast archives. The fundamental goal of any image retrieval model is to accurately organize and retrieve photographs that demonstrate a visual semantic association with the user's entered search query.

At present, majority of the web search engines utilize text-based methods to retrieve images. These methods rely on captions as input, where users enter keywords or text information that are subsequently compared against the keywords present in the image archives. The outcome is generated based on keyword matches, which can lead to the retrieval of irrelevant images. The disparity among visual perception by humans and manual labelling/annotation is a major element in the development of irrelevant outputs. Manually labelling large image archives containing millions of images is practically unfeasible.

The use of automatic image annotation systems, which can identify images based on their content, is an alternate way for image retrieval and analysis. These systems rely on accurately detecting edges, color, space features, texture and for shape information. Prominent research experiments have been conducted to improve the performance of automated portray annotation. Nonetheless, variations in the interpretation of visual stimuli can still influence the process of retrieval.

[1]*Research Scholar, Department of Electronics and Communication Engineering, RIMT University, Punjab, India and Assistant Professor, Chandigarh College of Engineering, CGC, Jhanjeri, Punjab, India*
ORCID ID : 0000-0003-2327-1375
[2]*Professor, Department of Electronics and Communication Engineering, RIMT University, Punjab, India*
ORCID ID : 0000-0002-9194-3068
** Corresponding Author Email: kaurgagan10deep@gmail.com*

CBIR provides a framework to address the aforementioned challenges by focusing on the visual analysis of content present in the query image. CBIR necessitates the submission of a input query image by the user, which is analyzed with the visual characteristics of images stored in the archive afterthat. The proximity of visual similarity, determined by image feature vectors, forms the foundation for identifying images with similar content. CBIR analyzes various low-level visual attributes such as shape, texture, color and spatial features extracted from the user query image, and the correlation among these features enables the sorting of the output. [1]. Based on the existing literature, researchers have developed Query-By-Image Content retrieval models that focus on extracting low-level visual semantics to ensure simplicity and efficiency in the retrieval process [1]. These models have found successful implementation, leading to the application of CBIR. Remote sensing, Medical image analysis, video analysis, crime detection, crime detection and the military surveillance all use feature extraction methodologies.

The primary objective of any image retrieval system is to effectively locate and categorize relevant visual content from a database with minimal human intervention. According to the literature, a choice of visual characteristics for such systems is determined by the specific needs of end users. Another crucial requirement is the utilization of discriminative feature representations [2][3]. Enhancing the robustness and uniqueness of features through the fusion of low-level visual features can yield more reliable results, albeit at a higher computational cost [4] [5]. It should be considered that the incorrect selection of features might have a negative impact on the effectiveness of a visual retrieval model [6]. Enhancing the performance of CBIR can be achieved by incorporating machine learning algorithms, where models are trained and tested using image feature vectors as input [1] [7]. The algorithms for machine learning can be used in either a supervised or unsupervised training-testing environment. Recent trends in image retrieval focus on deep neural networks (DNNs), which offer better results at the expense of higher computational requirements [8] [9].

The aim of this paper is to provide a comprehensive and in-depth review of the latest developments in content-based image retrieval and feature representation, offering a detailed summary of the recent advancements in research in this field. The aim is to address the evolving landscape and highlight key advancements in the domain.

Furthermore, this paper introduces a novel hybrid algorithm designed to improve the efficiency of image retrieval, thereby addressing the need for more effective and accurate retrieval methods in the field.

Typically, an image retrieval system operates by taking a single query image as input and then generating a sorted list of similar images based on their feature similarity. The feature extraction component calculates descriptive feature descriptors that represents the contents present in the image, while the similarity matching module searches the database for images that closely match the user's query [10] . The results of the query matching can be presented in various formats, depending on the retrieval strategies employed. Each stage in the retrieval model plays a crucial role in the overall process, as shown in Figure 1, requires careful consideration to ensure the selection of appropriate techniques that deliver reliable and optimized retrieval results.

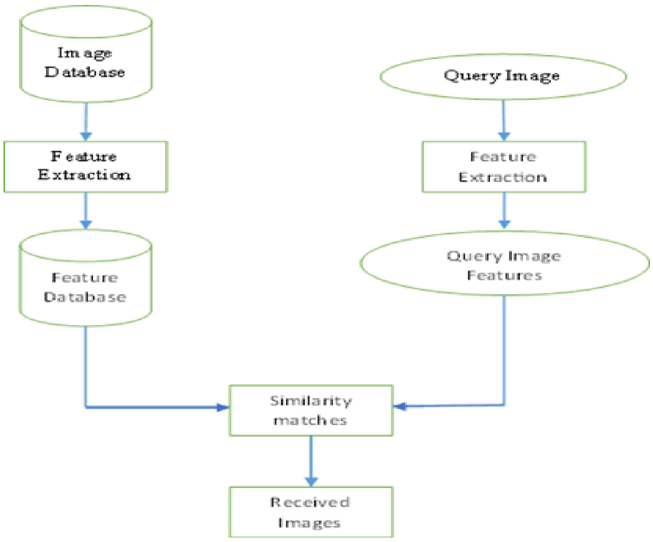

Fig.1. Basic image retrieval System

The research provides the following valuable contributions:

(1) Using low-level visual features, it investigates techniques to enhance the efficiency of CBIR.

(2) It stresses the significance of understanding image spatial layout both when retrieving images and when representing them.

(3) It explores the potential of machine learning-based approaches to enhance CBIR performance.

(4) It examines the advantages of integrating deep neural networks (DNNs) to facilitate more effective learning processes.

Different Approaches for Similar Image Retrieval

1. Color Features

Color features play a crucial role as essential low-level visual attributes, as they enable the human eye to discern and distinguish images based on color variations. Color variations play a crucial role in distinguishing images of practical-world objects that falls inside the spectrum of human visual perception. To record the overall color information of the image, the Dominant Color Descriptor (DCD) has emerged as a widely adopted color descriptor. This approach represents an image using a small set of representative colors. In the realm of CBIR, researchers [11] have leveraged the MPEG-7 color descriptor method to develop novel CBIR techniques. They identify eight dominating colours from each image, deploy the histogram intersection technique to assess the characteristics, and optimize the computing cost of similarity assessment. [12] technique focuses on obtaining photos that reflect the information they contain rather than annotations or labels. Their approach utilizes a compact image descriptor that adapts to the image context using a two-stage clustering technique. Experimental results using the COIL-100 image library demonstrate the efficiency of the proposed method [12].

Wang et al. [13] present a color-based picture retrieval approach that integrates colour and texture data. This method gives an early and effective evaluation of how humans interpret visual content [13]. Colour image retrieval benefits from the combination of colour and texture characteristics, resulting in more accurate retrieval compared to traditional methods. However, these approaches may have high computational costs and the pairwise comparison of low-level features for similarity calculation can become a bottleneck [13].

Several studies have investigated the entire characteristic of such descriptors in the hunt for invariant descriptors.

Images have been characterized using a collection of distinct descriptors based on Zernike and pseudo-Zernike polynomials. These polynomials serve as orthogonal basis moment functions, enabling the representation of various image features. These moment functions are orthogonal and rotate invariant. [14] present a novel method for obtaining a comprehensive collection of pseudo-Zernike moment invariants. The moments of the original image establish a connection with images that have the same shape but different scales and orientations. This connection results in the generation of a set of invariants that remain unaffected by changes in scale and rotation, resulting in increased pattern recognition performance when compared to previous methodologies [14].

2. Texture Features

The differentiation power of wavelet moments as texture features was demonstrated by Papakostas [15] using four datasets: ORL, COIL, TRIESCH I and JAFFE. The datasets consisted of 10, 40, 7, and 10 classes, respectively. Two wavelet configurations, WMs-1 and WMs-2, were evaluated. WMs-1 employed cubic B-spline wavelets, whereas WMs-2 utilized Mexican hat mother wavelets. The classification skills of wavelet moments were greatly improved by using an effective feature selection strategy. The suggested model's performance was compared against Zernike, pseudo-Zernike, Fourier-Mellin, and Legendre moments using varied dataset proportions (25%, 50%, 75%, and 100%). Each moment family behaved differently across the datasets, but the suggested model consistently outperformed the others.

[16] evaluated the proposed model (MSD) for image retrieval using Corel datasets. Specifically, the Corel-5000 and Corel-10000 datasets consisting of 15,000 images were utilized. The retrieval performance was assessed in three different color spaces: HSV, RGB, and Lab. Compared to other models, the suggested model performed better in the HSV and Lab color spaces than others. To balance store space, retrieval accuracy, and speed, MSD used 72 colour and orientation quantization levels. On Corel datasets, comparison with other approaches, such as Gabor MTH, proved the superiority of the suggested model.

Another texture-based picture retrieval investigation employed 10,000 colour photos gathered from public sources [17]. Smoothness, regularity, dispersion, and coarseness were all considered for retrieval results, as was the incorporation of colour information. When the proposed model was compared to the gray-level co-occurrence matrix technique, it was discovered that the colour co-occurrence matrix performed better. This can be attributed to the additional property of color information incorporated in the model, providing an advantage over the gray-level co-occurrence matrix method.

3. Features

The analysis by Zhang and Lu [18] extensively explored the significance of shape attributes in visual representation and retrievals, highlighting their role in distinguishing real-world objects and forms. Shape attributes can be categorized in two main types: contour-based and region-based [19].

4. Spatial Features

Spatial features in images focus on the arrangement of the objects within 2-D image space is crucial for understanding their spatial positioning. The Bag of Visual Words (BoVW) [20] framework, which represents images as histograms, is widely used but disregards spatial layout. A spatial attribute capture technique called SPM (Spatial Pyramid Matching) [21] [22] [23] is insensitive to scaling and rotation. BoVW's representation of histograms contains spatial information that is encoded using a method proposed by Zafar et al. [24]. They computed generalised geometric correlations between groups of comparable visual terms matching to the image's centre. The proposed scheme was evaluated using five databases, and its performance was assessed based on the incorporated spatial information.

Ali [25] put forward Hybrid Geometric Spatial Picture Representation (HGSIR), which is based on picture classification. This method requires creating various histograms for triangular, circular and rectangular image areas. The performance of HGSIR was evaluated using five datasets, demonstrating its superior image classification accuracy compared to state-of-the-art methods.

Yet another investigation, [26] creates a novel technique for incorporating geographical information into the BoVW model's inverted index. They added spatial information by calculating rotation-invariant universal equivalent spatial inclinations of visual words. The geometric correlation of comparable visual words was measured by producing orthogonal vectors at every individual point in triplets of identical visual words. The generated visual word histogram contains information on the position of linear visual words.

Four datasets were used to evaluate the suggested technique.

Ali [27][53] introduced a pair of methods for image representation that utilize triangle histograms, integrating spatial details into the inverted index of the Bag of Features (BoF) representation. The image is partitioned into two or four triangles, and individual triangle histograms are computed at two levels: level 1 and level 2. The presented techniques were evaluated using two datasets, demonstrating effective image retrieval performance.

5. Local Feature-Based Approaches

Kang [28][68] examined a technique for evaluating image similarity that utilizes sparse feature representation. The goal was to examine the resemblance of objects in different photographs in order to identify them. As an image similarity evaluation challenge, the problem of information fidelity was addressed. A feature-based technique was presented to assess the quantity of information that may be retrieved from a test image compared to a reference image [28]. The goal of this method was to measure the similarity of two photos by learning a descriptor dictionary and extracting different feature points and their corresponding descriptors from the images. The picture similarity evaluation problem was then developed using sparse representation. The suggested technique was used to image copy-move detection, recognition, retrieval including simulation and assessment using public datasets such as COIL-100, COIL-20, Corel1000 and Caltech-101 [28].

Zhao [29] presented cooperative sparse models in two opposing orientations for semi-supervised image annotation. Sparse representation has been found to be useful in a variety of computer vision tasks, and its kernel form offers strong classification skills. The goal of this study was to augment the labelled images accessible for training image classifiers by applying cooperative sparse representation to semi-supervised image annotation. The method used a set of labelled and unlabelled photos. Each unlabelled image was represented with numerous labelled images using the forward sparse representation methodology, and the unlabelled image was subsequently annotated based on the annotations of the labelled photos. In the backward sparse representation approach, the annotation process was reversed, assigning labels to images without semantic descriptions. The primary focus was on the role of backward sparse representation in image annotation. To assess the complementary nature of the two sparse representations in opposite directions, a semi-supervised approach known as cotraining was employed. This approach constructed a unified learning model in the kernel space to improve image annotation. Experimental results demonstrated the distinctiveness and independence of the two sparse representations In the task of image annotation, the Co-KSR (Cooperative Kernel Sparse Representation) technique demonstrated superior performance when compared to other state-of-the-art semi-supervised classifiers such as LGC, GFHF and TSVM.

6. CBIR Research Using Deep Learning Techniques

QBIR is commonly used for searching digital images in large databases or storage. To tackle this challenge, researchers have employed various strategies, such as scale-invariant transform and vector of locally aggregated descriptors, in order to effectively address the issue at hand. Among these approaches, DCNN’s Shave shown remarkable performance, leading to the proposal of a novel method called term frequency-inverse document frequency (TF-IDF) with weighted convolutional word frequencies based on CNN for CBIR. In this method, the learned filters of the convolutional layers in the CNN model are utilized as visual word detectors, with the activation of each filter serving as the TF (term frequency) component, and three approaches for computing the IDF (inverse document frequency) component are proposed. By combining TF-IDF with CNN analysis, these approaches provide powerful image retrieval techniques with improved outcomes. The proposed model is validated through experiments conducted on four different image retrieval datasets, which demonstrate the effectiveness of the model.

Shi [30] proposes a mining technique for extracting visual characteristics and training binary representations to address large-scale image retrieval problems. Using a deep learning architecture, the authors develop a pairwise matrix and the function with objectives to train picture binary representations. The suggested method is tested on hundreds of histopathological photos, including 5356 skeletal muscle images and 2176 images of lung cancer from four different disease types, and achieves an amazing classification accuracy of 97.94%.

Zhu [31][74] present semantics aided visual hashing (SAVH), an unsupervised visual hashing technique. This approach is divided into two parts: offline learning and online learning. Image pixels are turned into mathematical vector representations in the offline learning phase by extracting visual and texture properties. The visual graph is then augmented by the addition of subject hypergraphs, and semantic information is retrieved from the textual data. To preserve the association between semantics and images, the image hash code is learned, and a hash function code is constructed using a linear regression model. These properties make SAVH suitable for real-world CBIR applications.

Therefore, CBIR research has explored the use of deep learning techniques, such as CNNs, for image retrieval tasks. The TF-IDF with weighted convolutional word frequencies based on CNNs provides an effective method for representing visual content in CBIR. Additionally, hashing algorithms and unsupervised visual hashing approaches have been proposed to handle large-scale image retrieval challenges. These techniques leverage deep learning frameworks to learn binary representations of images, improving retrieval accuracy. The experimental results demonstrate the efficacy of these approaches in various image retrieval scenarios.

2. Proposed Hybrid CBIR System using ML Approach

Use CBVIR, is an approach that utilizes machine vision techniques to address the problems related to search with respect to digital images in large databases. Unlike previous concept-based methods, CBIR focuses on analyzing the visual contents of an image rather than depending on metadata linked with the image such as keywords, tags, or descriptions. In this context, "content" refers to numerous visual elements such as colors, forms, textures, and other information taken directly from the image itself.

Content-based image retrieval is preferred because it eliminates the reliance on human-generated annotations, which can take a lot of time and may not accurately record the desired keywords for describing the image. Evaluating the effectiveness of keyword-based image search is subjective and lacks a well-defined framework. In contrast, content-based approaches overcome these limitations by directly using the visual content of the images for retrieval purposes. They offer a broader scope of queries and are more reliable compared to keyword-based systems that rely on predetermined criteria.

A. Methodology

Convolutional neural networks (CNNs) have gained significant popularity as deep learning models, particularly suited for processing data organized in the form of arrays [32]–[35]. This characteristic makes them well-suited for handling multiband remote-sensing image data with regular pixel arrangements. The CNN architecture consists of three primary hierarchical components: convolutional layers, pooling layers, and fully connected layers.

In CNNs, each layer operates by convolving the input image with a set of K kernels and adding biases, resulting in the generation of new feature maps Xk. These features undergo element-wise nonlinear transformations, and the process is repeated for each convolutional layer l: X (*)k W X. In contrast to traditional Multi-Layer Perceptrons (MLPs), CNNs employ permutation invariant functions, such as max or mean operations, to aggregate pixel values within a neighborhood of a specific size. This enables CNNs to capture spatial information effectively.

The network typically ends with fully connected layers, often referred to as regular neural networks. This layer does not share weights as did convolutional layers. This allows for more flexible and specific feature extraction and mapping in the network architecture.

Though some literature has made use of profound features for a RS recruitment mission, no comprehensive research exists yet on the optimization of CNN models transferability for RS recovery. Deep characteristics for RS image recovery. In this context, nearly all variables related to the property of CNN representations are evaluated on various public HRRS datasets and the effects for each factor are analyzed.

In this section, methods for the extraction of profound characteristics for HRRS imaging are considered . At least two phases are required for a simple content-based imaging procedure. For example, Convolutional and FC features are presented at various rates from different depths of the CNN architecture. The Features generate local responses in each field of image and FC features provide detailed global image information that can affect various data in various ways. The other issue is that the offshelf CNN model can only translate to RS data in a specific manner. This defect would possibly reduce the performance of the HRRS image recovery. In work proposed the Three representative CNN models, in light of the aforementioned considerations: VGG-M, VGG-VD16, GoogLeNet using different methods for extraction of features.

B. Hybrid Approach architecture

The study proposes a hybrid approach combining a CNN with KNN (K-Nearest Neighbors) can be used for CBIR to leverage the strengths of both methods. The CNN extracts high-level visual features from images, while KNN performs similarity-based retrieval using these features. Here's an overview of the hybrid architecture:

Input Data: The diagram begins with the input data, which can be images or any other form of structured or unstructured data.

Preprocessing: The input data is preprocessed to prepare it for the CNN architecture. This step may include resizing, normalization, data augmentation, or other preprocessing techniques specific to the data type.

CNN: The preprocessed data is passed through the CNN architecture. CNNs are frequently used for image categorization, object detection, and feature extraction. The CNN layers consist of convolutional, pooling, and activation functions. The output of the last layer in the CNN is flattened into a feature vector. A vector represents each image that is present in the image dataset, which captures the high-level visual information learned by the CNN.

KNN: The feature vectors obtained from the CNN are then used inputs for the KNN algorithm. KNN is a non-parametric algorithm that classifies or retrieves new instances based on their proximity to the training instances. In the case of CBIR, it retrieves images from the database based on the similarity measure of their feature vectors to the query image's feature vector.In the KNN algorithm, choosing the distance metric is crucial. Popular distance metrics in CBIR include Euclidean distance, Cosine similarity, and Manhattan distance. The distance metric measures the similarity or dissimilarity between feature vectors and is used by KNN to determine the nearest neighbors. With the chosen distance metric, the feature vector of a query image is compared to the feature vectors of all images in the database. The K-nearest neighbors, which refer to the images with the most similar features, are retrieved from the database and displayed as the retrieval outcomes.

Classification: Based on the majority vote of its nearest neighbors, the KNN algorithm provides a class label to the input data.

Prediction: Finally, the system generates predictions based on the assigned class label. This output could be the classification result or any other task-specific outcome.

By combining the feature extraction capabilities of CNNs with the similarity-based retrieval of KNN, this hybrid approach can enhance the accuracy and effectiveness of CBIR systems. It enables the CNN to capture complex visual features and KNN to perform efficient retrieval based on those features.

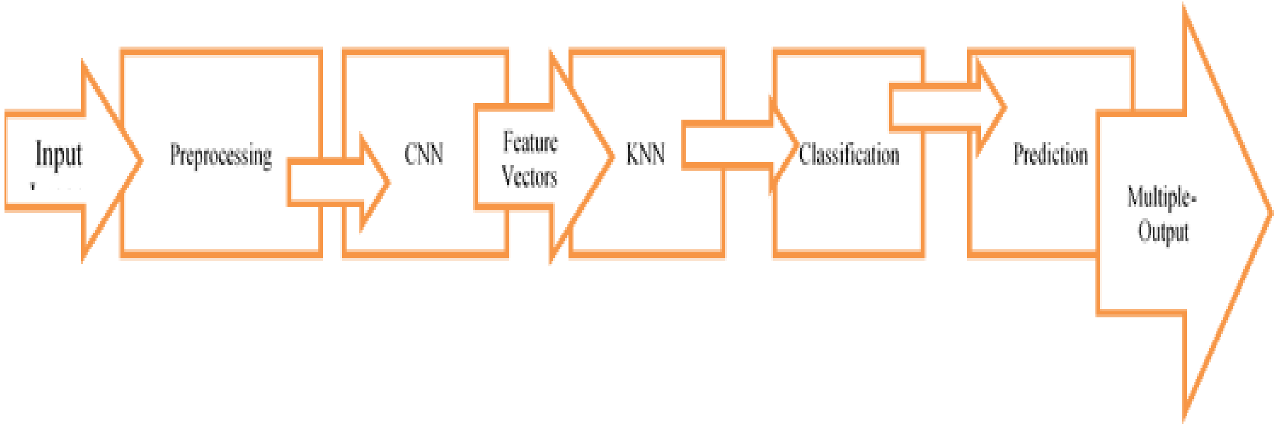

Fig.2. Architectural block diagram of the proposed hybrid approach

3. Sample Results

To illustrate the effectiveness of our approach for the querying of images using hybrid approach, here discussing some screenshots obtained from our system. The figures displayed below depict a set of examples where a query image is showcased alongside the associated retrieved images.

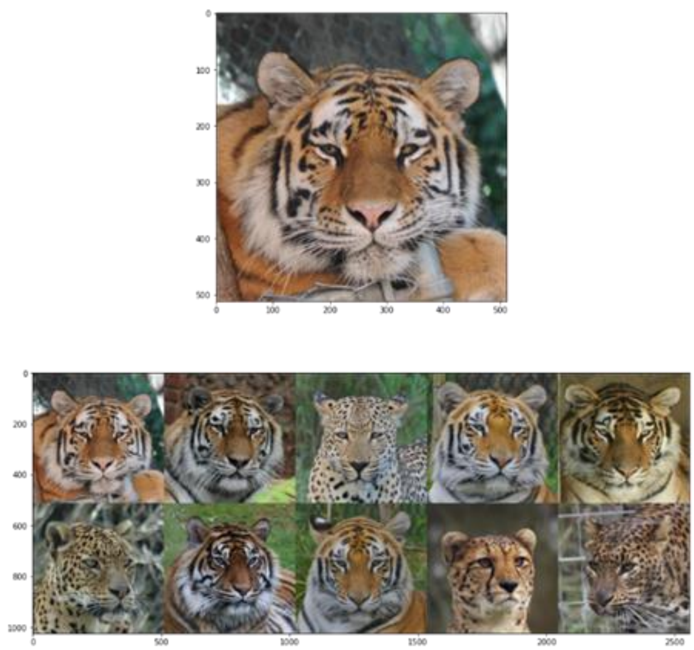

Fig.3. Sample result 1

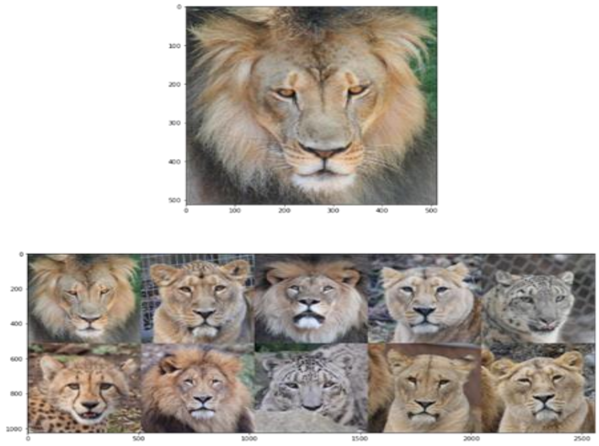

Fig.4. Sample result 2

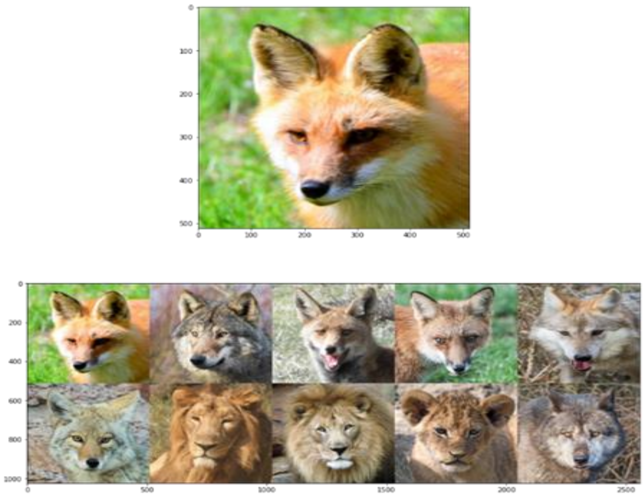

Fig.5. Sample result 3

Table 1. **s**hows parameter comparison for different ML algorithms using labelled data

Approaches	Accuracy	Precision	Recall	F-score
KNN	93.23	93.45	94.32	93
SVM	95.23	94.34	95.34	94
Decision Tree	86.34	86.23	85.34	86.22
CNN	74.23	54.34	67	53.22
Hybrid(proposed)	98.34	98.22	98.45	98.23

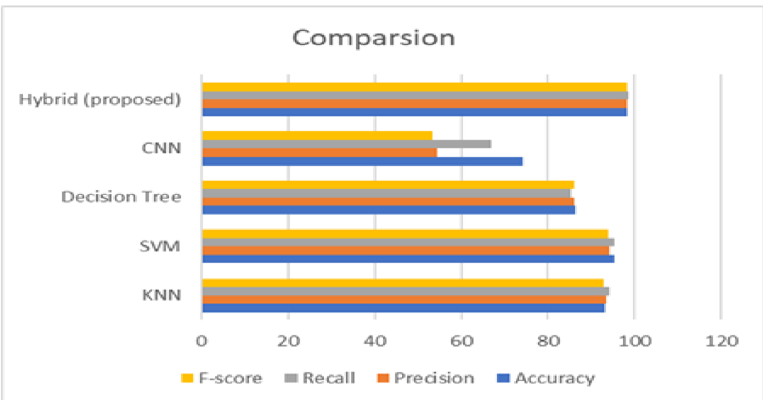

Fig.6. Shows graphical representation of the comparison of ML approaches

The results were calculated using Image Data set containing 4735 images. The data set was created by authors. The implementation was carried out on CIFAR-10 dataset as well. The results were obtained using labelled data and was found that hybrid algorithm perceives accuracy of 98.4%.

When implementing a hybrid CNN-KNN algorithm, the typical approach involves using CNNs for feature extraction and KNN for classification. CNNs are powerful deep learning models known for their ability to extract hierarchical features from input data, particularly in image-related tasks. KNN, on the other hand, is a simple yet effective algorithm for classification based on nearest neighbors.

The result of a hybrid CNN-KNN algorithm depends on the specific implementation and the task at hand. However, in general, this hybrid approach can provide improved performance compared to using either CNN or KNN alone. By leveraging the feature extraction capabilities of CNNs, the algorithm can automatically learn relevant features from the data, which are then used as input for the KNN classifier.

The CNN part of the hybrid algorithm is typically trained on a large dataset, often using techniques such as transfer learning or fine-tuning, to capture general image patterns and extract discriminative features. These features are then used to build a feature vector for each input image. The KNN classifier then classifies the images based on the similarity of their feature vectors to the training data.

The main advantage of the hybrid CNN-KNN algorithm is its ability to combine the power of deep learning with the simplicity and interpretability of KNN. CNNs excel at extracting complex features, while KNN can make decisions based on similarities with known data points.

The hybrid approach can provide enhanced retrieved images and can work on any dataset. On the other hand, the accuracy may vary depends upon the task at hand.

4. Conclusion

The result of a hybrid algorithm based on CNN and KNN can offer improved performance and accuracy in tasks like image classification by combining the strengths of both algorithms. However, the specific outcome would depend on the implementation details and the specific task being addressed.

Furthermore, the authors are actively engaged in research within the domain of unlabeled data.

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Author contributions

Gagandeep Kaur: Conceptualization, Methodology, Software, Writing-Original draft preparation, Validation **Satish Saini:** Visualization, Investigation, Writing-Reviewing and Editing.

Conflicts of interest

The authors declare no conflicts of interest.

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