Exploiting Local Features from Deep Learning For Image Retrieval

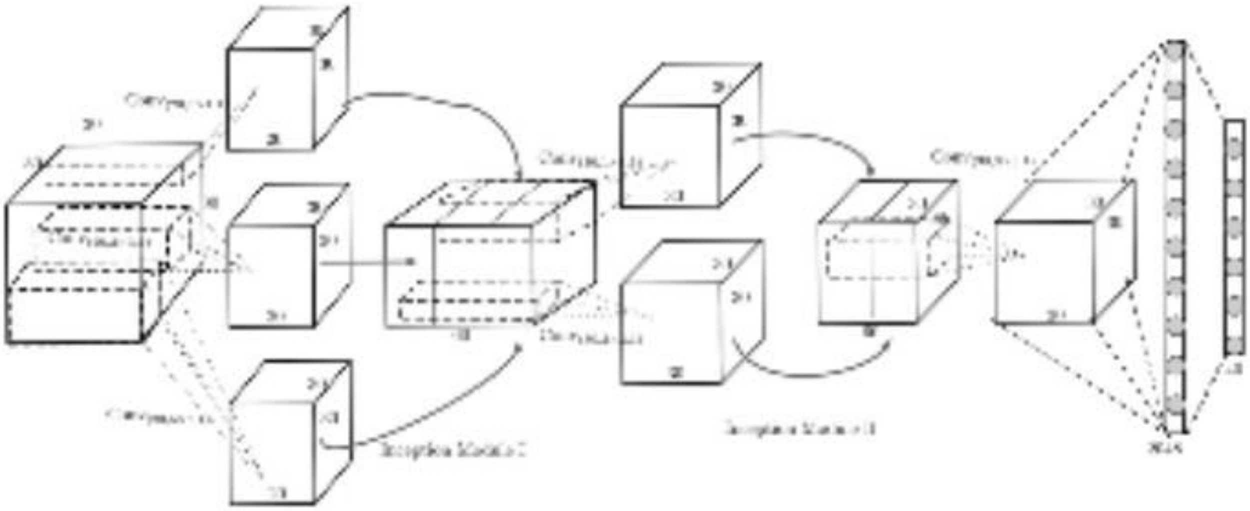
Problem Statement:

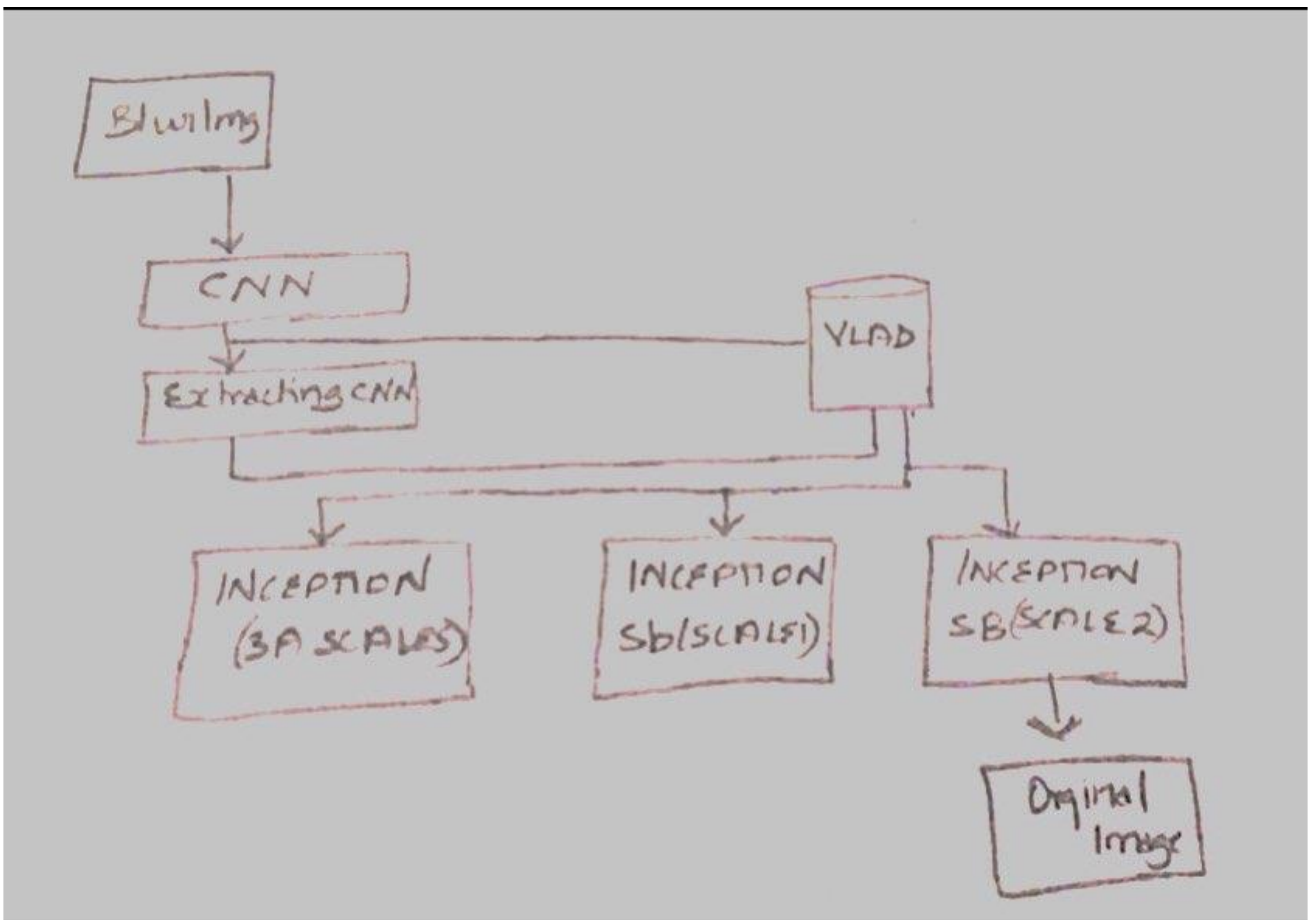
Gap is the problem that what we see in an image is not what we think of in our mind. This problem resembles the problem known as symbol grounding argued in the context of the advocation for the combination of the connectionists' approach and the symbolic inferences to derive the semantics from the existing physical entities. The fundamental problem of semantic gap will be recapped as a lack of information within images. named the following example entities that are actually invisible in images, but are of importance to users: time, space, events and significance, abstract and emotive concepts, and unwanted features carefully crafted visual features will not help automatically annotating these entities.

Motivation for Deep Learning For Image Retrieval:

A good content-based image retrieval must provide a robustness to the spatial changing problem of an image which causes from different acquisition, such as, zooming image, same image but different color, etc. These mentioned problems is the main cause to degrade the retrieval performance. To achieve the best retrieval result, an optimal feature must be invented to represent an image semantic. At present, instead of using single feature, most image retrieval system utilizes combining features between two low-level features in an image to retain high precision when faces to the mentioned problem. However, the retrieval error still remains. It causes from the combination of two unsuitable features. Thus, choosing two compatible features is another interested research issue in this area. This paper proposed a new feature combination between color correlograms and edge direction histogram (EDH) in order to give precedence to spatial information in an image. Using color correlogram will treat information about spatial color correlation, while EDH provides the geometry information in the case of the same image but different color. Performance evaluation performs by simple calculation like Euclidean Distance between the query image and image in the database.

Architecture:





Comparison other tools: -

Tensor flow: -

It is purposes of conducting machine learning and deep neural networks research, but the system is general enough to be applicable in a wide variety of other domains as well.

Matlab: -

Matlab in not only a programming language, but a programming environment as well. You can perform operations from the command line, as a sophisticated calculator or you can create programs and functions that perform repetitive tasks, just as any other computer language.

There are so many tools for image processing like **MeVisLab, Microscope image processing, OpenCV, Openlab**

Validation Verification:

References

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