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A New Multimedia Web-Data Mining Approach based on Equivalence Class Evaluation Pipelined to Feature Maps onto Planar Projection

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Multimedia information are semi-organized or unstructured information elements whose essential substance is separately or by and large utilized for correspondence. Sight and sound information mining recognizes, arranges, and recovers important highlights from an assortment of media to recognize enlightening examples furthermore, connections for information acquisition. Computer Vision (CV)-based systems have been increasingly popular in recent years, owing to the growing number and complexity of datasets. In CV, finding meaningful photos in a huge dataset is a difficult task to solve. Traditional search engines retrieve photos based on text such as captions and metadata, but this strategy can result in a lot of irrelevant output, not to speak the time, effort, and money required to tag this textual data.
In this paper, we proposed a pipelined deep learning oriented methodology framework for multimedia web-data mining based on content extracted feature maps in planner projection as input. Color, texture, form, and other high-level properties of images are represented as numerical feature vectors. This technique is based on the following computer vision tasks in general i.e., Image segmentation, Image classification, Object detection etc. In order to prove the computational efficiency and to validate its statistical behaviour, we have also presented the experimental evaluation on an standard multimedia dataset. The obtained performance results are then compared with some significant existing approaches in the terms of various statistical measures/parameters.

Povzetek: Predstavljena je metoda rudarja multimedijev z globokim učenjem, ki temelji na lastnostih vsebine slik. Uporablja se za različne naloge računalniškega vida, kot so segmentacija, klasifikacija in zaznavanje objektov. Preizkušena je bila na standardnem multimedialnem naboru podatkov.

1 Introduction

Multimedia information mining involves identifying, categorizing, and retrieving relevant features from a variety of media to identify educational patterns and relationships for data acquisition. The performance of multimedia information mining is directly impacted by the level of information contained in the data, which can be recognized during the data pre-processing stage. Data pre-processing aims to reduce data dimensionality by preserving useful features, which are factors (or attributes) used as input for selection algorithms. This greatly improves runtime (training time), predictive accuracy, and result readability when working with human interpretation and knowledge. There are two key steps in data pre-processing: feature extraction (FE) and feature selection (FS). FS techniques are a subset of the broader field of FE. While FE extracts multiple features from the original data to generate a dataset, FS selects a subset of original variables to build the model. However, identifying related features provides insights into underlying phenomena. On the other hand, eliminating irrelevant variables enhances the accuracy of data classification. Multimedia web-information mining includes various applications such as face recognition, pattern recognition, text detection and recognition in images and video frames, biomedicine, emotion recognition, image retrieval and classification, and image annotation, among others.

1.1 Multimedia

Multimedia information are semi-organized or unstructured information elements whose essential substance is exclusively or all in all utilized for correspondence. The term sight and sound covers a variety of media article like a mix of text, picture, video, sound, numeric, sound, liveliness, graphical, and straight out information on a PC show terminal. In the approach of programming innovation, sight and sound is characterized as ”a PC program comprised of messages, realistic, sound and pictures and animations”.
Text is made out of an enormous number of disorganised and nebulous characters of normal language text [22, 23]. Writings can be inserted in recordings in two structures,

specifically, inscription and scene messages [24]. Subtitle text alludes to the writings overlapped during video altering, while scene oriented text is the writings that normally exist during the video catches. To manage the implanted content for a proper trade of data (e.g., title as well as date of an occasion, name of the speakers), subtitle text can be extricated straightforwardly from recordings and pictures since it is just positioned in comparison to these visual representations. Sound is a sign coming about because of motions or pressing factor varieties created by a moving or vibrating body tempestuous liquid stream in a flexible medium like air, water, and solids [25]. Uzun and Sencar [26] characterized sound into discourse, music, non-discourse as well as non-musical signals, as well as complicated sound combinations that emerged from a few particular acoustic sources. Sound substance can be naturally examined and looked inside itself. For instance, discourse with in sound discovery is generally utilized for distinguishing proof or acknowledgment, for example, supporting proof assortment and diagnosing Alzheimer's disease.

1.2 Challenges in multimedia data mining

There are plentiful measure of difficulties in the multimedia information mining. Information with high and complex measurements experience the ill effects of the scourge of dimensionality [27]. In these wonders, the measure of information required to help the outcomes develop dramatically with dimensionality, accordingly sabotaging the presentation of information mining [28-29]. At the end of the day, the volume of data space increments and involves the sparsity of dependable information through an additional measurement in the investigation information. High dimensional information entangle sight and sound examination, stockpiling, and recovery. The significant component space effectively prompts overfitting; when the information digging mechanism looks for the best boundaries utilizing restricted information, it evokes both the overall examples in the information and the commotion explicit to the information. As far as precision, effectiveness, and dependability, recovering an ideal mixed media content (e.g., image) in a continually developing information base is confounded in light of the trouble in acquiring a legitimate image highlight set.
However, it has been on the whole concurred that the article image explanation is fundamentally an order issue, most web pictures are multi-marked. Along these lines, an image can likewise mirror a few semantic ideas. Multi-name characterization likewise has an alternate set of assessment measures contrasted with single-name grouping. The traditional calculations for the most part change multi-name arrangement issues several parallel order issues for each idea. Two sorts of commotion existed in multimedia information. The main kind is identified with the foundation commotion in mixed media information. Foundation commotion can happen in recordings or sound information in light of a few reasons, counting foundation voices recorded through an amplifier and defective melody replicating framework. order precision may be made even better with the determination of appropriate discriminative element gatherings. Subsequently, a decent model with a decent FS capacity is needed to improve both exactness and productivity, that is a high AUC esteem with a similar chose highlight measurement shows a agreeable execution with a low involved component unit number. Assessment of highlights individually implies that the significance of each features are exclusively chosen for the unmistakable includes as opposed to considering the relationship among attributes.

1.3 Generalized methods for multimedia web-data mining

The general methods of multimedia web-data mining can be categorized in the following two ways i.e. (i) based on input text word(s) query as input (ii) based on extracted feature maps in planner projection as input.

1.3.1 Multimedia web-data mining based on input text word(s) query as input

Words or sentences that convey content are known as catchphrases. They may be used to represent photos, text archives, database entries, and Web pages as metadata. Setting up catchers for a photo allows you to retrieve, record, sort, and see large amounts of image data. Catchphrases are utilized on the Web in two unique manners: I) Keywords as a scan terms for web crawlers ii) Keywords that recognize the substance of the site. A comment is metadata appended to text, picture, or other information. It alludes to a particular piece of the unique information or image.
Limitations in this type of methods:- The limitations in this type of methods are as follows:-

- The assignment of envisioning picture content is profoundly emotional.
- Accompany the significant list items; it very well may be a huge number of unessential query items It might mean that the evidenced pursuit's precision is low.
- The text based portrayals given by an annotator ought to be unique in relation to the next client. For different people, an image represents different things. It might also imply different things to different people at different times.

1.3.2 Multimedia web-data mining based on extracted feature maps in planner projection as input

To overcome the limitations of multimedia Web-Data Mining based on input text word(s) query as input, we can use the extracted feature maps in planner projection as input based mining. It is the use of computer vision for recovering the image object. Data recovery implies the way toward changing over a solicitation for data into a significant arrangement of reference. It is an innovation that in rule puts together computerized image files as per their visual substance. This framework recognizes the extraordinary locales present in a image dependent on their similitude in shading, surface, shape, and so on and chooses the comparability between two pictures by retribution the closeness of these variety of areas.

1.4 Related work

This section presents state of the art developments carried out in this domain over recent past years. Cimino [1] proposed a hereditary span neural network architecture utilizing the dividing estimation of the data points on computational space. Froelich [2] proposed a definite time arrangement demonstrating technique that utilizes data granules as expected. Hmouz [3] proposed a time series oriented expectation model utilizing granular time series. Zhu [4] proposed a hybrid variety of fuzzy model that consolidates the Takagi–Sugeno (TS) fuzzy logic model and data division as well as allocation technique. Musaylh [5] proposed a kind of model that predicts transient power interest in Queensland utilizing SVR and ARIMA. Likewise, grouping technique for information investigation had been the subject of various examinations, among them, a specific interest was paid to setting based fuzzy C-implies (CFCM) grouping utilizing fuzzy C-implies (FCM) grouping. Emmanuel D [6] given description of Evolutionary Deep Networks for Efficient Machine Learning. A. Sellami et al. [7] given the similar investigation of dimensionality reduction strategies for images examination and exploration. M Kayed et al., in their work [8], performed categorization of the garments from fashion MNIST dataset exploiting CNN LeNet-5 specific architecture. Image object's pattern analysis is performed by Imran K. et al. [9]. Rim Rekik et al. [10] proposed a computational cycle of gathering and separating information (measures including sites) from a rundown of studies.

M. Stamenovic et al. [11] given a visual classifier, valuable for deducing a record's general appearance, and a text classifier, for settling on content-informed decision choices. Reshma P.K. et al. [12] given a soft computing framework for web mining of multimedia data. MJ Sindhu [13] given a framework for multimedia retrieval using web mining. Seema S [14] given an extensive survey machine learning techniques for data mining. The measurable data and probabilistic information is utilized for meta information creation. In [15], Bayes' hypothesis is exploited with basic freedom guesses among highlights. The augmentation of data set application to deal with sight and sound articles requires synchronization of various media information streams [16]. Peter et al. [17] portray the significance of pre-preparing information in the web use mining and the effect of errors to the investigation of the information during this stage. It is fundamental for not disparage the information pre-processing stage during the time spent web use mining, as the pre-handling stage straightforwardly influences the nature of the gained information. In [18], The Remote Sensing (RS) image recovery strategies and applications are completely inspected. The assessment datasets and measurements of RS image recovery are summed up. Exhibitions on two sorts of exemplary RS image recovery assignments are likewise talked about by the authors. G. Suseendran et al.[35], in their work, have illustrated deep learning Semi-structured Tree Miner for Data Stream's algorithm focused on frequent pattern mining used in data streams on semi-structured data. Singh et al., in their works [36][37][38][39] have given robust frameworks and methods for processing multimedia data exploiting variety of soft computing based computational primitives.

Table 1: Research gap / limitations

Approach	Research Gap
Froelich et al. [2]	Increased complexity, Difficulty in capturing long-term trends, Data sparsity.
Zhu et al. [4]	Interpretability, Overfitting, Scalability, Lack of generality.
Musaylh et al. [5]	Limited ability to capture complex patterns, Sensitivity to outliers, Limited ability to handle seasonality.
Sellami et al. [7]	Loss of information, Selection of features to reduce, Lack of transparency, Suffers from Overfitting.
Kayed et al. [8]	Computationally intensive, Lack of generalization, Data requirements.
Peter et al. [17]	Massive Data requirements, Computationally intensive, Sensitivity to image quality.
Yansheng et al. [18]	Atmospheric interference more, Limited ground truth data, Limited spectral coverage.

Some significant state of the art approaches along with their limitations in the form of research gaps are given in Table 1.4.

1.5 Contribution(s) in this paper

The contribution(s) in this work are as follows:-

- As research contribution, we proposed a pipelined deep learning oriented methodology framework for multimedia web-data mining based on extracted feature maps in planner projection as input.
- In order to prove the computational efficiency and to validate its statistical behaviour, we have also presented the experimental evaluation on an standard multimedia dataset. The obtained performance results as compared to others significant existing approaches in terms of various statistical measures/parameters.

1.6 Organization of the paper

The remaining portions of this paper are structured in a logical and organized manner to present the research methodology and results in a clear and concise manner. In Section 2, the proposed method is described in detail. This section provides an overview of the key components and techniques used in the research, highlighting the unique aspects of the proposed method. Section 3 is dedicated to discussing the experimental evaluation and the results obtained from the research. Finally, in Section 4, the paper concludes with a conclusive summary of the research and the future scope of this work. This section provides a brief overview of the main contributions of the research and highlights its potential impact on the field.

2 Proposed method

This section presents our proposed framework, architecture and methodology overview along with the detailed algorithmic flow.

Algorithm 1 Feature Extraction

Five methods have been used in this phase -
{

- *Color* ▶ performs color feature extraction
- *Daisy* ▶ performs daisy features like intensity
- *Edge* ▶ performs edge feature extraction
- *Histogram of gradient* ▶ extracts gradient orientation in the image
- *Scale-invariant feature transform (SIFT)* ▶ The gradient at every pixel is viewed as an example of a three-dimensional rudimentary component vector, shaped by the pixel area and the angle direction.

}

These methods individually does not provide the results as each method only deals with a particular specification like color, intensity, edges etc. So all these methods are combined in the form of an Ensemble.

Algorithm 2 Inconsistency Measurement

$\forall\ \mathcal{Z} = \{V_1, V_2, \cdots V_n\}$ in approximation universal space for particular concept $\mathbb{C}$, compute -

- $\underline{\mathcal{Z}}\mathbb{C} = \{x \in U | [x] \subseteq \mathbb{C}\}$
- $\overline{\mathcal{Z}}\mathbb{C} = \{x \in U | [x] \cap \mathbb{C} \neq \emptyset\}$

where, $[x]$ is equivalence class

Compute, $\mathcal{R}_I = \overline{\mathcal{Z}}\mathbb{C}$ - $\underline{\mathcal{Z}}\mathbb{C}$

IF ($\mathcal{R}_I$ == NULL)
{
No inconsistent region
}

Algorithm 3 Optimal Variable's / Features Selection

BEGIN
$\mathbb{F}$un (A, L, I, δ)
A: Set of attributes / features / variables
L: Label column
I: Set of instances
δ: Threshold
fun$_{cal()}$: Function to calculate core features
$\mathcal{R} \leftarrow$ fun$_{cal()}$
while $\gamma_{\mathcal{R}}(L) < \delta$
  I $\leftarrow$ I - $POS_{\mathcal{R}}(L)$
  $\forall$ x $\in$ (A - $\mathcal{R}$)
    $p_a = |POS_{\mathcal{R}\cup\{a\}}(L)|$
    $q_a \leftarrow |EquivClass_{MAXLEN}(POS_{\mathcal{R}\cup\{a\}}(L))|$
  Choose a value with largest of $p_a \times q_a$
  $\mathcal{R} \leftarrow \mathcal{R} \cup \{a\}$
Return $\mathcal{R}$
END

2.1 Architecture and methodology overview

Computer vision techniques and deep learning algorithms together are used for the feature extraction process. Each image has been represented as a feature vector. Similarity techniques such as Cosine Similarity and Euclidean Distance are used to measure the closeness between feature vectors of the query image and the images available in the dataset. Soft computing based statistical algorithmic module is adopted for an optimized variable's selection.

2.2 Detailed algorithmic flow

Our approach Removes the typical method of storing photos in databases, which involves labelling them according to their content and retrieving them using key words. In this proposed methodology, multimedia web-data mining is performed based on extracted feature maps in planner projection as input rather than based on the input meta-data such as keywords, tags, or descriptions associated with the image.
There are in total four main algorithmic modules in it. It is primarily based on equivalence class evaluation pipelined to feature maps onto planar projection. Algorithmic block 1 is performing features extraction. Algorithmic block 2 is performing inconsistency measurement. Computationally optimal variables' selection is carried out in algorithm 3. Algorithmic block 4 is performing transfer learning procedure.

Algorithm 4 Transfer Learning Proc()

1: *VGGNET + RESNET architecture exploitation:*

- Input $\rightarrow$ fixed 224×224 dimension pixels image
- Subtract mean RGB value, computed on the training set, from each pixel
- Use filters in convolution layer: 3×3 dimension
- Fix convolution stride to 1 pixel; padding is 1 pixel for 3×3 conv. layers
- Exploit $\mathrm{Lr}_{MAXPOOLING(1)}$ $\cdots$ $\mathrm{Lr}_{MAXPOOLING(5)}$
- Max-pooling $\looparrowright$ {pixel window = 2×2, stride = 2}
- Process in Fully-connected layers: 4096 channels
- Process in soft-max layer

Our proposed methodology framework has some computational advantages over other methods available in the literature. The discussion regarding the same is given as points below:-

- Proposed algorithmic module of Dimension reduction based feature selection has the ability to reduce the number of features or variables in a dataset, which can make the dataset more manageable and reduce the computational complexity of subsequent analyses or modeling tasks. This can result in faster computation and reduced resource requirements.
- Proposed module for transfer learning based classification can learn complex non-linear relationships in data without requiring explicit feature engineering, which can save time and effort in the data mining process.
- Our proposed methodology can perform well in tasks with imbalanced datasets, where the number of examples in each class is different, by adjusting the decision threshold. This can improve the model's performance on the minority class.

3 Experimental analysis

This section presents the experimental evaluation in form of simulation set-up details, dataset summary, exploited computational libraries and packages, obtained results summary and comparisons of our proposed method results with some significant existing approaches.

3.1 Simulation set-up

In this study, the simulation environment is built up as follows: Our operating system was Ubuntu 18.04 LTS, and our hardware included 8 GB of RAM and an Intel Core i7 4032U CPU processor running at 3.2GHz.

3.2 Dataset overview

For the purpose of experimental analysis, Corel 10K dataset [34] is utilized here that features 10,000 pictures from various substances such as dusk, seashore, bloom, building, car, horses, mountains, fish, food, and doorway, among others. Each class includes 100 JPEG images with a resolution of 192 $times$ 128 or 128 $times$ 192. Ten classes were chosen for trial simulation purposes from the dataset's total of 100 classes.

3.3 Exploited computational libraries and packages

Python 3.7.4 is used for the implementation. The computational libraries and packages used are - NumPy, SciPy, pandas, Matplotlib, Statsmodels and PyTorch. PyTorch is an essential requirement for running ResNet and VGGNet modules.

3.4 Results summary

The generated confusion matrix is a 10×10 matrix as the total number of classes considered here are 10. Table 2 represents the statistical performance measures corresponding to each individual category in terms of precision, recall and accuracy. Numerous test cases for experimental evaluation are carried out and obtained results images are given for input query instances and corresponding output result instances (Figure 3 - Figure 12).

3.4.1 Confusion matrix

```
[[5 0 0 0 0 0 0 0 0 0]
 [0 5 0 0 0 0 0 0 0 0]
 [0 0 5 0 0 0 0 0 0 0]
 [0 0 0 5 0 0 0 0 0 0]
 [0 0 0 0 5 0 0 0 0 0]
 [2 0 0 0 0 3 0 0 0 0]
 [1 0 0 0 0 1 3 0 0 0]
 [0 0 0 0 0 1 0 4 0 0]
 [2 0 0 2 0 0 0 0 1 0]
 [0 0 0 0 0 0 0 0 0 5]]
```

Figure 1: Confusion matrix

3.4.2 Statistical performance measures

Table 2: Statistical performance measures

Label / Category	Precision	Recall	Accuracy
0	0.6	1	0.9
1	1	1	0.89
2	1	1	0.9
3	1	1	0.93
4	1	1	0.98
5	0.6	0.6	0.71
6	1	0.6	0.89
7	1	0.8	0.94
8	1	0.2	0.78
9	1	1	0.98

The depiction for statistical performance measures is represented as Figure 2.

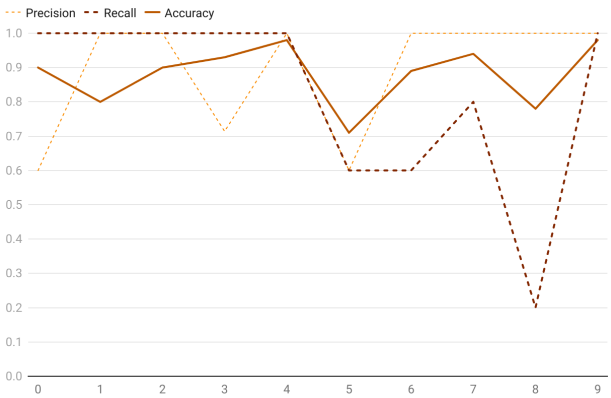

Figure 2: Depiction for Statistical Performance Measures

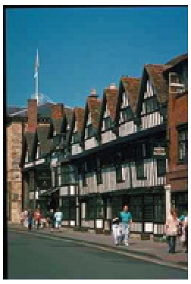

Figure 3: i/p query instance **(buildings)**

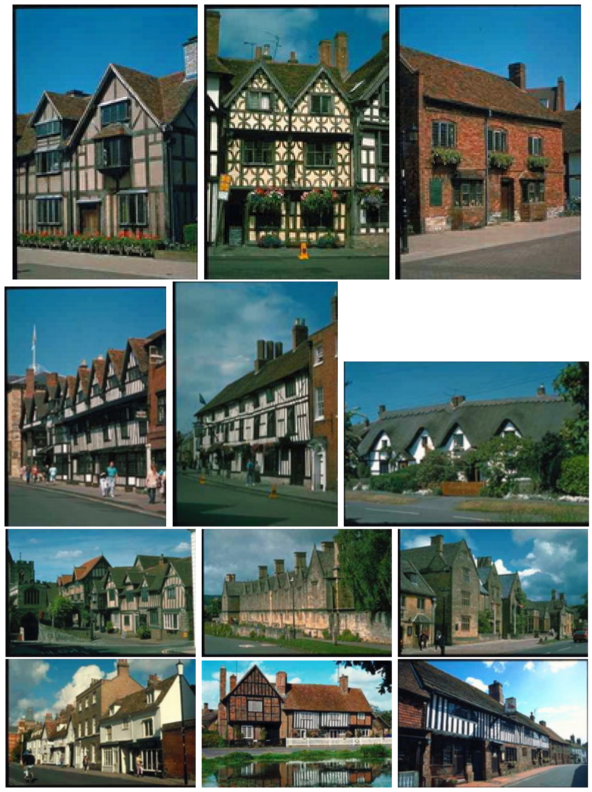

Figure 4: o/p result instances **(buildings)**

Figure 5: i/p query instance **(flowers)**

Figure 6: o/p result instances **(flowers)**

Figure 7: i/p query instance **(trees)**

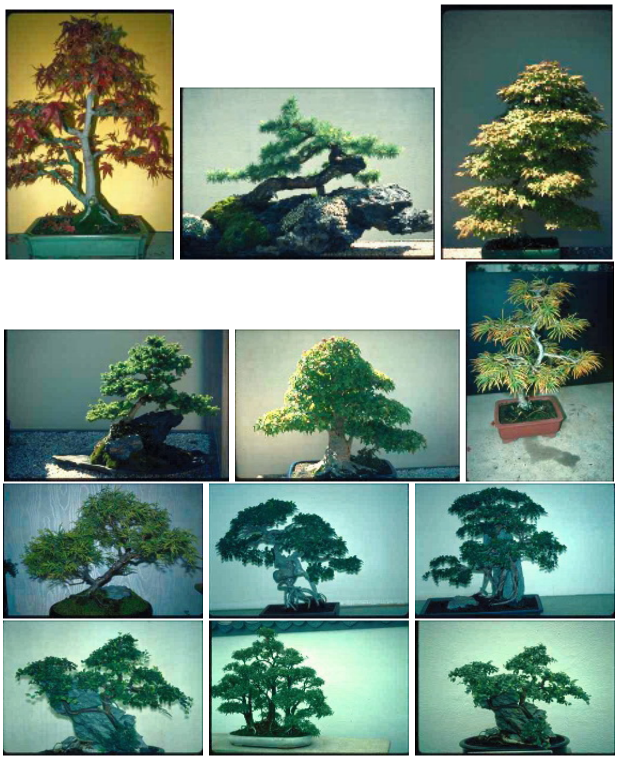

Figure 8: o/p result instances **(trees)**

Figure 9: i/p query instance **(mountains)**

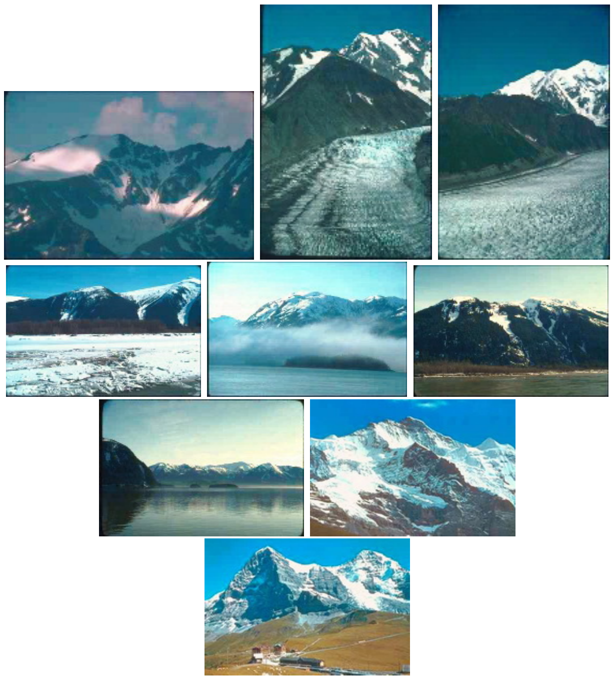

Figure 10: o/p result instances **(mountains)**

Figure 11: i/p query instance **(vegetables)**

Figure 12: o/p result instances **(vegetables)**

3.5 Comparisons on performance metrics

In order to prove the computational novelty of proposed framework, comparisons are performed with some significant existing approaches and the results are provided in table 3. From this table, it can be observed that the proposed framework outperforms over other existing approaches.

Table 3: Comparative analysis

Method	Precision Values	Recall Values
MTH [30]	40.87	49.1
CPV-THF [31]	52.28	62.7
STH [32]	48.03	57.6
CMSD [33]	50.25	60.3
Proposed framework	92.0	82.0

4 Conclusion and future scope

The performance of media information mining is directly influenced by the level of information contained in the data, which can be recognized during the data pre-processing stage. This paper presents a pipelined deep learning methodology framework for multimedia web-data mining based on extracted feature maps in planner projection as input. The framework is designed to be oriented towards deep learning techniques. An experimental evaluation is also conducted on a standard multimedia dataset [34]. The obtained performance results are compared with some significant existing approaches in terms of various statistical measures and parameters.

4.1 Future scope

The future scope of this research work is to analyze and identify interrelationships within Multimedia data sets as well as to derive a composite score from several different sub-scores.

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