MAGIC WALL VISUALIZER

A PROJECT REPORT

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in partial fulfilment for the award of the degree

of

BACHELOR OF ENGINEERING

IN

ELECTRONICS AND COMMUNICATION ENGINEERING

KUMARAGURU COLLEGE OF TECHNOLOGY

(An Autonomous Institution Affiliated to Anna University, Chennai)

MAY - 2021

KUMARAGURU COLLEGE OF TECHNOLOGY
COIMBATORE

BONAFIDE CERTIFICATE

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ACKNOWLEDGEMENT

First, we would like to express our praise and gratitude to the Lord, who has showered his grace and blessings enabling us to complete this project in an excellent manner.

We express our sincere thanks to the management of Kumaraguru College of Technology and Joint Correspondent **Shri. Shankar Vanavarayar,** for his kind support and for providing necessary facilities to carry out the work.

We would like to express our sincere thanks to our beloved Principal **Dr. D. Saravanan Ph.D.,** Kumaraguru College of Technology, who encouraged us with his valuable support.

We would like to thank Prof **Dr.S.A.Pasupathy M.E.,Ph.D. (UK)** Head of the Dept., Electronics and Communication Engineering, for his kind support and for providing necessary facilities to carry out the project work.

We want to thank everlasting gratitude to the project coordinator **Ms. A. Kalaiselvi, ME., (Ph.D.,)** Assistant Professor II, Department of Electronics and Communication Engineering, for her consistent support throughout the course of this project work.

We are privileged to express our heartfelt thanks to our project guide**, Dr. S.N Shivappriya M.E.,Ph.D...,** Department of Electronics and Communication Engineering, for her expert counselling and guidance to make this project to a great deal of success and we wish to convey our deep sense of gratitude to all teaching and non- teaching staffs of ECE Department for their help and cooperation.

Finally, we thank our parents and family members for giving us the moral support and abundant blessings in all our activities and my dear friends who helped us to endure our challenging times with their unfailing support and warm wishes.

ABSTRACT

Our work introduces an effective system named **“Magic Wall Visualizer”** that makes use of Convolutional Neural Network (CNN) and image processing techniques to visualize the room decoration in a remarkably effective manner. Given an image of a room, our system can effectively replace the colour and texture of the wall according to the user’s desire. Our approach makes use of “DeepLabV3”, a CNN based architecture, capable of segmentation. This model was trained on “ADE20K” which is a landmark image segmentation dataset consisting of 25,000 images belonging to 150 classes. An image when fed into the model provides the corresponding segmentation map. Each classes of object in the image will be segmented by a unique colour. Once the segmentation map is obtained, a mask should be created to extract the wall region alone. After successful creation of the mask, the colour of the wall can be changed by substituting it with the desired colour. In addition to this, the texture of the wall can also be changed by spatial layout estimation. These approaches will strengthen the reality of visualisation and provides visually pleasing results.

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CHAPTER 1

INTRODUCTION

In the interior decoration of houses, selection of colours plays a significant role. Nowadays, there exist a wide variety of colours. But many of us might not have known whether a particular colour suits our house or not. It is important to pick a correct colour for our dream house. Keeping this motive in mind we have developed an Image Processing based technique called "MAGIC WALL VISUALIZER." Our system can efficiently solve this issue by visualising how a wall will look before painting. Thus, it becomes ease to select the colours and to visualize it. At first user will upload an image that he/she should desire to visualize. The uploaded image will be fed to the proposed model. At last, the output image with the desired colour and texture can be visualized in a realistic manner.

OBJECTIVE

The main aim of our system is to help people to visualize room decoration of their dream houses by replacing the colour and the texture of the wall according to the user's desire. With the advancement in Artificial Intelligence, nowadays **Convolutional Neural Network** (CNN) can be widely used to solve image recognition problems due to their advancement in the model's architecture. Our approach uses Segmentation model such as "**DeepLabv3+",** which was introduced by Google in the year 2016. Thus, we aim to provide realistic colour and texture replacement with reserving brightness.

CHAPTER 2

LITERATURE SURVEY

Si Lui *et al* proposed a model named **Edge Aware FCN (Fully Convolutional Neural Network**), in [1] for visualizing room decoration. Their approach concentrates on wall segmentation and colour replacement. Their approach can effectively segment the objects and can detect the edges in the wall. For colour replacement they have used HSV (Hue Saturation Value), which is one of the colour spaces. In addition, Alpha Matting process is carried out to refine the segmentation results further. Thus, providing a realistic colour for the walls.

Ting Leu *et al* proposed a model called **Enhanced-Net** in [2] for removing flickering near the corners thereby providing realistic look. For efficient segmentation of walls, they have used **Edge-Aware-FCN (Fully Connected Network)** followed by **Enhanced-Net** which provides better segmentation and can able to locate the edges accurately. This approach results in Intersection of Union (IOU) to reach 77%. For replacement of colours the input image is convolved with a coloured image. In addition to that they have also used a simple **colour space conversion** for reserving brightness. Similarly, texture replaced image can be obtained by repeating the desired texture horizontally and vertically. But however, their approach fails when the input image has mirrors because they can reflect the colour of the wall. As a result, the colour of the wall reflected in the resultant image remains unmodified. Secondly, their approach cannot replace the texture accurately when there is a corner in the wall.

Sharmin *et al* proposal in [3] makes use of **YOLO** (You Only Look Once) object detection to detect the objects in the room for colouring walls based on the room's attributes. After successful detection of the objects, pixel level information is detected and dominant colours in the identified objects are collected. Then, **room attributes** such as type of the room, size of the room etc are collected from the user. From the input attributes collected, a recommendation of three colours is made by the model by ranking the class probabilities. At last, the model replaces the wall with the desired colour. But the colour suggested by the model is limited, therefore the customer cannot view the colour of the wall with all the possible colours. Secondly, their approach fails when the colour of the furniture and the wall are same.

David *et al* proposal in [4] makes use of basic image processing techniques for colouring of walls in video frames Canny edge detector is used for predicting the edges. Then the resultant image is passed through flood fill technique as an input mask. It is then followed by dilation which together forms the segmentation process. At last, for transforming the colour of the walls, alpha blending process is carried out. But this approach cannot able to detect the corners accurately resulting in flickering.

Saumitro DasGupta *et al* proposal in [5] for spatial layout estimation. For generating layouts Fully Convolutional Neural Network (FCNN) as well as an optimized framework is used. Their approach can successfully detect the boundaries of the wall, ceiling, ground etc. They can provide the box layout and can output the corresponding layout labels namely Left Wall, Right Wall, Front Wall, Ceiling and Ground. This approach has gained the outstanding results .

Kang Chen *et al* proposal in [6] can learn the local material rules for material suggestion and global aesthetic rules for harmony of colours from the image dataset and can generate material suggestions for furniture. The colour dataset that they have used were “COLOUR Lovers” consisting of 3,83,938 five colour palettes which provides generic colour prediction. Their approach outperforms the initial scene decorations by 78%. However, their approach cannot able to generate suggestions for material if spatial information is considered.

Hung Jin Lin *et al* proposed a method in [7] for predicting layout estimation. Their approach makes use of Vanilla ResNet (Residual Network) which acts as feature extractor and can effectively estimate five planes namely ceiling, floor, frontal-wall, right-wall and left-wall. The dataset they have used was LSUN Room Estimation dataset which consists of 4000 training images, 1000 testing images and 394 validation images. Their approach outperforms the other models with error rate of 6.25% .

Chen Liu *et al* proposed a method in [8] for planar reconstruction. Their approach makes use of Dilated Residual Networks (DRN) which can output three predictions namely plane parameters, non-planar depth map and segmentation masks. The dataset that they have used was ScanNet, which is an indoor video database . Upon extracting the segmentation mask, a new texture can be appended to with the help of UV Co-ordinates thus giving a realistic texture appearance.

Chenggang Yan et al proposed a method in [9] for 3D layout estimation. Their approach is carried out in two stages. In the first stage, they make use of Neural Network architecture based on PSPnet for estimating 2D layout of the input image. In the second stage Topology Anchor Point Optimization (TAPO) is used to estimate the 3D room layout of the input image by identifying layout topology. They have evaluated their model with three Datasets namely LSUN, Hedeau and 3DGP which have outperformed several approaches.

Alexander G. Schwing et al provide a solution in [10] to the problem of 3D room layout estimation. They used Novel branch and bounding approach for splitting the label space and also it bounds the energy for entire sets by constructing

Upper-bounding contributions of each individual face .They have employed Integral geometry in order to evaluate these bounds in constant time, and show that it not only obtain the exact solution, but also in less time than approximate Inference tools such as message-passing. The effectiveness of their approach is demonstrated in two benchmarks that shows the bounds are tight and only a few evaluations were necessary. Reason for failure modes is non-informative image features due to a failing prediction in case of geometric context or wrong line detections causing misleading orientation maps.

Varsha Hedeau *et al* proposed a structured learning algorithm in [11] for estimating room layout. Their algorithm makes use of perspective cues such as long line segments, vanishing points etc. to predict a rough room layout. These layouts produce maps for classes such as “object”, ”left wall” ,”floor” and “right wall”. These layout maps are used to re-estimate the features again and finally produce the exact desired room layout. Their approach is robust to clutter and can provide better estimation of room layout.

Weidong Zhang *et al* proposed a Neural Network architecture in [12] for estimating the room layouts. At first, a deconvolution network is used to predict the edge maps of the room. In addition to deconvolution network , Convolution Networks which do not have Fully connected layers are used to predict edge maps in a large perspective view. They have evaluated their works on 2 different datasets namely LSUN and Hedeau and their approach outperforms several other benchmark approaches.

CHAPTER 3
METHODOLOGY

This project is carried out to visualize room decoration by replacing color and the texture of the wall according to the user's desire. Our system makes use of "Deep Labv3+" model, capable of segmentation. The dataset used was "ADE20K", which is a large image segmentation dataset consisting of both indoor and outdoor images. This dataset totally consists of 20,000 images belonging to 150 classes such as ceiling, wall, sofa etc. This model can effectively segment the objects and in turn produce the corresponding segmentation map.

3.1 SEGMENTATION

Image Segmentation is relevant to masking of image into several segments. Segmentation can be broadly classified into Semantic Segmentation and Instance Segmentation. Semantic Segmentation partitions each and every pixel to a particular label whereas Instance Segmentation gives unique label to every instance of a particular object in an image. But in this project Semantic Segmentation is carried out to provide fixed labels to every instance.

3.2 DEEP LAB V3+

Deep LabV3+ consists of an Encoder- Decoder based architecture for providing segmentation. It consists of an effective Decoder module which smoothens segmentation along object boundaries thus avoids flickering. For effective feature extraction "Xception" model is used and depth wise separable convolution is applied thus making it a stronger model for semantic segmentation.

3.2.1 ARCHITECTURE:

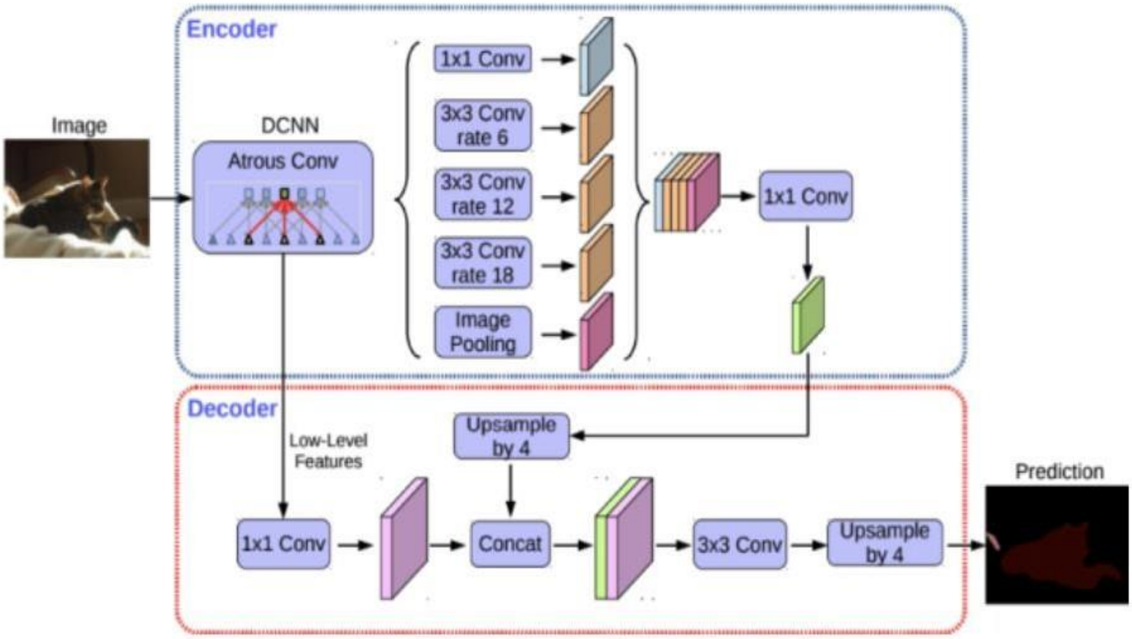


Figure 1: Architecture of DeepLabV3+

3.2.2 XCEPTION:

The Aligned Xception model is adapted for the process of semantic image segmentation. This model has been fine-tuned by addition of extra features such as

1. Replacing Max pooling operations by depth wise separable

convolution with striding.

2. Extra Batch Normalization.

3. Addition of Rectified Linear Unit (Relu) activation function after 3*3 depth wise convolution.

This model can extract dense feature maps by Atrous Convolution.

The below figure depicts the architecture of modified Xception model.

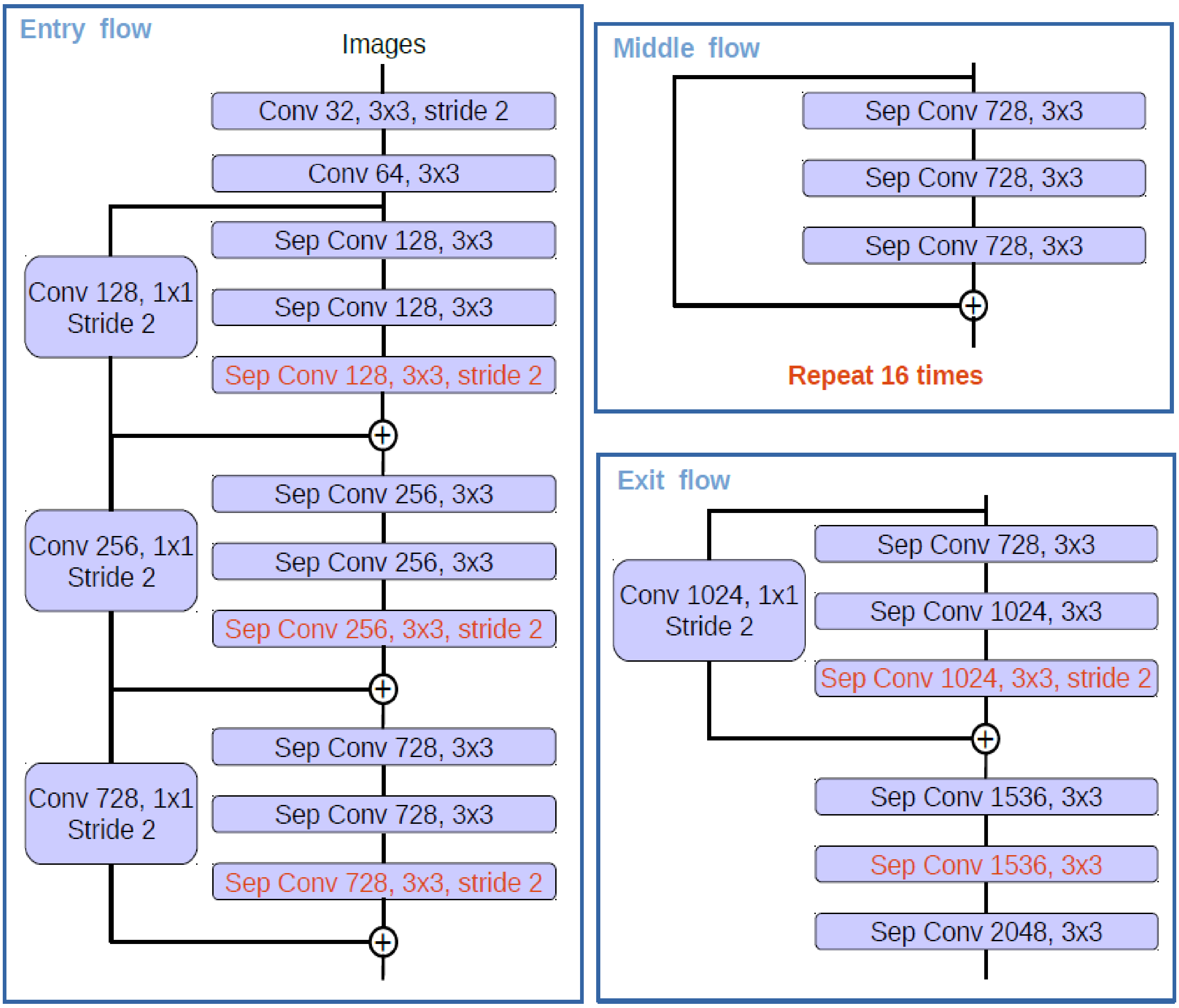


Figure 2: Architecture of Xception

3.2.3 ENCODER

The Encoder part of DeepLabv3+ consists of Atrous convolution which can extract the features, control the feature's resolution, and can adjust filter's view. Instead, if traditional convolution is used, the resolution of the feature map keeps on shrinking at each layer making it unfit to be used for segmentation. Thus, it is necessary to preserve the size of feature's resolution to provide segmentation result. The Atrous Separable Convolution consists of a parameter called Atrous rate (r) which determines the stride for sampling the input. This Atrous Spatial Pyramidal Pooling (ASPP) can extract the image level features so accurately. The output feature map obtained from this model contains semantic information.

3.2.4 DECODER

The encoded features from the Encoder are computed with an output stride of 16 for segmentation. Then the features are up sampled and merged with features from the Xception model. Afterwards 1*1 convolution is applied to the features for reducing the channel count as it makes the training harder. To refine the features, 3*3 convolution is done followed by bilinear up sampling. Thus, the output stride's value strikes the tradeoff between speed and accuracy.

3.3 DATASET

The dataset that we have chosen for our model is "ADE20K", which is a fully annotated image dataset. It consists of totally 25,000 images. Out of which the 20,000 images are used for training, 2000 images for validation and 3000 images for testing. It is one of the Landmark image segmentation datasets consisting of large corpus of indoor and outdoor images. The images in the dataset have been categorized into 150 classes. The dataset can be downloaded from the below link "https://groups.csail.mit.edu/vision/datasets/ADE20K/ADE20K_2016_07_26.zip."

CHAPTER 4
COLOR REPLACEMENT

4.1 PRE-PROCESSING

It is the very first step in Image Processing and is very essential to pre-process the image before uploading it to the model. To achieve this, the height and width of the image is resized according to resize ratio.

Resize ratio = Input size * max (Width, Height)

Where Input size=513

Width = actual width of the input image

Height = actual height of the input image

The expected target size of an image is given by,

Target size = Resize ratio*width, Resize ratio*height

Thus, pre-processing outputs an image by resizing it to a target size and further converts the image to “RGB” mode.

4.2 PRE-TRAINED MODEL

The pre-processed image is then passed through DeepLabv3+ model trained on ADE20K dataset which in turn returns the segmentation map for the corresponding image. Every instance in an image will be indicated by a unique color map**.**

4.3 MASKING

The segmentation map thus obtained consist of mask for regions belonging to 150 classes. As our objective is to color the wall region alone, we should extract a mask for the wall from the segmentation map. This can be achieved by replacing the pixels belonging to the class “wall” as 1 while the latter as 0. That is how we can obtain a binary mask for the wall.

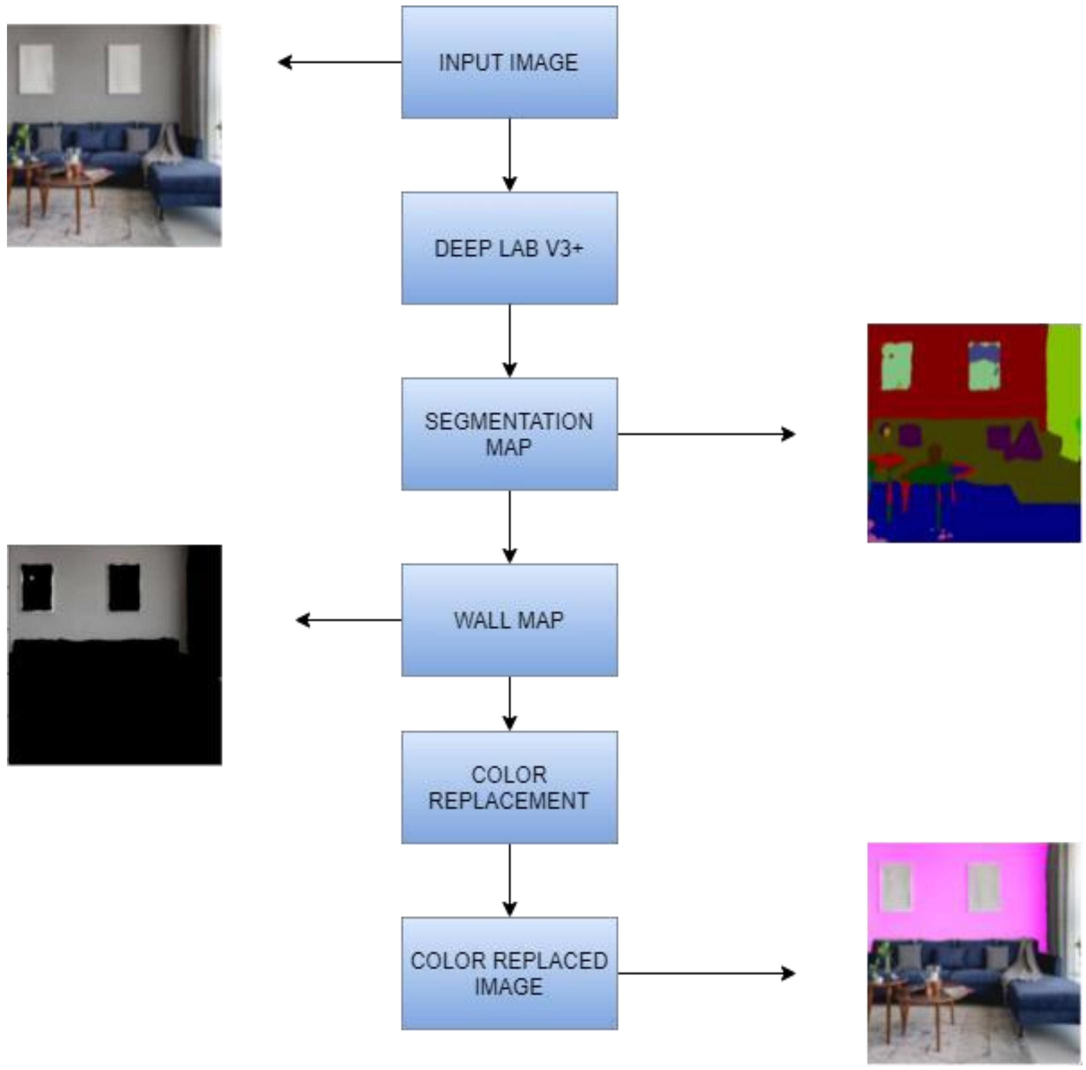


Figure 3: Block Diagram (Color Replacement)

4.4 COLOR REPLACEMENT

Upon extracting the mask for the wall, now color replacement can be carried out by substituting the pixels belonging to the wall with the desired color. (i.e.) using RGB values. Now the wall region's color will be changed. At last, the resultant wall color modified image is blended with the input image to provide a realistic color replacement with reserving brightness.

4.5 ACCURACY METRICS

4.5.1 Mean IoU (mIoU)

Mean IoU defines the Intersection over Union between ground truth pixels and predicted pixels over the classes used**.** Deep LabV3+ trained on ADE20K dataset exhibits performance with **78.6 %** of mIoU.

4.6 COLOR REPLACEMENT RESULTS

a) Before applying color b) After applying color

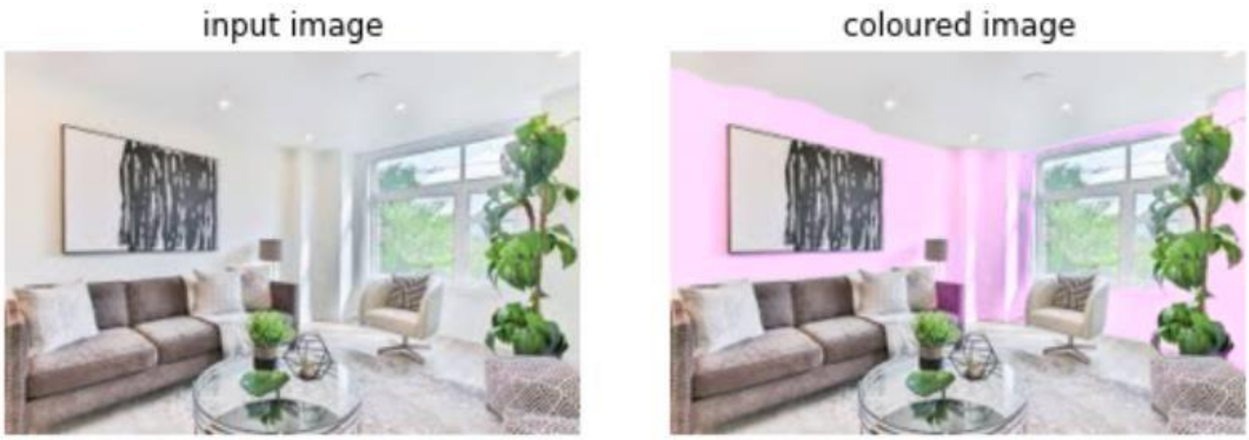
Figure 4 : The visual effect of proposed approach (Sample No-1)

The Figure 4 shows Sample No-1 input image and colored image. We can infer that brightness is reserved in (b) after applying color.

a) Before applying color b) After applying color

Figure 5 : The visual effect of proposed approach (Sample No-2)

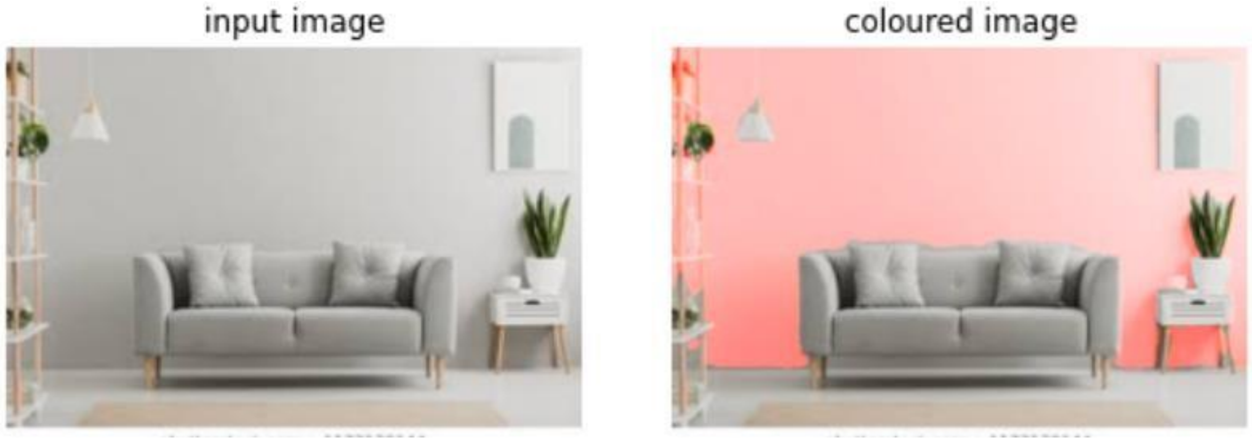
The Figure 5 shows Sample No-2 input image and colored image .We can infer that brightness is reserved in (b) as well as the shadow of sofa is also retained.



a) Before applying color b) After applying color

Figure 6 : The visual effect of proposed approach (Sample No-3)

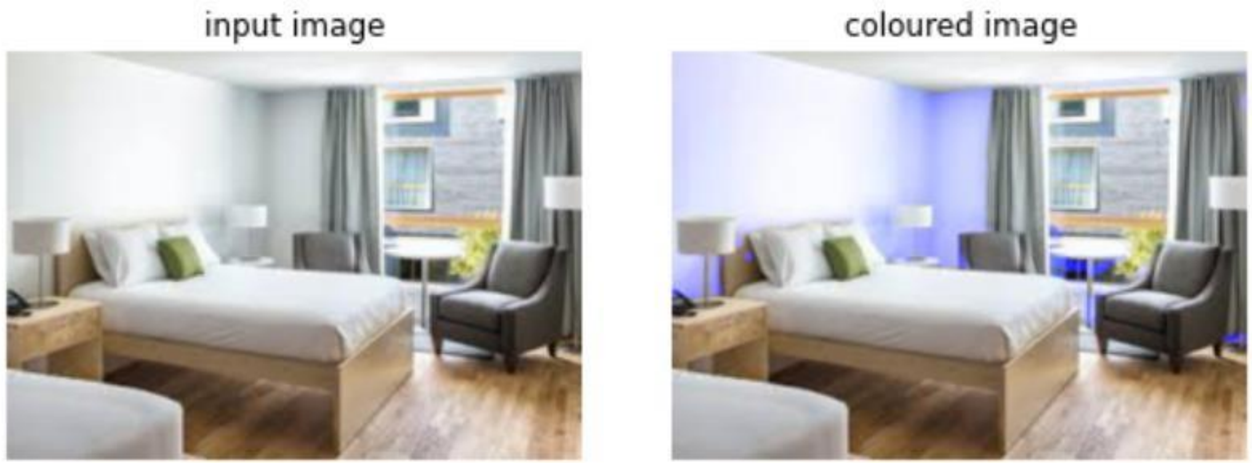
The Figure 6 shows Sample No-1 input image and colored image. We can infer that brightness is reserved in (b) after applying color near the window and the wall region behind the plant is well segmented and colored perfectly.



a) Before applying color b) After applying color

Figure 7 : The visual effect of proposed approach (Sample No-4)

The Figure 7 shows Sample No-4 input image and colored image. We can infer that brightness is reserved near the plant.



a) Before applying color b) After applying color

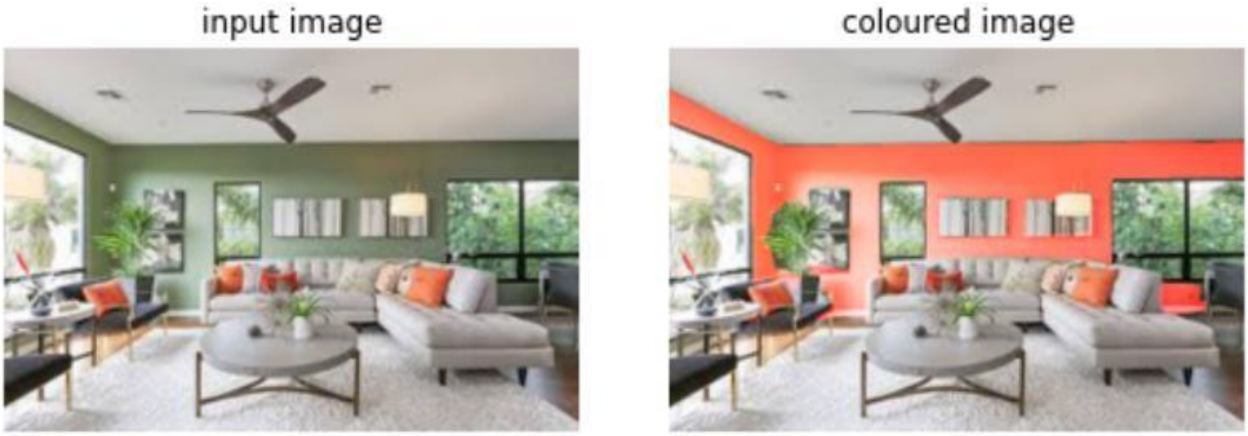
Figure 8: The visual effect of proposed approach (Sample No-5)

The Figure 8 shows Sample No-5 input image and colored image. We can infer that after applying color, brightness is reserved well above the pillow thus giving a realistic look.

a) Before applying color b) After applying color

Figure 9 : The visual effect of proposed approach (Sample No-6)

The Figure 9 shows Sample No-6 input image and colored image. We can infer that brightness is reserved after applying color near the television and the wall region behind the plant is colored perfectly.



a) Before applying color b) After applying color

Figure 10 : The visual effect of proposed approach (Sample No-7)

The Figure 10 shows Sample No-6 input image and colored image. We can infer that brightness is reserved near the window and in the floor.

a) Before applying color b) After applying color

Figure 11 : The visual effect of proposed approach (Sample No-8)

The Figure 11 shows Sample No-8 input image and colored image. We can infer that brightness is reserved after applying color near the night lamp and has a realistic look.

CHAPTER – 5

TEXTURE REPLACEMENT FOR SINGLE SIDE IMAGES

Just like color replacement, texture of the wall can also be modified by extracting the mask for the wall region and substituting the pixels belonging to the wall with the desired texture. The input image whose texture is to be changed is first passed through “DeepLab V3+” model which will then provide the segmentation map for the corresponding image. Then we create binary mask for the wall by pre-processing the segmentation map and blend it with the desired texture to get a desired realistic texture map for the input image.

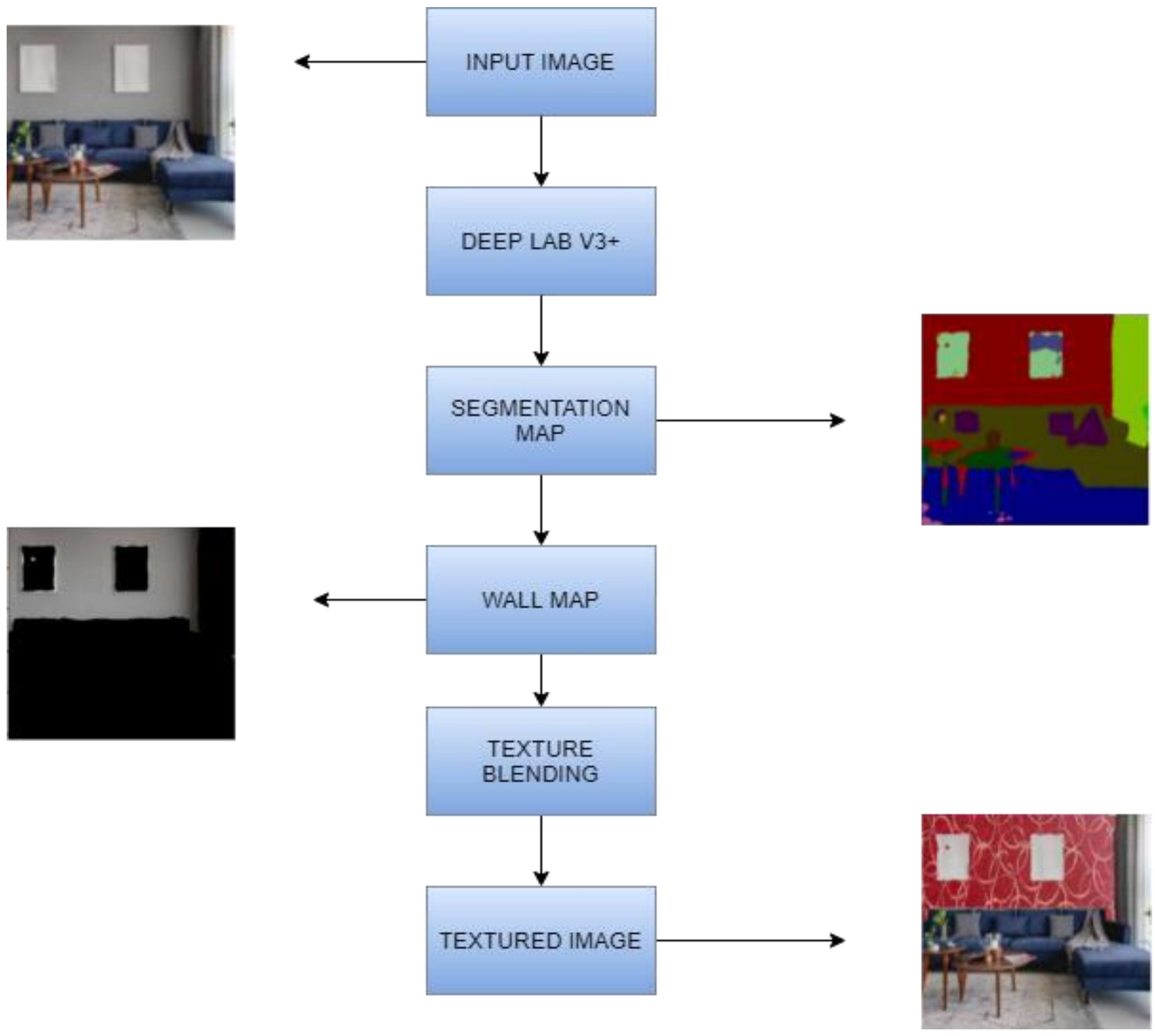


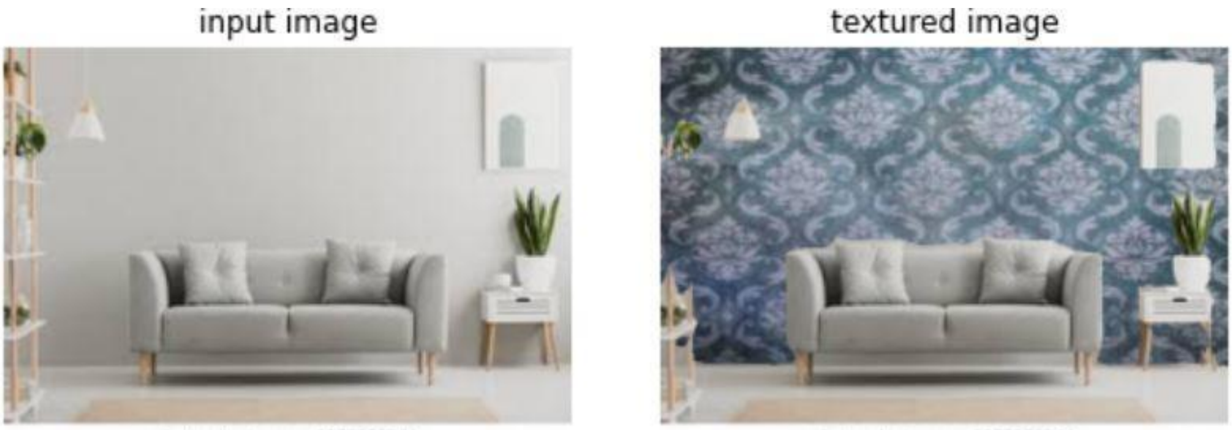
Figure 12: Block Diagram (Texture Replacement)

5.1 TEXTURE REPLACEMENT RESULTS

a) Before applying texture b) After applying texture

Figure 13: The visual effect of proposed approach (Sample No-9)

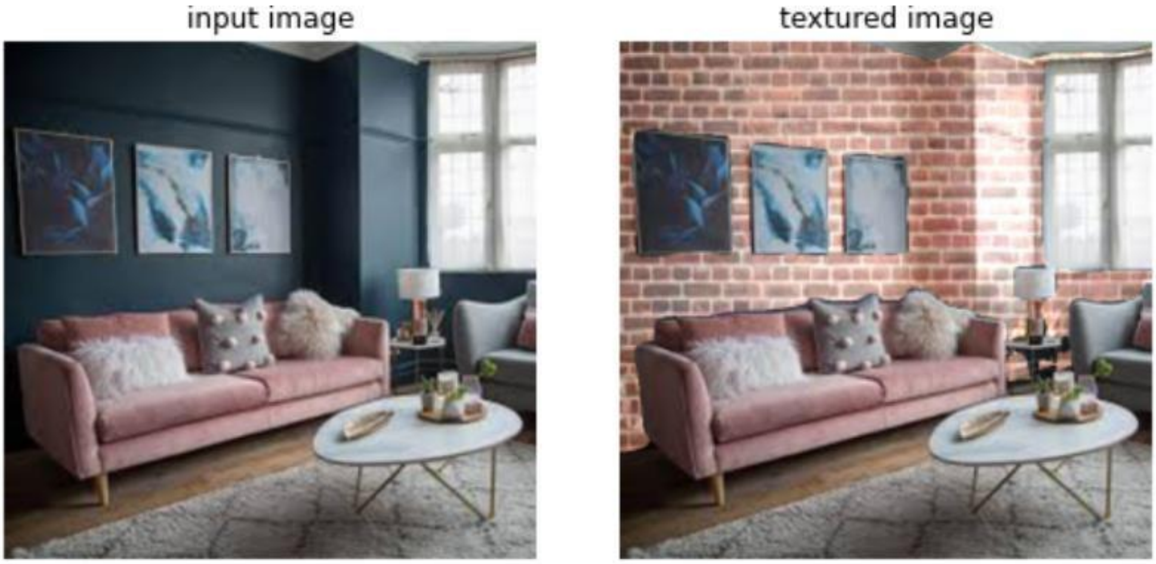
The Figure 13 shows Sample No-9 input image and textured image. We can infer that the texture gets mapped to the wall effectively and brightness is reserved in the wall region.



a) Before applying texture b) After applying texture

Figure 14: The visual effect of proposed approach (Sample No-10)

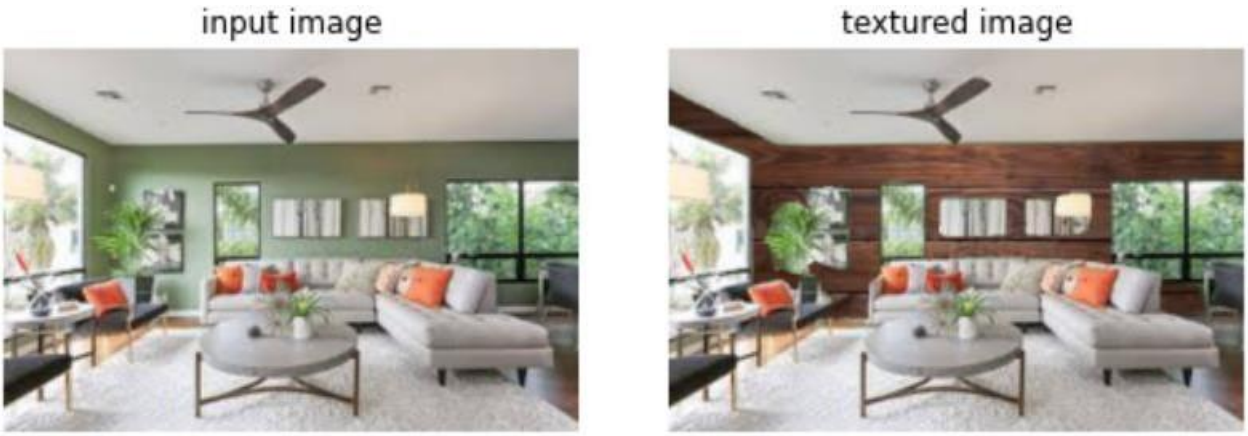
The Figure 14 shows Sample No-10 input image and textured image. We can infer that the texture gets mapped to the wall effectively and provides a realistic look.



a) Before applying texture b) After applying texture

Figure 15 : The visual effect of proposed approach (Sample No-11)

The Figure 15 shows Sample No-11 input image and textured image. We can infer that the texture got shifted near the corner of the wall giving a realistic texture replacement.



a) Before applying texture b) After applying texture

Figure 16 : The visual effect of proposed approach (Sample No-12)

The Figure 16 shows Sample No-12 input image and textured image. We can infer that texture gets replaced in the wall region thus giving a realistic look.

a) Before applying texture b) After applying texture

Figure 17 : The visual effect of proposed approach (Sample No-13)

The Figure 17 shows Sample No-13 input image and textured image. We can infer that the texture got shifted near the corner of the wall giving a realistic texture replacement and the brightness is reserved near the window .

a) Before applying texture b) After applying texture

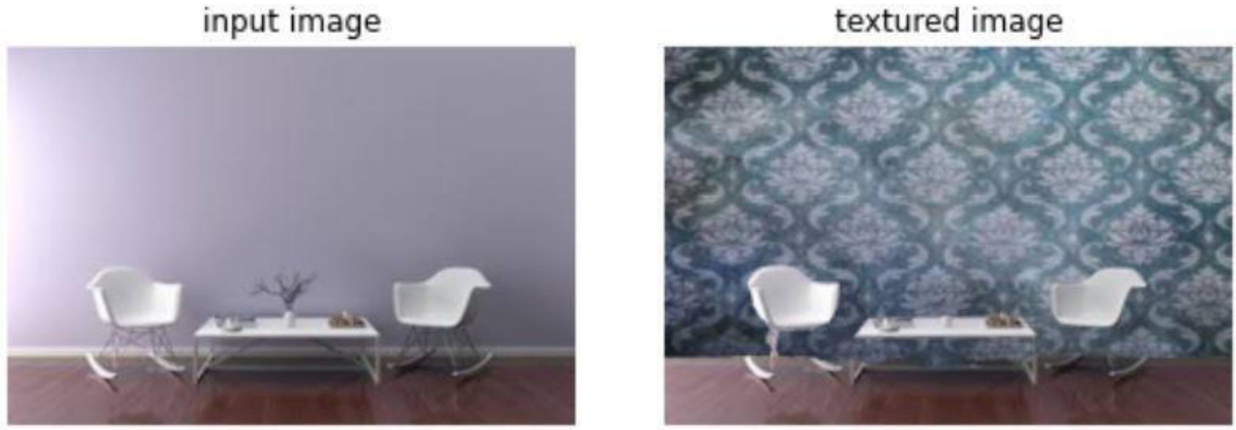
Figure 18: The visual effect of proposed approach (Sample No-14)

The Figure 18 shows Sample No-14 input image and textured image. We can infer that the texture mapping in the wall is effective and looks realistic.

a) Before applying texture b) After applying texture

Figure 19: The visual effect of proposed approach (Sample No-15)

The Figure 19 shows Sample No-15 input image and textured image. We can infer that texture gets replaced in the wall effectively thus providing realistic look.



a) Before applying texture b) After applying texture

Figure 20: The visual effect of proposed approach (Sample No-16)

The Figure 20 shows Sample No-16 input image and textured image. We can infer a realistic texture map in the wall and the result look visually pleasing.

CHAPTER -6

TEXTURE REPLACEMENT FOR DOUBLE SIDE IMAGES

The approach that we used for texture replacement for single side images can't be applied to double side images because it can't provide realistic texture replacement around the corners. To overcome this issue, we make use of Spatial Layout estimation to estimate layouts in a room and blend textures to each layout thereby we can retrieve a realistic texture replaced image.

6.1 SPATIAL LAYOUT ESTIMATION

Spatial Layout Estimation or Planar Segmentation is the ability to estimate layouts in the room into five categories such as frontal-wall, left-wall, right-wall, ceiling and floor. To estimate the layouts, we make use of "Residual Network" (ResNet) trained on LSUN (Large Scale Scene Understanding) dataset which consists of 4000 images for training, 1000 images for testing and 394 images for validation. It consist of images belonging to rooms and it's corresponding ground truth.

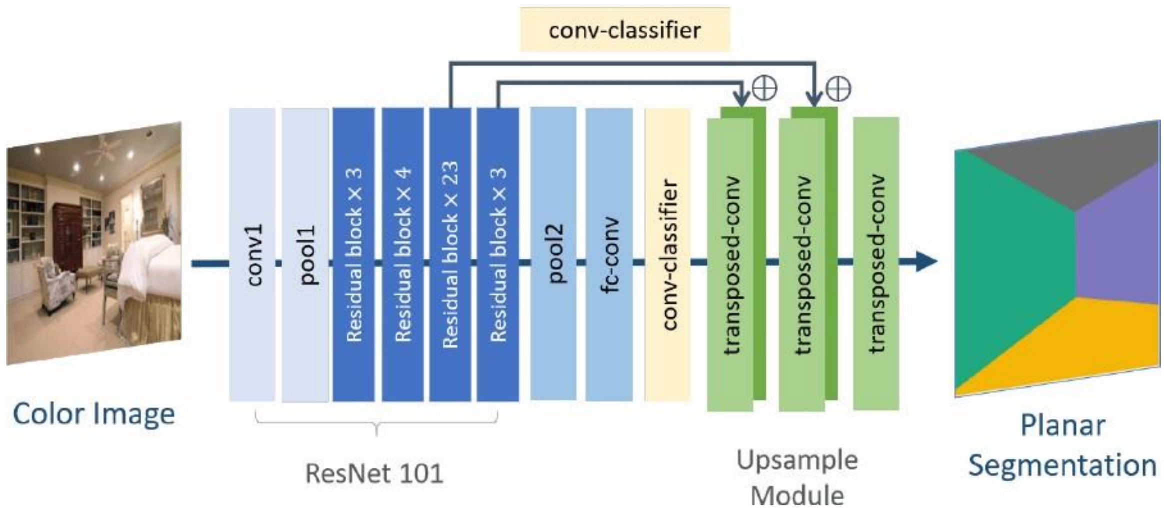


Figure 21: Architecture of Proposed ResNet -101

These skip connections from earlier layers in the network provide the necessary detail in order to reconstruct accurate shapes for segmentation boundaries. More fine-grain detail can be extracted with the addition of these skip connections. The transposed convolutions are used to upsample the features.

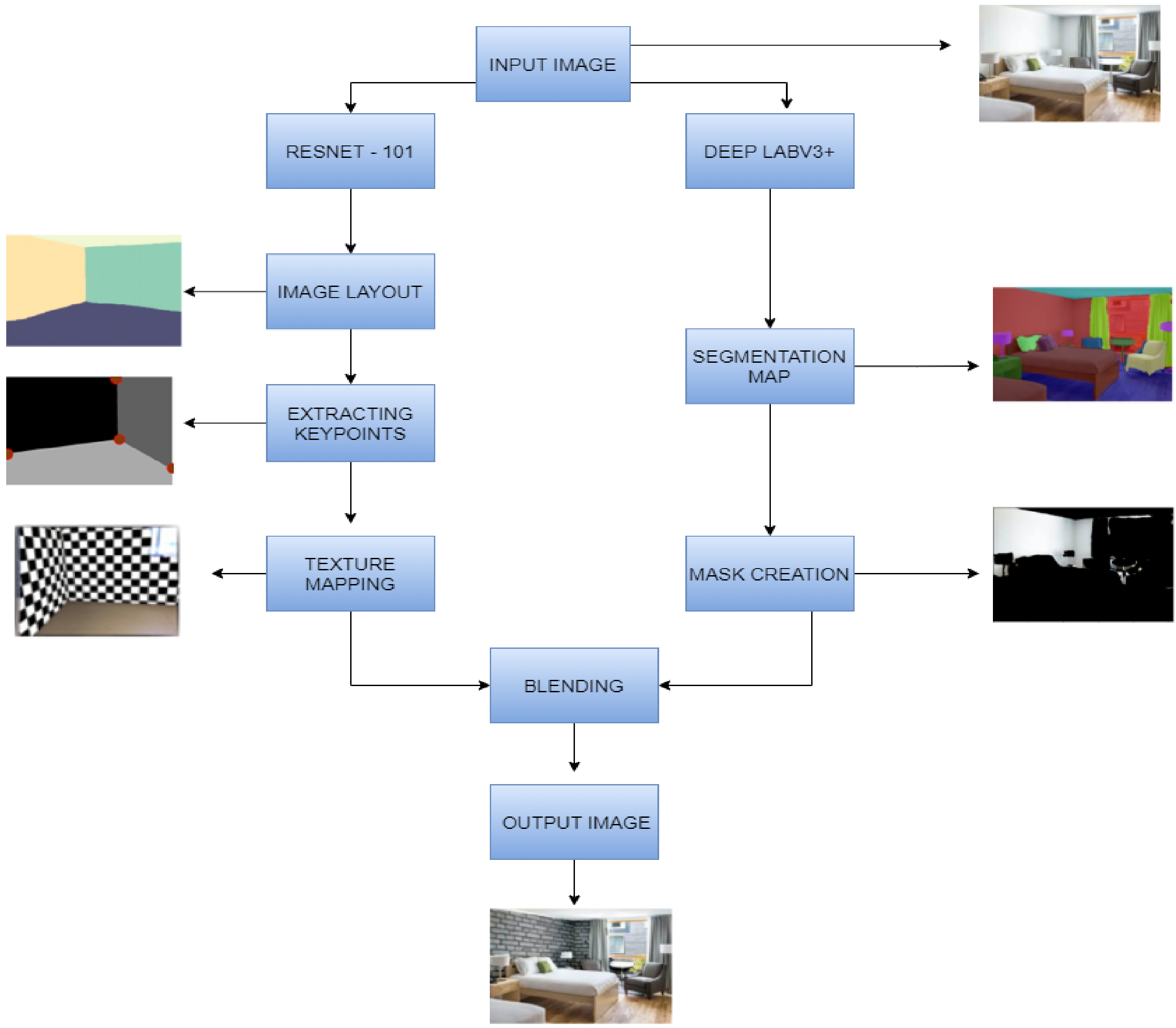


Figure 22: Block Diagram (Texture Replacement for double side images)

6.2 RESNET

Our proposed approach makes use of state-of-the-art network ResNet-101 for feature extraction. ResNet was the first ever architecture proposed with skip connections to avoid vanishing gradient problem. Vanishing Gradient Problem mostly occur in Neural Networks having large number of layers. Therefore, during Back Propagation, while updating weight even if the repeated multiplication makes the gradient small, ResNet overcomes this issue by allowing alternate path for the gradient to flow through thereby preserves the features effectively.

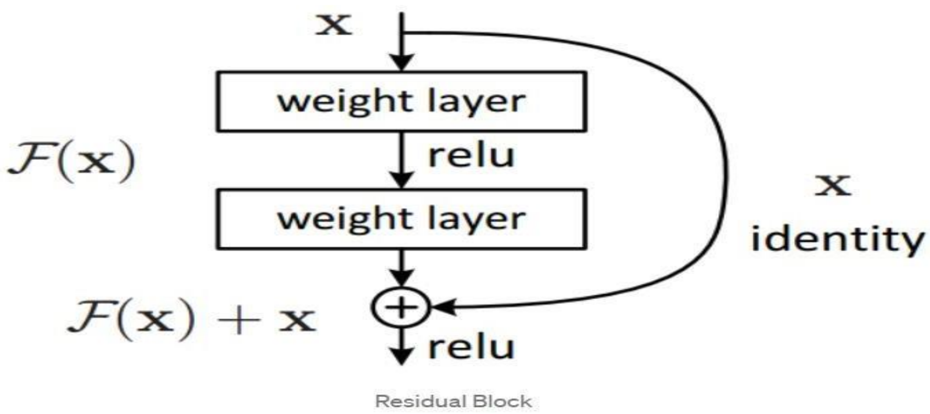


Figure 23 : Residual Block

6.2.1 PROPOSED RESNET -101

For achieving Layout estimation we have selected ResNet – 101 as our feature extractor and have incorporated few modifications which include replacement of average pooling layer to max pooling layer, replacement of last fully connected layer with 1x1 Convolution layer and addition of transposed Convolution at the last for up sampling the features. Room Layouts are classified into 11 types of layouts as follows.

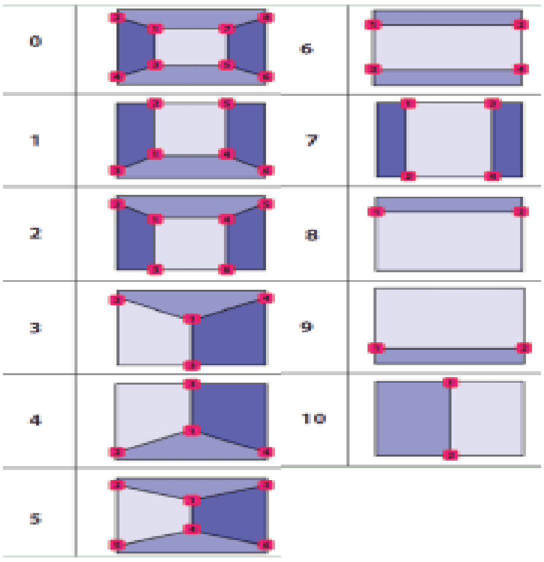


Figure 24: Categories of Room Layouts

6.3 KEY POINTS EXTRACTION

For mapping the desired texture to the wall, we should need a mask for the desired region where texture should be mapped. This mask can be created by retrieving the co-ordinates of the layouts which in turn multiplied with the segmentation map of the wall to form a desired mask. The desired texture that is going to be mapped should be tilted by a respective angle with the help of retrieved co-ordinates. Finally, the tilted texture can be mapped to the input image to get a desired texture replaced image with realistic look around the corners.

6.4 DATA AUGMENTATION TECHNIQUES

Data Augmentation Techniques are mostly used to avoid overfitting. These techniques include horizontal shift , vertical shift, zoom in, zoom out, cropping, flipping of images so that it helps model from getting biased to certain input images. But the usage of cropping and rotation may corrupt the semantic relationship within the layouts, therefore we incorporated color jittering techniques by adjusting saturation, contrast, brightness and horizontal flipping to exchange the semantic labels in the left and right side of the wall. Secondly, to improve the imbalanced distribution of images in dataset, we make use of a technique called Layout Structure Degeneration. This will help to degenerate one layout to another by removing floor, ceiling etc. Thereby we can build a relationship between all the 11 room layouts through Directed Acyclic Graph (DAG).

6.5 ACCURACY METRICS

6.5.1 PIXEL ACCURACY

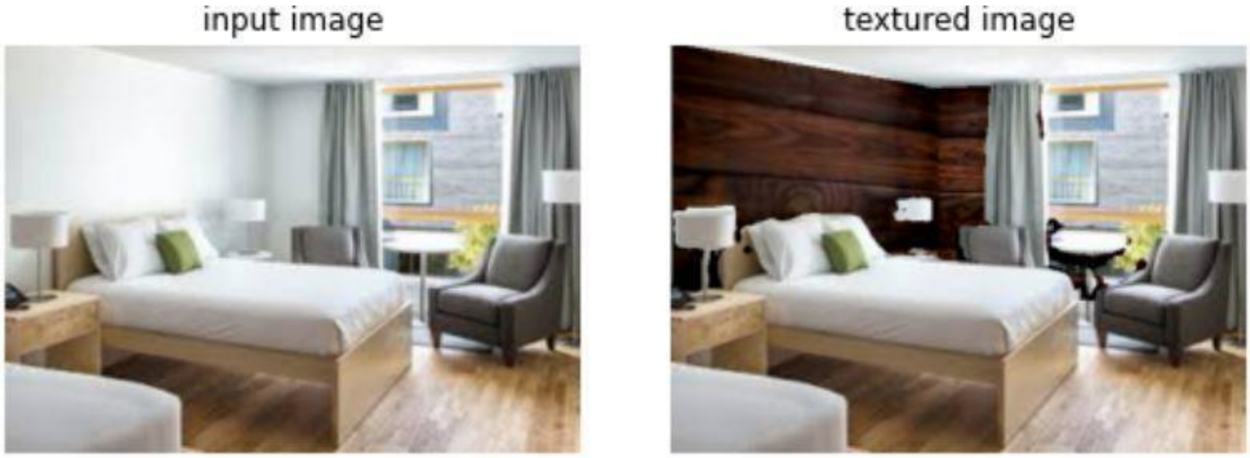
Pixel accuracy evaluates the percentage of pixels in the image which were correctly classified. ResNet-101 model trained on LSUN Dataset achieves **6.25 %** pixel-wise error rate.

6.6 TEXTURE REPLACEMENT RESULTS (Double side)

a) Before applying texture b) After applying texture

Figure 25 : The visual effect of proposed approach (Sample No-17)

The Figure 25 shows Sample No-17 input image and textured image. We can infer a realistic texture replacement at the corners and the brightness is reserved in the wall region .



a) Before applying texture b) After applying texture

Figure 26 : The visual effect of proposed approach (Sample No-18)

The Figure 26 shows Sample No-18 input image and textured image. We can infer a realistic texture replacement at the corner of the wall region.

a) Before applying texture b) After applying texture

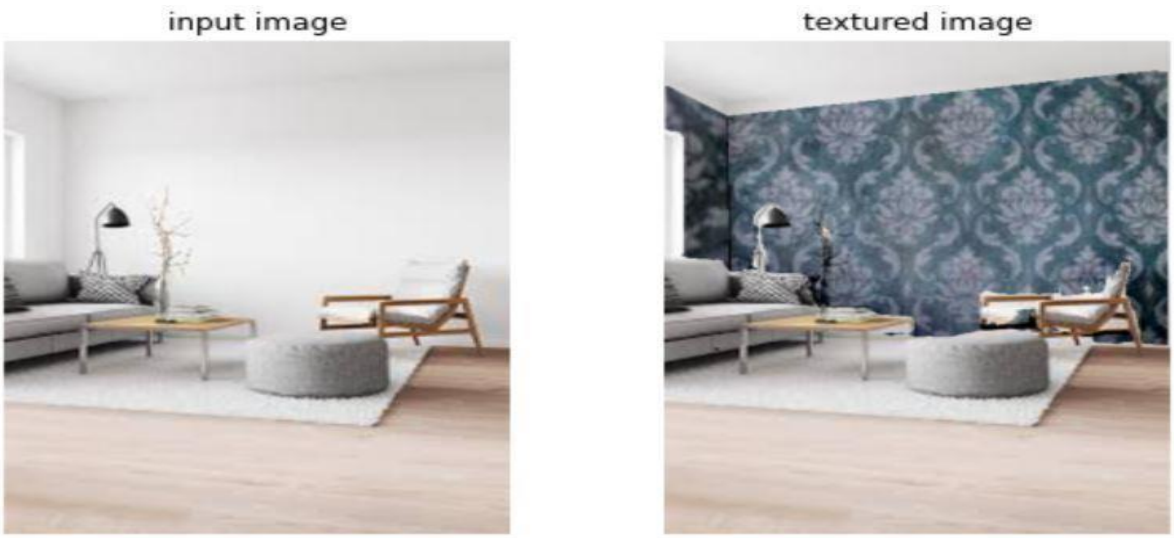
Figure 27 : The visual effect of proposed approach (Sample No-19)

The Figure 27 shows Sample No-19 input image and textured image. We can infer that texture got replaced even in the small region below the sofa thus giving a realistic look.

a) Before applying texture b) After applying texture

Figure 28 : The visual effect of proposed approach (Sample No-20)

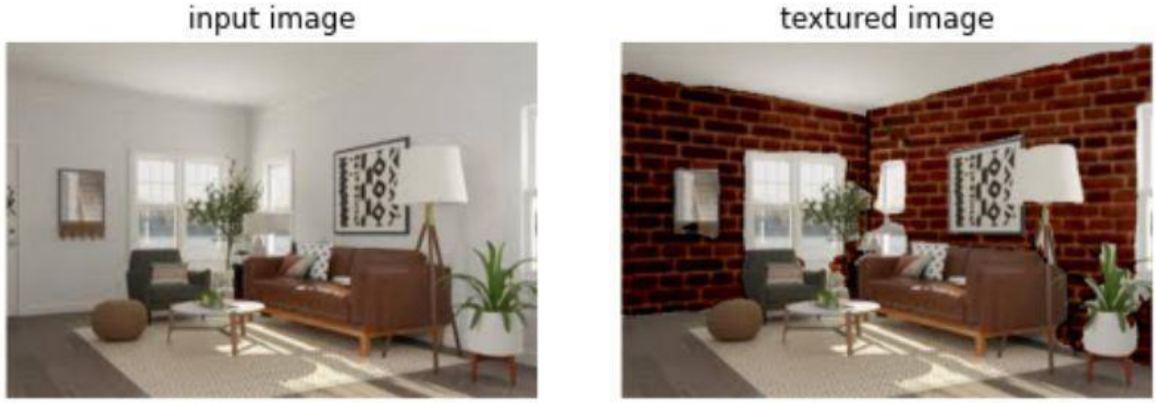
The Figure 28 shows Sample No-20 input image and textured image. We can infer that the pattern in the left wall and the right wall gets merged accurately thereby providing realistic look.



a) Before applying texture b) After applying texture

Figure 29 : The visual effect of proposed approach (Sample No-21)

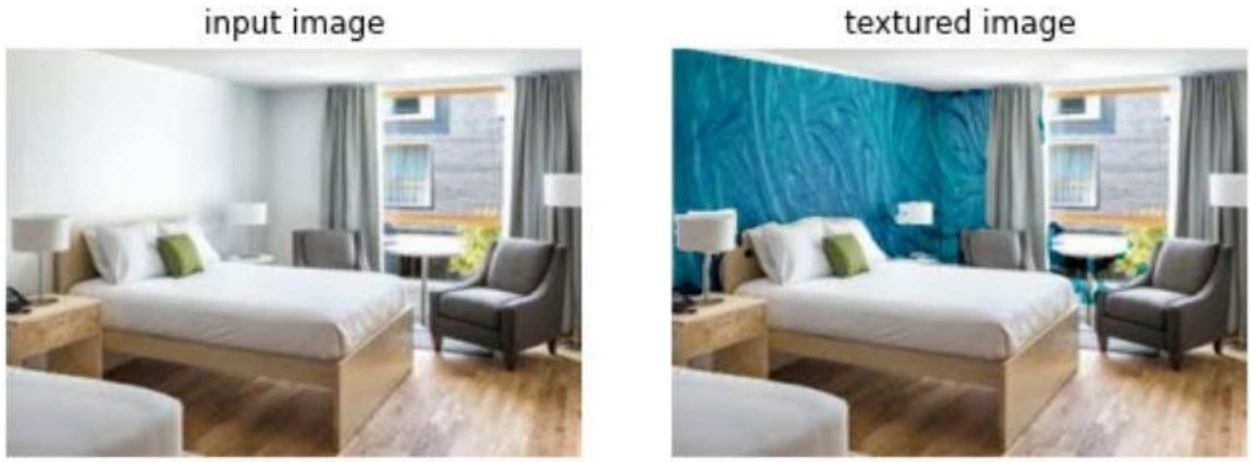
The Figure 29 shows Sample No-21 input image and textured image. We can infer a realistic texture replacement near the corners.



a) Before applying texture b) After applying texture

Figure 30 : The visual effect of proposed approach (Sample No-22)

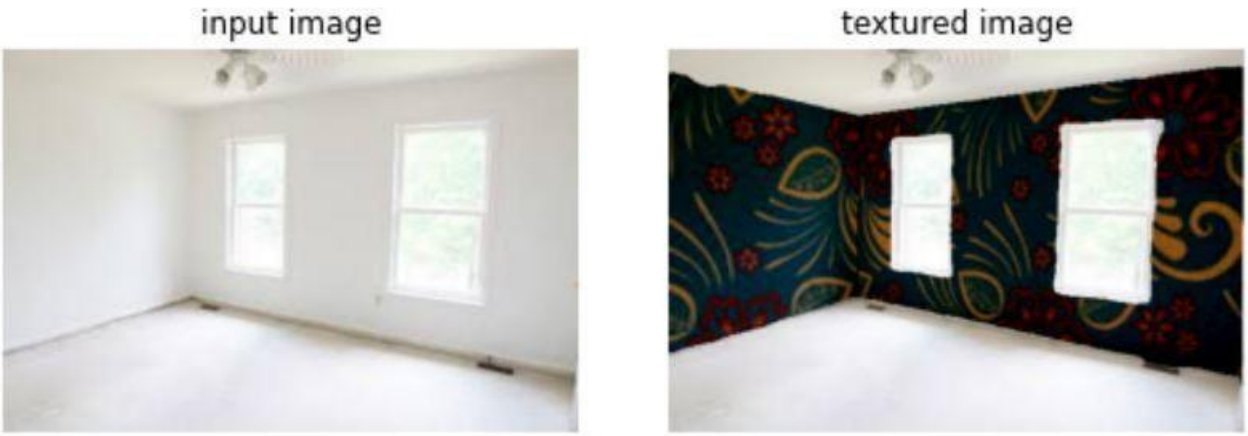
The Figure 30 shows Sample No-22 input image and colored image. We can infer that the textured image has a realistic texture replacement with reserving brightness across the corners.



a) Before applying texture b) After applying texture

Figure 31: The visual effect of proposed approach (Sample No-23)

The Figure 31 shows Sample No-23 input image and textured image. We can infer that the texture in the left wall gets shifted to the right thereby providing a realistic Texture replacement.



a) Before applying texture b) After applying texture

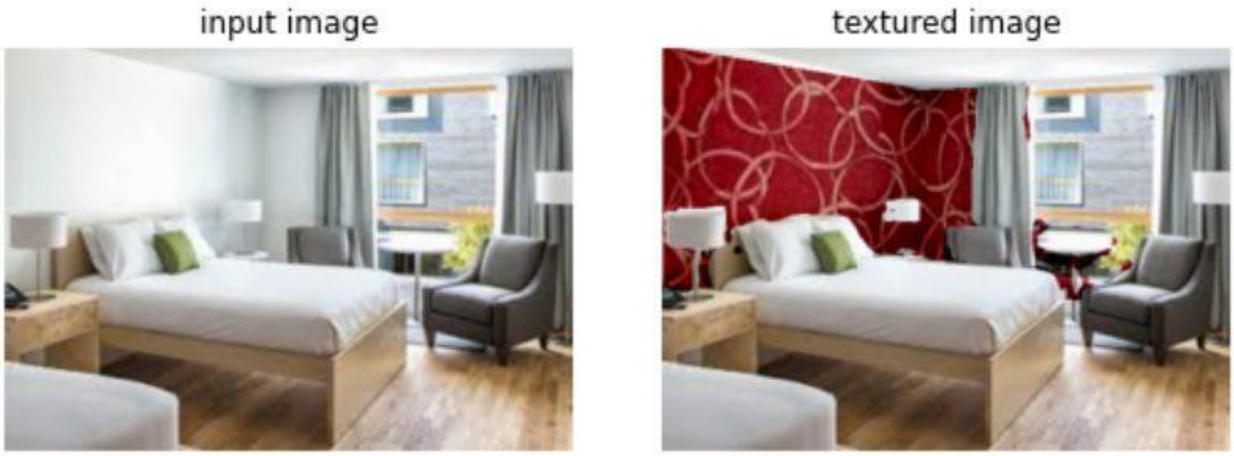
Figure 32: The visual effect of proposed approach (Sample No-24)

The Figure 32 shows Sample No-24 input image and textured image. We can infer that texture gets mapped well across the corners thereby providing realistic look.

a) Before applying texture b) After applying texture

Figure 33: The visual effect of proposed approach (Sample No-25)

The Figure 33 shows Sample No-25 input image and textured image. We can infer a realistic texture replacement across the corners and the brightness is reserved near the walls.



a) Before applying texture b) After applying texture

Figure 34: The visual effect of proposed approach (Sample No-26)

The Figure 34 shows Sample No-26 input image and textured image. We can infer a realistic texture replacement across the corners and the brightness is reserved near the walls.

a) Before applying texture b) After applying texture

Figure 35: The visual effect of proposed approach (Sample No-27)

The Figure 35 shows Sample No-27 input image and textured image. We can infer that the texture has a realistic shift across the corners and brightness is reserved thereby providing a realistic look.

CHAPTER -7
NOVELTY OF OUR APPROACH

There are several existing methods available for color and texture replacement which include “Color with Asian Paints” App from Asian Paints, “Color Visualizer” App by Nippon Paints and a Deep Learning based Approach mentioned in [1],[2]. The “Color with Asian Paints” App fails in providing a realistic texture replacement as well as fails to figure out the wall region successfully . Similarly, methodology proposed in [1],[2] fails to provide a realistic texture replacement if an input image contains a corner. As our approach makes use of **“DeepLab V3+”** trained on ADE20K dataset, it has the ability to segment wall, ceiling separately. Therefore, it can replace color and texture only in the wall region. Similarly, to address the issue stated in [1],[2] we make use of **“Layout Estimation”** therefore we can map texture to each and every layouts of the room therefore provides a realistic texture replacement.

EXISTING METHOD	PROPOSED METHOD
Makes use of Photoshop tools to paint the area of interest.	Makes use of Neural Networks to effectively segment wall, ceiling etc.
Unrealistic texture replacement across the corners due to Blending.	Makes use of “Layout Estimation” for effective texture replacement.

Table 1: Methodology Comparison

CHAPTER -8
FRAMEWORKS USED

7.1 TENSORFLOW

With the advent of several Deep Learning frameworks, training of neural networks become ease and even a neural network having large number of layers can be trained within a short span of time thus time consuming. One of the main advantage of Tensorflow is that it offers free GPU (Graphic Processing Unit) facility so that it avoids additional hardware setup thus saving cost. It is an open sourced framework developed by Google and is very flexible to use. It also has built-in functionalities to save the model that we have trained thus eliminating the need for training the model again and again.

7.2 PYTORCH

Pytorch is also one of the most popular Deep Learning Frameworks next to Tensorflow. It is an open- sourced Framework developed by Facebook Team. It is widely used in applications such as Computer Vision,(NLP) Natural Language Processing etc. It also has functionalities for incorporating Neural Network model in Mobile Applications .

CONCLUSION

Thus, our system can effectively segment the wall regions using DeepLabV3+ which is the backbone of our project and can replace the color of the wall accurately. Similarly, texture of the wall can also be replaced according to the user’s desire with the help of Spatial Layout Estimation which achieves an **error rate of 6.25%** which is very much smaller in comparison to all the existing works available thereby helps people to visualize their dream houses before painting.

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