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Digital Colour Assistant

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ABSTRACT—

Creative and explorative changes of research, In the field of design industry have been significantly influenced by technologies belonging to Artificial Intelligence and Machine Learning. There is huge outgrowth in the field of research and creative application which appear as a bridge between Visualization and design industry which drive us to explore well known technologies under suitable Circumstances. With regard to Research based on AI for learning of efficient designs we create a wide scale implemented datasets of various design and works that perform various vital jobs such as object detection, classification, similarity retrieval, multimodel represen- tations, computational aesthetics. We discuss many theoretical and practical features of design industry in relation to its function in producing the design, and we gather works that go into greater detail about those issues. Finally, we offer a succinct vision on the development of AI technologies in the future and their possible influence on how we perceive and produce art. Computers utilise machine learning algorithm to detect objects, scenes and classification of different color shades. But still it is a very challenging task to detect and identify objects accurately with fast speed. Recognising in what type of environment one is located is an important perception task, classification of color shades under ideal and different non-ideal conditions. Our main project goal is to detect the objects in the scenes and apply a different coloring model by learning from previous datasets according suitable lightning conditions and user request.

***Index Terms*—Image Processing, Convolution Neural Network (CNN), Machine Learning, Visualization, Scene Detection, Colour classification**

I. INTRODUCTION

The usage of computer vision techniques for image process- ing in the precision of design sector has increased significantly in the recent years. There is a huge growth in the field of convolution neural network. There are a lot of studies taken place on CNN and has found out to give profound results. Using machine learning techniques, we are training the model to categorize colour hues under different ideal and non-ideal circumstances. In addition to this experiment, another goal is to develop, test and fine tune a learning model to identify the patterns, forecast the test data and evaluate the test predictions under different lightning test conditions. The colour categorization challenge can be resolved using advanced method of machine learning algorithm. The machine vision area is switching from conventional technique to neural network technique.

In common neural network method seems to be more conve- nient for solving a specific problem compared to conventional methods. One of the conventional method for colour recog- nition is K-Nearest Neighbours Machine Learning algorithm with feature extraction. K Means algorithm is another well known machine learning approach to extract colours from images based on colour space values which are RGB, CYMK, HSV etc. CNN is one of the best example which is commonly used to solve any kind of image driven pattern recognition problem. A Machine can be trained in 3 different ways:

1. Supervised Learning: When good amount of data is known we demonstrate the machine, the relationship among different variables and predetermined results.
2. Unsupervised Learning: This learning process progresses with the method of trial and error. The unlabelled data is fed to the machine by studying and observing the data that uses unsupervised learning which is a data-driven (clustering) learning algorithm.
3. Reinforcement Learning: Supervised and unsupervised learning is a complete different approach from reinforcement learning. The machine generates a sequence using reinforce- ment learning to constantly improve the results and produces output according to the suitable environment

The 2D picture classification issue was the first to examine scene recognition [1], [2]. It has also been suggested to use RGB-D pictures and 2.5D operation for interior settings.From stereo rigs or range cameras [3, 4]. On the other hand, as far as we are aware, no attempts have been made to do scene categorization using 3D point cloud or voxel data. Given that the scene and, in most situations, a robot’s sensory input are three-dimensional, this is a little unexpected. We identify two causes for this disparity. In 3D, machine learning is computationally more expensive. In particular, effective deep learning architectures for 3D point clouds or voxel data have just been created in the last three years. There are no appropriate public datasets, other than 2D pictures and 2.5D range scans. The only benchmark that is currently available, as far as we are aware, is ScanNet with a meagre 1611 scans encompassing 20 distinct scene types, which represents a very small portion of the current 2D image , range image , and video datasets.

In order to bridge the gap, we examine scene recogni- tion using 3D data in this research as a first step. In that perspective, the following is a crucial finding: The ”small” aspect of the datasets is the quantity of scenes and, as a result, the information content of the ground truth, which consists of roughly

1000 integer labels. The dataset, on the other hand, offers substantially richer per-point labels and is also intended for semantic segmentation. According to our argument, the pointwise labels provide useful and much more side information to direct learning toward semantically significant characteristics. In order to do this, we use multi-task learning, where semantic segmentation is learnt as a support task during training, using a common encoder for both the segmentation and scene classification tasks

Our 3D encoder-decoder network significantly advances the state-of-the-art for categorising scenes. compared to earlier 2D techniques, on ScanNet. We also discover that multitask learning improves classification performance even further, re- sulting in an overall accuracy of 90.3Additionally, we conduct ablation investigations to separate the effects of geometry, object semantics and colour, and 3D point density. We discover that the various stimuli are kind of complementing. Scene ge- ometry performs the bulk of the work in the absence of object information, while incorporating colour can occasionally dra- matically enhance classification results. On the other hand, a remarkably accurate predictor is also found in the distribution of object classes in the picture without any geometry.

Furthermore, contrary to popular belief, our research shows that scene identification involves more than just recognising individual, distinctive items. most scenes

distinct object classes has just a minor impact on types. Unexpectedly, if one substantially downsamples the input point cloud, classification performance only slightly suffers: portraying an entire room with 1024 randomly sampled points is sufficient to almost match the performance on the complete point cloud. The fact that the scene type can be accurately anticipated from a quick ”overall glance” at the surroundings supports our decision to infer it early on in order to tailor later, more precise perception and action tasks.

II. LITERATURE SURVEY

[1]. There is a wide range of CNN architectures which are available for image classification, segmentation and object detection. This paper is a comparative study of different CNN architecture and provide the suitable architecture based on application or hardware attributes.Each CNN architectures is estimated with the CIFAR 10 data set to gauge the perfor- mance, accuracy and memory. Drawbacks:Noise Reduction technique has not been implemented on the images and experiments are executed on the images directly . Stochastic Gradient descent is used as optimizer in the study which may not give the precise output and it may work slow on large datasets.

[2]. In this paper Innovative, Ensemble Learning Method in a Dynamic Imaging System is unveiled .The Crack is the target to be analysed and the wall was monitored by the drone flight path setting and then the horizontal image was immediately sent using a wireless transmission of the system. Integrated Learning methodology gave a favourable output in the Crack Detection. Classifier had 96 percentage precision and can automatically compare the target area range. Drawbacks:The Preprocessing method for each and every image collected should remain the same which is difficult.Huge amount of Sample Images required to get the accurate results.

[3]. This paper recognizes an indoor scene from 3D point cloud data. Multitask learning is used to improve scene recognition we know that successful scene recognition is not only about recognizing individual object but also it involves recognizing many cues which are coarse 3D geometry colour and distribution of object categories. There 2 different cues which provides greater accuracy. One is based on global scene geometry and other is based on distribution of semantic object labels. Drawbacks:The final model is a combination of two cues in a Multitask learning framework.Hence the confusion regrading irregular point clouds or voxels may occur

[4]. This paper aims to be a state of the art in scene recognition with deep learning models from visual data.Scene Recognition has addressed by a single image and dynamic image perspective. This helps in selecting the models for the scene recognition.This paper helps to make decision about taking which approach in best for scene recognition images. Drawbacks:It faces difficulties in the getting video data cap- tured in static camera motion. For the places CNN approach two main types of miss-classifications occur: on one hand, less-typical activities happening in a scene context. scene context and on the other hand,images depicting multiple scene parts.

[5]. In this paper object detectors appear from training CNN’s to carry out scene classification, scenes are collection of objects.CNN for scene classification automatically locates meaningful object detectors which represent the learned scene categories. This leads to scene recognition and object localiza- tion in single forward pass.Object detectors are the result of learning to classify scene category. Drawbacks:It only works on informative objects for specific scene recognition task Object classes cant be learned Without explicit supervision of object labels.

[6]. In this paper it is evaluating the cracks and spalls on wall surface, it plays a major role in building maintenance. For detecting the condition of the walls image processing algorithms of steerable filters and projection integrals are used to get the information from the digital images. This model uses SVM and LSSVM algorithm to broaden the categories and classification limits into five labels. The predictive perfor- mance of the experimental results of SVM and LSSVM are 84.3 and 85.13 percent respectively. Drawbacks:In this study the image segmentation and colour texture analysis could not be achieved.

[7]. In this paper to detect the wall cracks of buildings, the improved single shot multi box detector algorithm combined with infrared thermal imaging technology that can detect the cracks under the building coating or wallpaper. This approach efficiently implements not only large scale detection, enhances the speed and accuracy of crack detection but also avoids subjectivity of detection. Drawbacks:It works only on the small datasets. It works effectively only with infrared thermal imaging technology.

[8]. In this paper the approach for object detection are CNN models like RCNN, Fast RCNN, Faster RCNN and YOLO. After implementing five models non parallelly and calculating its accuracy to determine which model is best suited for the particular problem. Drawbacks:In YOLO V3 Anchor Box offset prediction , focal loss and linear prediction could not be achieved.

[9]. In this paper for object detection the improvised neural network model and improved version of YOLO which is more fluid and feasible for solving the network error. This new network is trained on end to end manner. The extensive experiment on pascal VOC dataset reveals the effectiveness of the enhanced new network with detection rates of 65.6 and 58.7 percent respectively. Drawbacks:The hybrid detection for small object using scientific programming could not be achieved.

[10]. In this paper the author shows how YOLO is differ- ent from other models like RCNN and DPM. RCNN uses region proposal methods. DPM uses sliding window approach. During training and testing YOLO sees the complete image and implicitly learns circumstantial information about classes in addition to their appearances. Drawbacks:It is difficult to generalize things with novel or peculiar aspect ratios or configurations. The number of near by objects is limited by spatial constraint.

[11]. In this paper advancement and the difficulties faced in real time object detection is discussed. The evolution of the technology from CNN to RCNN to ResNet to YOLO is discussed. YOLO-V1 and YOLO-V2's characteristics are reviewed. This paper reviews the dominating real-time object detection algorithm You Only Look Once (YOLO). YOLO's spatial constraints on bounding boxes. YOLO also has a weakness in generalizing objects in unusual or new aspect ratios

[12]. This paper discusses a method for obtaining unvarying features from images that can be utilized to perform reliant matching techniques between various angles of an object or scene. This article provides image characteristics that may be used to match various photographs of an item or scene because they possess a variety of attributes. The fastest nearest- neighbour algorithms that can quickly complete this computa- tion against huge databases will be covered in this study. The chance that a specific collection of characteristics indicates the presence of an item is then thoroughly calculated given the fit's precision and the quantity of likely false matches.

[13]. This paper sheds light on the fact that even though deep CNN has better classification performance, they are harder to train and an efficient method to overcome this hindrance is hinted in Residual Network (ResNets). ResNets' primary distinction is that their short-cut connections run parallel to their regular convolutional layers. These shortcut connections are always active, in contrast to convolution layers, and the gradients can readily back propagate through them, resulting in a speedier training. The unwanted overfitting is more likely to occur in residual networks

[14]. This paper present thorough experiments on ImageNet to demonstrate the degradation issue and assess our methodol- ogy. They have exhibited that: 1) Our extremely deep residual nets are simple to optimise; however, the counterpart "plain" nets (which just stack layers) exhibit higher training error as the depth increases; and 2) Our extremely deep residual nets can easily enjoy accuracy gains from greatly increased depth, producing results that are significantly better than those of previous networks. The difficulty is the gathering of sizeable data sets for training and validation.

[15]. This paper gives a brief overview of the input data and the chosen colour space. A method for pixels to be automatically labelled is shown in Section 4. The condensed data is provided in Section 5. Section 6 presents the neural network's design, while Section 7 outlines the process for dividing the data space into regions. Section 8 provides two plans for combining the responses from the modules, and Section 9 details how the network was designed. The findings of experimental investigations are summarised in Section 10, and the work's conclusions are given in Section 11. What labels the pixels along the edges of the dots should have is unclear. Additionally, hand labelling is an extremely time-consuming process.

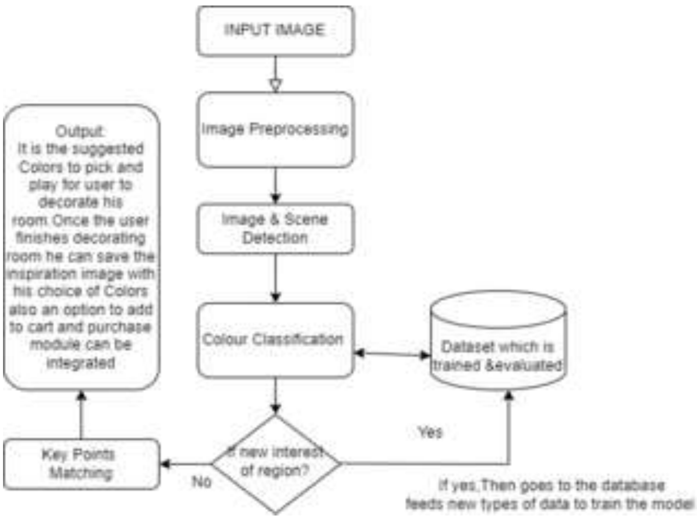

Fig. 1. Data Flow Diagram

Sl. No	Paper Name	Author	Summary	Drawbacks
1	Real-Time Object Detections using YOLO	Upulie H.D.I, Lakshini Kuganandamurthy	In this paper advancement and the difficulties faced in real time object detection is discussed. The evolution of the technology from CNN to RCNN to ResNet to YOLO is discussed. YOLO-V1 and YOLO-V2's characteristics are reviewed. This paper reviews the dominating real-time object detection algorithm You Only Look Once (YOLO).	YOLO's spatial constraints on bounding boxes. YOLO also has a weakness in generalizing objects in unusual or new aspect ratios.
2.	Indoor Scene Recognition in 3D	Shengyu Huang, Mikhail Usvyatsov and Konrad Schindler	This paper recognizes an indoor scene from 3D point cloud data. Multitask learning is used to improve scene recognition we know that successful scene recognition is not only about recognizing individual object but also it involves recognizing many cues which are coarse 3D geometry colour and distribution of object categories.	The final model is a combination of two cues in a Multitask learning framework Hence the confusion regrading irregular point clouds or voxels may occur.
3.	Artificial Intelligence In Object Detection	Ashish Kumar	In this paper the approach for object detection are CNN models like RCNN, Fast RCNN, Faster RCNN and YOLO. After implementing five models non parallelly and calculating its accuracy to determine which model is best suited for the particular problem.	In YOLO V3 Anchor Box offset prediction , focal loss and linear prediction could not be achieved
4.	You Only Look Once: Unified, Real-Time Object Detection	Joseph Redmon, Santosh Divvalay, Ross Girshick, Ali Farhad	In this paper the author shows how YOLO is different from other models like RCNN and DPM. RCNN uses region proposal methods. DPM uses sliding window approach. During training and testing YOLO sees the complete image and implicitly learns circumstantial information about classes in addition to their appearances.	It is difficult to generalize things with novel or peculiar aspect ratios or configurations. The number of near by objects is limited by spatial constraint.
5.	Study of Residual Networks for Image Recognition	Mohammad Sadegh Ebrahimi,Hossein Karkeh Abadi	This paper sheds light on the fact that even though deep CNN has better classification performance, they are harder to train and an efficient method to overcome this hindrance is hinted in Residual Network (ResNets). ResNets' primary distinction is that their short-cut connections run parallel to their regular convolutional layers.	The unwanted overfitting is more likely to occur in residual networks.

CONCLUSION

In our experiment we are trying to inculcate all the machine learning algorithms and solving our problem statement of detecting interior design or a image of a wall given as an input by the user for suggesting the required colour, design based on the preferences of the user and the pattern which can match the interior design according to different light conditions and scenarios. As discussed earlier we are using unsupervised learning to train our model and get the required output.

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