

Machine Learning Techniques and Ransomware Attacks

Vishal Soni, Research scholar, Department of Computer Science, Janardan Rai Nagar Rajasthan Vidyapeeth University, Udaipur (Rajasthan)

Dr. Manish kumar, Associate Professor, Janardan Rai Nagar Rajasthan Vidyapeeth University, Udaipur (Rajasthan)

ABSTRACT

Over the years, our dependence on technology has risen tremendously. Many scenarios need our use of information technology (IT), though. Since our dependence on technology has resulted in a major shift in how we interact with the rest of the world, Systems that were formerly entirely autonomous are now designed to work in concert with one another as well as human users. A vast range of applications and devices are being networked all over the place and for many different reasons.

Analytical models may be built using numerous sorts of digital data, including numbers, phrases, clicks, and photographs. Today's ML algorithms can grasp images in the same manner that our brains can when it comes to image data. Automating grueling manual labor, self-driving automobiles, and everything in between all need the use of facial recognition technology. It's one of the most rapidly evolving technologies, and it's changed a lot over time. As a result, image processing is now widely employed by a wide range of businesses and organizations across several industries for a wide range of tasks such as visualizing data and identifying patterns in photos as well as identifying objects in images.

INTRODUCTION

From the internet, news stories, schematics in papers, and advertisements, we are exposed to a substantial amount of pictures every day. Visitors are tasked with deciphering the meaning of these sights. Despite the fact that most images are devoid of text descriptions, people can nonetheless make meaning of them. It is necessary that the system be able to interpret some form of image caption if automated captions are required by the public. There are several reasons why image captioning is essential. It is possible to use them to index images automatically, for example. Image indexing is essential for Content-Based Image Retrieval (CBIR), which may be utilized in a range of industries, including health care and the military. For example, photos on Facebook and Twitter may automatically produce captions. What we're doing, where we are, and what we're wearing are just few of the things that can be included in the descriptions.

LITERATURE SURVEY

Jennet Elizabeth Dickinson (2017) It is the goal of Machine Learning (ML) to make predictions about unknown data using a large set of example data as a starting point. Since the development and maturation of machine learning tools, they have been used with great success to analyse data from the LHC's proton–proton collisions and detailed Monte Carlo simulations produced by theorists, among other applications.

Myasar Mundher, Adnan, Mohd Shafry et. al, (2017) Picture annotation has recently gained a lot of interest because of the fast expansion of image data. Probabilistic modeling and classification-based approaches have been used to study AIA extensively. A review of picture annotation approaches that have appeared in the previous two decades is provided by this article. Also included were a breakdown and explanation of the evaluation measures employed. Picture annotation projects in the future will benefit greatly from careful consideration of the issues raised here when devising new methods and datasets for image annotation.

Neeraj Kumar, Aaisha Makkar (2017) Machine learning systems not only follow the instructions programmed into them, but they also learn from their mistakes. This is what distinguishes machine learning from other intelligent tools such as artificial intelligence. No human being is capable of memorising each minute value of every experiment in the same way that machine learning is capable of doing. When it comes to face recognition, the system is trained with a machine learning algorithm to recognise the smallest pattern that can be remembered. The knowledge is put to use in order to carry out some action, which can take on a variety of forms depending on the input. The type of machine learning algorithm used to transform input into output determines the process by which the input is transformed. The project can be loaded at any time and modified at any point during its

Santo shachandra, Rao Karanam et. al, (2017) Images are critical to a variety of sectors including medical imaging and image processing as well as other areas like web mining and other forms of data exploitation. It is vital to the database's underlying structure that medical photos may be quickly searched and retrieved using Content Based Medical Image Retrieval (CBMIR) methods. The goal of this article is to offer a thorough knowledge of how deep learning algorithms may be used to segment images. Various deep learning applications in medical imaging and image mining, as well as their limits, are discussed in this article. Identifying a medical picture fault and content-based image retrieval are additional crucial insights provided by this study.

Sirisha Kopparthi, Konadala Kameswara et. al, (2016) One of the datasets used in the trials is the UC Merced Land Use Dataset. utilizing a model that has been pre-trained on millions of photos and is optimized for image retrieval A pre-trained CNN model is employed to create picture feature descriptors during the retrieval process. To extract features from the VGG-16 and VGG19 networks, this approach uses transfer learning, as well as a variety of similarity metrics, to get feature vectors. In terms of extracting and learning information from photos, the suggested architecture does an excellent job.

Amir Vatani, Milad, Taleby Ahvanooey et. al, (2016) Nowadays, there is a wide variety of photographs to choose from. Finding the picture you're looking for might be tough with computer vision systems. There has been a lot of progress in the field of automatic picture annotation during the past two decades, which has usually been focused on content-based image retrieval. One of the most common methods for bridging the semantic divide is to use machine learning to extract semantic information from images. When it comes to determining which features are most important, the annotator uses the long-short-term memory network (LSTM). For performance criteria, the suggested model is superior than earlier models, according to experiments on two datasets.

PROPOSED METHODOLOGY

This chapter focuses on the annotation system's framework. It divides the system into three sections: the proposed system, the architecture of the developed annotation system, and the datasets utilized during system construction.

PROPOSED FRAMEWORK

This section discusses the architecture proposed by preliminary research from the evaluated literature. The proposed system is divided into three key parts. Training is a crucial component of any system that makes use of a database of annotated images. In the second phase, the trained system works on raw data to output the annotated image, and in the last phase, image retrieval should be performed to evaluate annotation outcomes.

In the first phase, training, a typical training database that has been segmented is employed. Annotations are necessary for text-based image retrieval. Annotation adds semantic information to photos to improve retrieval performance. The segmentation method generates regions, from which features can be easily extracted by comprehending the contents of the images. The next step is to model the features using a learning technique. It creates an annotation model in order to annotate new photos.

CONTENT-BASED IMAGE RETRIEVAL

Content-based image retrieval seeks out images in a vast collection that are similar to a query image. An image's ranking for retrieval is often based on how closely its representative characteristics match those in the dataset photographs. First, a wide range of manually created feature descriptors for pictures based on visual signals like color, texture, shape and so on were studied. To replace hand-designed feature engineering, deep learning has gained prominence over the previous decade. It automatically learns the characteristics from the data.

Since then, the term has been used to describe the process of sifting through a large array of images to pick the best ones based on their color, texture, and shape. Preferably, the extraction process should be fully automated, regardless of the retrieval features. CBIR is not what we call image retrieval when we use manually supplied keywords, even if those keywords represent

What is Content-Based Image Retrieval (CBIR)

Digital photographs can be organized based on their visual properties using Query by Image Content (QBIC). Image retrieval in large datasets is solved using computer vision algorithms. Image retrieval relies on features taken directly from image data rather than keywords or annotations.

Extracting photos from a collection based on their resemblance. An image's intended content can be deduced through the use of character quantity extraction techniques. Furthermore, appropriate querying, matching, indexing, and searching strategies are necessary.

Architecture of CBIR

Depicts the general CBIR framework, which includes certain essential and optional stages. The user submits the query image as the first stage in CBIR. Each picture in the database will be processed in the same sequence as the query image, regardless of whether or not it has been previously processed. However, the same procedures may be executed to dataset pictures before query submission and are referred to as offline processes. These operations are commonly performed on the query image upon user input and are referred to as online processes. Architecture of the framework may include an optional pre-processing stage, which may include among other things: rescaling and de-noising. As a final but not least step, feature extraction involves converting a visual notion into numerical form. Color, shape, texture, and spatial information are examples of low-level qualities that can be extracted. After feature extraction, pre-processing steps like as normalization or classification may be used. The final step is to compare the derived characteristics of the query image to those of all other photos in the collection to identify the most relevant ones. User input can help us determine which returned photos are relevant and which are not through a process known as "relevance feedback." Many approaches for using relevance feedback to improve CBIR performance have been proposed.

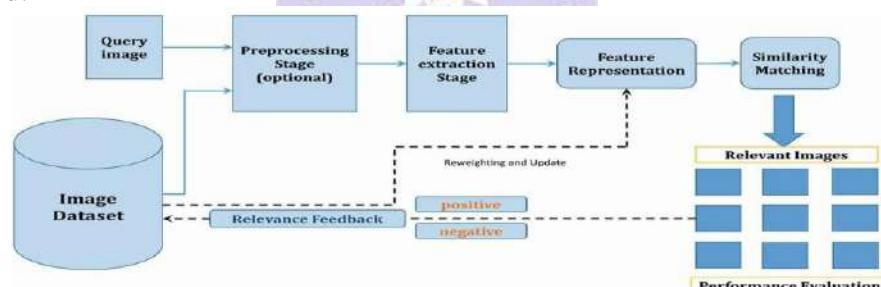
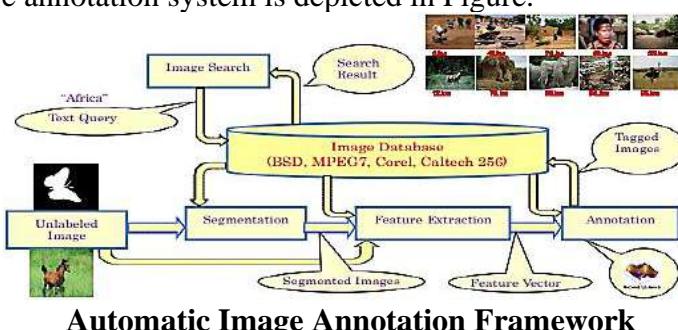


Figure Framework of the CBIR system

ARCHITECTURE OF AUTOMATIC IMAGE ANNOTATION SYSTEM

In the research work carried out, the proposed system in section, the architectural framework, is created and implemented. The created annotation system performs three main operations: picture segmentation, feature vector construction, and learning and tagging. The framework of the automatic picture annotation system is depicted in Figure.



Automatic Image Annotation Framework

The framework accepts two types of images as input from the image dataset: form image objects (black and white images) and colour images. If the input image is a form image, it is segmented using the canny edge detector; otherwise, it is segmented using the clustering algorithm. Segmentation is investigated using six edge detection strategies for form tagging and grid

division of colour images, as well as four segmentation algorithms. The framework's second module is feature extraction and feature vector preparation. The edge detection border gives the contour of the shape from which geometric features are retrieved, and the vector is then prepared for learning by picking salient features. Color strength of images can be considered both globally on the entire image and locally on patches from grid-based segmentation. Color strength is taken from the split regions at the local level. Using the discrete gabor wavelet transform, the texture is retrieved. To extract textural features, the mean and standard deviation of the magnitude of the converted coefficients for 6 orientations and 5 magnitudes are obtained. The system framework's next stage is machine learning. In this step, classifiers based on artificial neural networks (ANN) and its derivatives, rough set (RS), decision trees (DT), k-closest neighbor (K-NN), and multiple instant learning (MIL) are utilized. The system's final stage is image retrieval utilizing tagging findings and evaluation using precision and recall.

DATA ANALYSIS AND RESULTS

IMAGE SEGMENTATION

Splitting up an image into meaningful structures is known as segmentation, and it is the process by which a digital image is broken up into several parts. Segmenting an image is a common practice in image analysis, object representation, visualization, and a number of other image processing operations. Because of this, an image's depiction is given new depth and significance. It's common to use the term "segmentation" to distinguish between interesting and uninteresting parts of a scene, as well as between foreground and background material. When a picture is broken down into smaller, more uniform chunks, the user has an easier time deciphering what is going on. Grid-based and content-based image segmentation techniques are the most often used. Grid-based techniques are the simplest and use a grid pattern to split the image without consideration to its content. Depending on the characteristics used to segment, content-based techniques can be divided into a variety of categories.

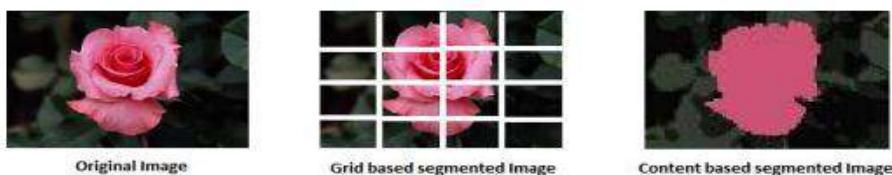


Figure Segmentation of Image

Using a 4 by 4 grid and a content-based technique. In order to identify the region's boundaries, shape-based retrieval must be used. In order to do this, edge detection techniques are employed. SNR, PSNR, and root-mean-square error are some of the metrics used to assess the effectiveness of edge-based segmentation (RMSE). Rand index (RI) and probabilistic rand index (PRI) allow comparisons between segmentations conducted by various algorithms and hand segmentations subject to human intervention, making it feasible to conduct quantitative valuations of financial assets.

CONCLUSION

Segmentation, feature extraction, and annotation are all steps in the system framework proposed in this thesis for automatic image annotation. Four standard datasets were used to build and test the annotation system. Because the quantity of digital photographs in both public and private collections is continuously increasing, image content analysis technologies are needed. Any digital image collection can be beneficial if the user can extract required content from it. Image content management is a method for organizing and retrieving photographs from a collection. The automated system's goal is to interpret the contents of the image by employing the features in the contents, which can vary in quality and size.

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