House Interiors Suggestion

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Abstract- Real Estate is a clear industry in our ecosystem. The ability to extract data to extract relevant information from raw data makes it very useful to suggest house interiors, important housing features, and much more. Housing prices continue to change from day to day and decorating it with our interiors makes it much more unaffordable. Research has shown that fluctuations in housing prices often affect homeowners and the housing market. Literature research is done to analyze the relevant factors and the most effective models for suggesting house interiors. In this study we have proposed a machine learning algorithm that combines the best features of existing algorithms by using resnet50. The ResNet-50 model, a state-of-the-art convolutional neural network, is employed to extract high-level features from a vast collection of interior design images. These images are curated from various sources, including professional design portfolios, online platforms, and magazines. The model's pre-trained weights allow it to capture intricate patterns and characteristics that define different interior design styles. This study will be of great benefit, especially to housing interiors developers and researchers, to find the most important criteria for determining interiors prices and identify the best machine learning model used to conduct research in this field.

Indexed Terms- CNN, House interior suggestion, KNN, ResNet50

I. INTRODUCTION

The process of selecting suitable interior designs for houses is often a daunting and time-consuming task for homeowners and designers alike. Existing methods for interior design suggestions primarily rely on manual searches through magazines, online platforms, or professional portfolios. These approaches are not only labour-intensive but also prone to biases and limited in their scope. The absence of an automated solution that can leverage the power of artificial intelligence to analyse vast collections of interior design images and provide personalized suggestions hinders the efficiency and effectiveness of the design process.

Therefore, there is a need for an innovative solution that addresses these challenges by providing a streamlined and personalized approach to suggest house interiors. Such a system should leverage advanced technologies like deep learning and image recognition to analyse a vast database of interior design images and extract relevant features and styles. It should also incorporate user-provided parameters and constraints to generate tailored design suggestions that meet individual requirements. By addressing these limitations, the proposed solution aims to enhance the efficiency, creativity, and satisfaction of the house interior design process.

II. METHODOLOGY

1. DATA COLLECTION

The dataset used in this project was from Kaggle website. Our dataset consists of 9346 images of house interiors from different angles. It consists of all types of interiors such as traditional, modern, Asian, Italian etc. It comprises of images of sofas, closets, dressing table, chairs, beds etc. It might also include variations in interiors styles, designs, colours, and materials to represent a diverse range of options available to homeowners.

Fig 1 House interiors

2. DATA PREPROCESSING

The datasets used cannot be directly applied. If the product is present in the scene image, it will make the model biased. For training a generalised model, the products have to be cropped out from the scene image. All the missing/NaN values are being handled which images are being broken, or the json files bounding boxes coordinates are not cleared properly. The specific features listed will be required to form the feature vector and extracted images specific to the classes of these features. An automated curating and cleaning of data is done to eliminate duplicates and nonrelevant images. A manual check is done to eliminate images that were not specific to the class they were meant to belong to for training. We can use the images as the training and validation dataset and separate out a well-represented section for the test.

III. MODELING

In this research paper, we propose a model that uses Convolutional Neural Network and the Nearest neighbour backed recommender. As shown in the figure Initially, the neural networks are trained and then an inventory is selected for generating recommendations and a database is created for the items in inventory. The nearest neighbour's algorithm is used to find the most relevant products based on the input image and recommendations are generated.

1. FEATURE EXTRACTION

In this step, the features of the scene and the product images are extracted using the Resnet-50 model. The feature map obtained from an intermediate Resnet block is used for the subsequent computation of the embedding. Once the data is pre-processed, the neural networks are trained, utilising transfer learning from ResNet50. More additional layers are added in the last layers that replace the architecture and weights from ResNet50 in order to fine-tune the network model to serve the current issue. The figure shows the ResNet50 architecture.

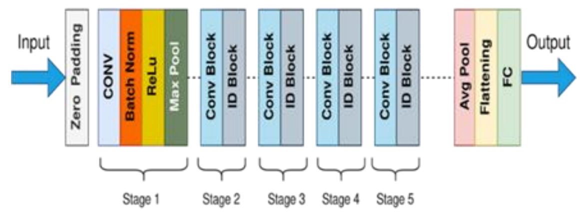


Fig 2 ResNet50 Architecture

The proposed method takes images of 224x224x3 and after taking the images it extracts all the features and gives back a vector of 2048 features. For ex we have an image of sofa it takes it as an input in size 224x224 and extracts an 2048 features vector, so if we have 9024 images it will create 9024 features vectors each vector size 2048 and their corresponding filenames.

2. K NEAREST NEIGHBOURS

After we have received our feature vectors in feature extraction step using ResNet50 model, the model processes the input image and use KNN to extract the 5 most close images to the input and outputs it as our suggestion.

We use embedding generation to represent images/products such that similar ones are grouped together whereas dissimilar ones are moved away so that in order to retrieve products that are similar to the products present in the query image. There are various ways to calculate similarity between images after they are converted into a vector with n-dimensions. Cosine similarity and Euclidean distance are two examples.

IV. EXPERIMENTS

There isn't a specific way to determine the best K value – in other words – the number of neighbours in KNN. This means that you might have to experiment with a few values before deciding which one to go forward with. One way to do this is by considering (or pretending) that a part of the training samples is "unknown". Then, you can categorize the unknown data in the test set by using the k-nearest neighbours algorithm and analyse how good the new categorization is by comparing it with the information you already have in the training data.

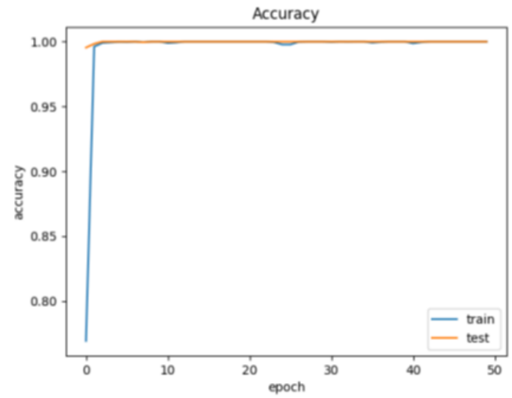
When dealing with a two-class problem, it's better to choose an odd value for K. Otherwise, a scenario can arise where the number of neighbours in each class is the same. Also, the value of K must not be a multiple of the number of classes present. Another way to choose the optimal value of K is by calculating the sqrt(N), where N denotes the number of samples in the training data set. However, K with lower values, such as K=1 or K=2, can be noisy and subjected to the effects of outliers. The chance for overfitting is also high in such cases. On the other hand, K with larger values, in most cases, will give rise to smoother decision boundaries, but it shouldn't be too large. Otherwise, groups with a fewer number of data points will always be outvoted by other groups. Plus, a larger K will be computationally expensive.

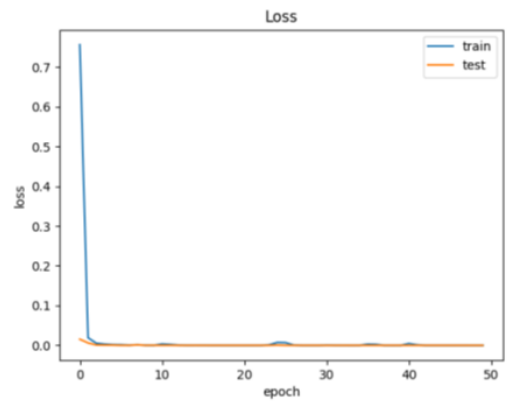
V. RESULT

The concept of Transfer learning is used to overcome the issues of the small size interiors dataset. Therefore, we pre-train the classification models on the house interiors dataset that consists of 9346 images.

Method	Accuracy Score	Precision	Recall
Resnet50	0.9625	0.9458	0.9466
VGG-16	0.9056	0.8974	0.8862
Proposed Model	0.8657	0.8574	0.8255

Table 1 Accuracy comparison in models





We observed that the baseline models that were pretrained on Image-Net features such as Res-net and VGGNet performed better, which indicated that the visual compatibility differs from the visual similarity which makes it important to learn the notion of compatibility from the data. The model was trained with the images, which made it more effective and thus, boosting the performance of the model. Our proposed method deals with both global and local appearance thus considering the key context of the scene. Using category guided attention enhances the ability of the model to identify key details of the scene image and compare it with the product. It takes a decision by incorporating the scene, product and the category of the product as well.

CONCLUSION

In the current proposal, we gave a model that suggests house interior on the basis of input image by finding the closest matches to it in our 9346 images dataset. The proposed methodology provides a systematic approach for integrating ResNet50 into the house interiors suggestion system. By preprocessing the image dataset, training the ResNet50 model, and implementing a recommendation engine, users can receive tailored suggestions for furniture and interior design elements that suit their preferences and complement their existing decor.

We also created a website where you can experience recommendation system yourself.

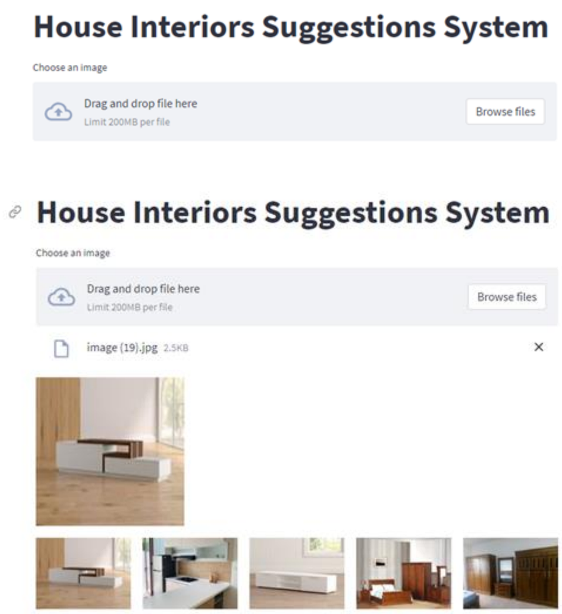


Fig 3 Suggestion System Website

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