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RECENT ADVANCEMENTS IN IMAGE AND SPATIAL MINING – REVIEW

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Abstract: Data mining (DM) helps in extracting useful patterns and information from large datasets. In recent years, image and spatial data have become a major focus of data mining research due to the increasing availability of digital images and spatial data. Spatial data mining involves the utilization of geographical (spatial) information to develop the intelligence and provide results for the business, healthcare and other industries. Similarly, the image mining involves the extraction of images from a large resource of images or extracting specific objects from an image through the use of mining techniques. Searching and identifying the valuable information and knowledge from the set of large image data involves the use of DM, image processing, image retrieval, artificial intelligence (AI) and machine learning (ML) techniques. The goal is to extract knowledge from images for many applications, including object recognition, and image classification. This paper aims to analyse the use of DM techniques for image and spatial mining. In this article, some of the recent image mining techniques are reviewed that have been presented in the literature. Some of the challenges and future directions for image and spatial mining research are also highlighted.

***Index Terms* - Data mining, Spatial mining, Image mining, Image retrieval, Object recognition, Machine learning, Deep learning**.

I. INTRODUCTION

DM techniques extract useful information and patterns from large data sets. Two specific applications of DM techniques are image mining and spatial mining [1]. Image mining involves the analysis of visual data to extract patterns and information from images. Image mining techniques include image segmentation, feature extraction, and classification [2]. Image segmentation splits the image into multiple segments or regions, while feature extraction involves identifying and quantifying distinctive characteristics of the image, such as texture, colour, or shape. Classification involves categorizing images into different classes based on their features or characteristics. Spatial mining, on the other hand, focuses on extracting patterns and relationships from spatial data, which includes geographical and environmental data. Spatial mining techniques include clustering, spatial association rule mining, and spatial regression [3]. Clustering is the process of grouping spatial data into clusters or regions based on their proximity or similarity, while spatial association rule mining involves discovering relationships between different spatial data sets. Spatial regression involves identifying and quantifying the relationship between a dependent variable and one or more independent variables, taking into account the spatial context of the data. Overall, image mining and spatial mining techniques are useful for extracting valuable insights and knowledge from large and complex data sets [4]. These techniques can be applied in a wide range of fields, including healthcare, agriculture, and urban planning

1.1 Overview of Image Mining

Image mining involves the application of DM techniques to image datasets for extracting useful information. Image mining can be used for various applications, such as medical diagnosis, surveillance, and pattern recognition [5]. Image mining techniques can be applied to both static and dynamic images. Static images are images that do not change over time, while dynamic images are images that change over time. Image mining has various applications in different fields such as medical imaging, remote sensing, and surveillance. In medical imaging, image mining is used for disease diagnosis, classification, and segmentation. In remote sensing, image mining is used for land cover classification, change detection, and object detection. In surveillance, image mining is used for activity recognition, object tracking, and anomaly detection.

DM techniques used for image mining include clustering, classification, association rule mining, and outlier detection. Clustering is a popular DM technique used for image mining. Clustering involves grouping similar images into clusters based on their features. The features used for clustering include color, texture, and shape. Clustering can be used for various applications, such as image segmentation, object recognition, and content-based image retrieval. Classification is another DM technique used for image mining. Classification involves assigning images to predefined classes based on their features. The features used for classification include color, texture, and shape. Classification can be used for various applications, such as face recognition, character recognition, and object recognition. Association rule mining is a DM technique used for finding interesting relationships between images. Association rule mining involves finding patterns in image datasets that occur together frequently. Association rule mining can be used for various applications, such as market basket analysis and image co-occurrence analysis. Outlier detection is a DM technique used for identifying images that are significantly dissimilar from the rest of the dataset. Outlier detection can be used for various applications, such as fraud detection and anomaly detection.

Data Mining Techniques for Image mining

1. Association Rule Mining: This technique is used to find frequent patterns and associations among data items in a dataset. It is widely used in market basket analysis and recommendation systems.
2. Clustering: It is used to cluster similar data items together based on their features or attributes. It is used in customer segmentation, image segmentation, and pattern recognition.
3. Classification: It is used to predict the class or category of a data item based on its features or attributes. It is used in spam filtering, credit scoring, and image recognition.
4. Regression: It is used to predict the numerical value of a data item based on its features or attributes. It is used in stock price prediction, weather forecasting, and medical diagnosis.

Image mining is a complex process that involves several steps, including image pre-processing, feature extraction, and DM [6].

Image Pre-processing: It involves several steps that are designed to prepare the image data for further analysis. The pre-processing steps may include image resizing, noise removal, and image enhancement. The goal of image pre-processing is to remove any noise or artefacts that may affect the accuracy of the analysis.

Feature Extraction: It is the process of identifying meaningful features from the image data. The features may include color, texture, shape, and spatial information. The goal of feature extraction is to identify the most relevant features that can be used for image analysis.

Image Retrieval Techniques

Image retrieval is a task in image mining that involves retrieving images from a database that are similar or relevant to a query image. The following image retrieval techniques have been presented in recent years:

1. Content-Based Image Retrieval (CBIR): CBIR is an image retrieval technique that involves comparing the features of a query image with the features of images in a database. The features can be Color histograms, texture descriptors, or deep features extracted from CNN models.
2. Hashing-Based Image Retrieval: Hashing-based image retrieval is a technique that involves mapping images to binary codes using hashing functions. The binary codes can be used to index and search for similar images in a database efficiently.
3. Metric Learning-Based Image Retrieval: Metric learning-based image retrieval is a technique that involves

learning a similarity metric between images. The similarity metric can be learned using Siamese networks, triplet networks, or contrastive loss functions.

Object Recognition

It is a process that involves the identification of objects in an image. The goal is to identify the objects in the image and classify them into different categories. Region-based object recognition is a technique that involves the identification of objects in specific regions of an image. The region-based object recognition techniques use object proposals to identify the objects in the image. The region-based object recognition techniques can be used for various applications, such as video surveillance and autonomous driving. The content-based object recognition used many model including the ML and Deep Learning (DL) models [7]. The DL models can learn the features of the objects and use them for object recognition. The most popular ML and DL model for object recognition are the SVM and CNN, respectively.

1.2 Overview of Spatial Mining

It involves the application of DM techniques to spatial datasets for extracting useful information. Spatial data includes geographical data, such as maps, and non-geographical data, such as sensor data. Similar to image mining, DM techniques used for spatial mining include clustering, classification, association rule mining, and outlier detection. Clustering is a popular DM technique used for spatial mining. Clustering involves grouping similar spatial data points into clusters based on their features. The features used for clustering include location, distance, and spatial relationships [8]. Classification is another DM technique used for spatial mining. Classification involves assigning spatial data points to predefined classes based on their features. The features used for classification include location, distance, and spatial relationships. Classification can be used for various applications, such as land-use classification and species classification. Association rule mining is a DM technique used for finding interesting relationships between spatial data points. Association rule mining can be used for various applications, such as market basket analysis and spatial co-occurrence analysis. Outlier detection is used for identifying spatial data points that are significantly different from the rest of the dataset. Outlier detection can be used for various applications, such as anomaly detection and fraud detection.

Data Mining Techniques for Spatial Mining:

1. Spatial Association Rule Mining: This technique is used to find frequent patterns and associations among spatial data items, such as points, lines, and polygons. It is used in location-based marketing, crime analysis, and urban planning [9].
2. Spatial Clustering: Spatial clustering is a technique used to group spatial data items together based on their proximity or similarity. It is used in land-use analysis, image segmentation, and spatial DM.
3. Spatial Classification: Spatial classification is a technique used to classify spatial data items into predefined categories or classes based on their attributes and spatial relationships. It is used in land cover classification, vegetation mapping, and land-use analysis.
4. Spatial Regression: Spatial regression is a technique used to predict the value of a spatial data item based on its attributes and spatial relationships. It is used in real estate valuation, environmental modeling, and disease mapping.

Applications of Spatial Mining:

Spatial mining techniques have a wide range of applications in various fields, including [10]:

1. Business and Marketing: DM techniques are used in market basket analysis, customer segmentation, and churn prediction. Spatial mining techniques are used in location-based marketing, site selection, and retail store layout optimization.
2. Healthcare: DM techniques are used in medical diagnosis, patient monitoring, and drug discovery. Spatial mining techniques are used in disease mapping, environmental modeling, and public health surveillance.
3. Environmental Science: Spatial mining techniques are used in land-use analysis, vegetation mapping, and natural resource management. DM techniques are used in climate modeling, remote sensing, and environmental monitoring.

II. LITERATURE REVIEW

In recent years, ML and DL-based techniques have dominated the field of image mining. Carpitella et al. [11] developed a hybrid multi-criteria approach to GPR image mining for water supply system maintenance. The authors combined different methods, including multi-criteria decision analysis, fuzzy logic, and DM algorithms to extract useful information from GPR images. They used fuzzy c-means clustering for image segmentation, followed by feature extraction using statistical measures and gray-level co-occurrence matrix (GLCM). The approach was evaluated on a real-world GPR dataset and achieved an overall accuracy of 95.1% for detecting water supply system leaks. However, the study did not consider the effects of the soil structure on GPR imaging and the influence of environmental factors on the detection results. Wazarkar and Keshavamurthy [12] developed a soft clustering technique for social image mining. The approach used a combination of color and texture features for image representation, and a layered clustering approach to group similar images. The method was evaluated on a dataset of Instagram images and achieved an average precision of 0.85 and clustering accuracy of 87.6%. However, the study did not compare the method with other clustering techniques, and the dataset used may not be representative of all social media platforms.

Acharya and Kumar [13] suggested an image mining method for detecting acute lymphoblastic leukaemia. The approach used K-means clustering for image segmentation, followed by feature extraction using texture and shape descriptors. The extracted features were then used for classification using support vector machine (SVM) and decision tree algorithms. The approach was evaluated on a leukaemia dataset and achieved an accuracy of 95.7%. The system outperformed other state-of-the-art methods in terms of accuracy and computational efficiency. However, the study did not consider the influence of staining techniques on the detection results, which may affect the segmentation accuracy. Haghshenas and Emam [14] introduced a green-gradient based canopy segmentation model for crop phenotyping and canopy studies. The approach used gradient-based segmentation with a greenness threshold to extract the canopy region from the input image. The extracted canopy region was then used for feature extraction and analysis. The approach was evaluated on a crop image dataset and achieved an accuracy of 96.3% for canopy segmentation. However, the study did not consider the effects of lighting conditions and camera settings on the segmentation results.

Chen and Chen [15] developed a multi-dimensional color image recognition and mining approach based on a feature mining algorithm. The approach used a combination of color and texture features for image representation, and a feature mining algorithm for feature selection and dimensionality reduction. The approach was evaluated on a color image dataset and achieved a recognition accuracy of 94.8%. However, the study did not consider the influence of image resolution and compression on the classification accuracy. Tang et al. [16] presented a DL-based pest detection approach for agriculture using YOLOv4 architecture. The approach used multi-feature fusion of RGB and infrared images for pest detection. The approach was evaluated on a pest image dataset and achieved a mean average precision (mAP) of 95.5%. However, the study did not consider the effects of lighting conditions and camera settings on the detection results.

Yao et al. [17] introduced a holistic approach for glomerular detection, segmentation, and lesion characterization using large-scale web image mining. The approach used a DL-based detection and segmentation model for glomerular detection, and a classification model for lesion characterization. The approach was evaluated on a glomerular image dataset and achieved a glomerular detection accuracy of 96.3% and a segmentation accuracy of 87.6%. Zhang [18] suggested a DL-based approach for the diagnosis and early detection of Parkinson's disease using imaging and clinical data. The approach used a DL-based model for feature extraction and classification, and a decision tree algorithm for disease prediction. The approach was evaluated on a Parkinson's disease dataset. The dataset is pre-processed by feature extraction and selection methods, followed by classification algorithms to detect and diagnose PD. The results showed that the approach achieved an accuracy of 86.9%, sensitivity of 90.5%, and specificity of 83.4%. The study demonstrates the effectiveness of ML-based approaches for the early detection of PD. However, the study has limitations in terms of its small sample size and limited scope of data sources. Also, the study only used MRI data and clinical data, which may not capture the entire complexity of the disease.

Alwageed [19] presented a novel approach for the detection of subarachnoid hemorrhage (SAH) in computed tomography (CT) images using association rule mining (ARM) techniques. The approach involves the extraction of multiple features from CT images, which are then used to generate association rules for the detection of SAH. The results showed that the method achieved an accuracy of 95.6%, sensitivity of 92.4%, and specificity of 96.7%. The study demonstrates the potential of ARM techniques in medical image analysis for the detection of SAH. However, the study has limitations in terms of the limited sample size and lack of diversity in the dataset used. Further validation on larger and more diverse datasets is needed to improve the generalizability of the method. Yu et al. [20] developed a method for detecting AI-manipulated fake faces using generalized feature mining. The authors introduced a novel dataset of manipulated faces and utilized a deep convolutional neural network (CNN) for feature extraction. They then trained a SVM classifier using the extracted features to distinguish between real and fake faces. The method was able to achieve an accuracy of 96.3% and an area under the curve (AUC) of 0.991. The study demonstrates the effectiveness of using generalized features for detecting AI-manipulated fake faces. However, the study has limitations in terms of the limited scope of the dataset used and the potential for over-fitting due to the small sample size.

Guo et al. [21] developed a data augmentation framework for fake face image detection by mining structured features. The authors used a DL-based approach to extract structured features from real and fake face images, which were then used to generate augmented samples. They trained a CNN on the augmented dataset and evaluated its performance on a separate testing set. Their method achieved a high accuracy of 98.2%, outperforming other state-of-the-art methods. The advantages of the framework are its effectiveness in increasing the size of the training dataset and its ability to improve the performance of fake face detection models. However, one potential limitation is that the performance of the framework may depend on the quality and diversity of the training data. Rajakumar and Ganesan [22] presented a hybrid model for remote sensing image mining. The method uses a modified extrema pattern to extract features from the remote sensing images, which are then decomposed using multi-linear matrix decomposition. The resulting decomposed features are used to train a classification model for remote sensing image classification. They then used a recursive local contrast (RLC) scheme to select the most representative extrema patterns and perform classification. The method was evaluated on three public datasets, and the results showed that it outperformed state-of-the-art methods in terms of accuracy and efficiency. The advantages of the method are its effectiveness in extracting discriminative features from remote sensing images and its ability to improve the performance of remote sensing image classification models. However, one potential limitation is that the method may be sensitive to noise and outliers in the data.

Liang et al. [23] introduced a multi-pattern mining method using pattern-level contrastive learning and multi-pattern activation map. The authors utilized a contrastive learning approach to learn discriminative features from multiple patterns in an image and generated a multi-pattern activation map for each pattern. They then combined the activation maps using a fusion network to obtain a final representation for the image. The method was evaluated on three public datasets, and the results showed that it outperformed state-of-the-art methods in terms of accuracy and efficiency. The advantages of the method are its effectiveness in identifying multiple patterns in the input data and its ability to improve the performance of pattern recognition models. However, one potential limitation is that the method may be computationally expensive for large datasets. Jiang et al. [24] proposed a trimap-guided feature mining and fusion network for natural image matting. The method consists of two stages: feature mining and fusion. In the feature mining stage, the authors use a multi-scale feature extraction network to extract features from the input image, and then use a trimap-guided attention mechanism to select the most informative features for each pixel. In the fusion stage, the authors use a fusion network to combine the selected features to generate the alpha matte. Their method achieved state-of-the-art performance on several benchmark datasets for natural image matting, demonstrating its effectiveness for feature mining in this domain. However, the method requires a trimap as input, which may be time-consuming to obtain manually. Also, it may not perform well on images with complex foregrounds and backgrounds.

Luo et al. [25] presented a deep CNN (DCNN) for detecting diabetic retinopathy (DR) based on mining local and long-range dependence features. The DCNN model includes three main components: a feature extractor, a feature mining module, and a classification module. The feature extractor is designed to extract high-level features from input images using convolutional layers. The feature mining module uses the extracted features to mine local and long-range dependence features by incorporating a self-attention mechanism. Finally, the classification module classifies the input images into five different DR severity levels. The model was trained and evaluated on a publicly available dataset called the Kaggle Diabetic Retinopathy Detection dataset, achieving an accuracy of 0.961. The advantages of the method include its ability to extract local and long-range dependence features from input images, which can capture subtle image details and improve the performance of DR detection. The limitations of the method include the limited evaluation questions its generalizability. Furthermore, the computational complexity of the method may limit its applicability in real-time applications.

Overall, these studies demonstrate the diverse range of image mining applications and techniques in various domains, such as healthcare, agriculture, and social media. The methods in literature achieved state-of-the-art results and showed the potential of image mining for solving real-world problems.

III. Comparison and Discussion

Image mining has become an essential tool in various fields such as healthcare, agriculture, and multimedia. There are several image mining methods available, and each has its strengths, weaknesses, and limitations. In this comparison study, we will discuss the effectiveness, limitations, and future research directions of different image mining methods.

1. ***Traditional image processing techniques:*** These techniques are effective in processing images with a high signal-to-noise ratio. However, they have limitations in handling complex images with various backgrounds, illumination, and noise. Future research direction includes the development of hybrid approaches that combine traditional techniques with ML and DL techniques.
2. ***ML-based techniques:*** ML-based techniques are effective in handling complex images with various backgrounds and noise. However, they require a large amount of labeled data for training, which is time-consuming and expensive. Future research direction includes the development of deep learning-based techniques that require less labeled data and can handle a wide range of image mining tasks.
3. ***Deep learning-based techniques:*** These techniques can handle complex images with various backgrounds and noise and require less labeled data than ML-based techniques. However, they require a large amount of computing power and time for training, and they may suffer from over-fitting. Future research direction includes the development of lightweight deep learning models and the integration of multiple deep learning techniques.
4. ***Multi-modal image mining:*** Multi-modal image mining techniques combine different modalities such as text, audio, and video with images to extract more relevant information. These techniques are effective in handling complex and large-scale data. However, they require complex data integration and pre-processing, and there are challenges in designing effective feature fusion techniques. Future research direction includes the development of advanced feature fusion techniques and the integration of multi-modal data with deep learning techniques.
5. ***Web image mining:*** Web image mining techniques extract relevant information from web images, such as product images, news images, and social media images. These techniques are effective in handling large-scale data and can provide real-time information. However, they require complex web scraping and pre-processing techniques, and there are challenges in dealing with copyright and privacy issues. Future research direction includes the development of advanced web scraping and pre-processing techniques and the integration of web image mining with deep learning and multi-modal techniques.

Overall, there are various image mining methods available, and each has its strengths, weaknesses, and limitations. The choice of method depends on the type of data and the specific application [26]. Future research direction includes the development of hybrid approaches, lightweight deep learning models, advanced feature fusion techniques, and the integration of web image mining with other techniques.

IV. Conclusion

DM techniques have become an important tool for image and spatial mining. These techniques can be used for various applications, such as medical diagnosis, surveillance, and pattern recognition. Clustering, classification, association rule mining, and outlier detection are some of the DM techniques used for image and spatial mining. As more data becomes available, DM techniques will continue to play an important role in extracting useful information from image and spatial datasets. This study provides a brief overview of the image and spatial mining approaches. This study improvises the image mining methods and analyses the limitations to form the future research goals. This will help the research community to move forward with the new strategies for effective image mining-based applications.

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