

# IMAGE INPAINTING USING MACHINE LEARNING

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**Abstract:** This project features a user-friendly method for person remover from images where the user has control of which object to remove. Our system removes only one object i.e person. However, it is capable of removing multiple persons through repeated application. Our model learns to detect the person in an image using the yolo algorithm. Then, the second stage removes the person in the image and fills the space with neighbouring pixels using the pix2pix concept. We show that by using this integration, the proposed network can learn a well-incorporated structure and also overcome the problem of visual discrepancies in the affected region of the image.

## I. INTRODUCTION

The primary motivation behind this project is to remove unwanted objects from photographs and fill in the gap in a visually plausible manner; we focus on removing people as unwanted background people is a frequent problem in photography, particularly when taking photos at popular tourist destinations. Common approaches require manual identification of the area to be removed, however we aim to be able to automatically detect the target area and create an end-to-end pipeline for background removal. Automation of this process can be extremely useful considering the prevalence of photo-taking nowadays, and could be incorporated into the image processing pipeline to produce better photographs without requiring user intervention.

## II. RELATEDWORKS

These techniques (Guillemot and Meur 2014) are considered to be one of the first algorithms to approach the problem of image inpainting. These algorithms are mainly dependent on the use of the variation method and the Partial Differential Equation (PDE). They work by completing/filling the missing region by smoothly propagating the content of the image from the surrounding region into the target region[1].

Another technique worked on the link between isophote direction and the Navier-Stokes equation (Bertalmio and A.L. Bertozzi, Navier-Stokes, Fluid Dynamics, and Image and Video Inpainting 2001). This observation inspired the authors to present a solution using the transport equation for the missing domain filling[2].

Texture techniques are also considered to be one of the early techniques used to solve the image inpainting problem (Criminisi, Pérez and Toyama 2004). The notation of patches was first introduced with these methods. Texture synthesis techniques use pixel information from the surrounding neighborhood in a random manner to fill the missing hole in images. i.e., to pick existing pixels from the same image with similar neighborhoods[3].

An image inpainting algorithm (Casaca, et al. 2014) also combining texture synthesis, transport equation, anisotropic diffusion, and a sampling technique to reduce the inpainting process computational cost. Consider an image with a missing region, initially, a cartoon image is generated using anisotropic diffusion, then a block-based inpainting method is used to combine the cartoon image generated and a measure derived from the transport equation to indicate the priority of pixels to be filled. Next, a sampling region is dynamically generated to preserve the propagation of edges towards the structures of the image to avoid redundant searches during the filling process techniques[4].

Exemplar-based algorithms are one of the popular image inpainting techniques. They are used to produce better results than diffusion-based techniques. The inpainting process fills the missing region from the neighbour surrounding pixels within the same patch (Ogawa and Haseyama 2013) [5].

Although the exemplar-based method was one of the most common widely used techniques, these techniques have suffered from several problems such as the patches filling order and patch size. A novel-based framework for inpainting using an exemplar-based method in (Meur, Ebdelli and Guillemot, First, a coarse instance of an input image followed by a hierarchical super-resolution update is used to retrieve the details of the missing

hole, as it is always easier to paint a low- resolution image than a high-resolution image.[6].

It is an image inpainting technique suitable for any type of hole pattern that was presented in (Daisy, Tschumperlé and Lezoray 2013). It is a fast and general technique used in artifacts reconstruction without affecting the inpainted image. Artifacts are defined as variations in brightness or color[7].

The reconstruction operation is performed equally in all isotropic directions instead of using a single patchwork. Spatial patch blending reduces the joint between pixels within patches as parts of these patches can be ignored, i.e., while containing useful information, if the order of filling is done differently. This method is a pixel-wise process where a group of overlapping patches is extracted for each pixel, followed by a gaussian weighting function. This weighting function is defined by the policy of blending patches[8].

### III. EXISTING SYSTEM

In the existing system the person has to remove and fill the gap manually, which takes time and skills.

### IV. PROPOSED WORKS

In the proposed system, the person in a given image will be removed and the gap will be filled automatically using machine learning technology.

### V. TOOLS USED

#### Tools Used

##### Anaconda Navigator

Boa constrictor Navigator is a work area graphical UI (GUI) remembered for Anaconda® dispersion that permits you to dispatch applications and effectively oversee conda bundles, conditions, and channels without utilizing order line orders.

##### Tkinter

Tkinter is a Python authoritative to the Tk GUI toolbox. It is the standard Python interface to the Tk GUI toolkit and is Python's true standard GUI.

### VI.METHODODOLOGY

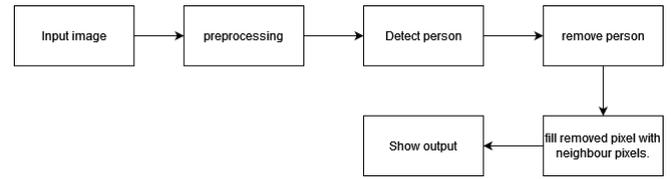


Fig 1 : System Architecture of Image Inpainting

### VII.IMPLEMENTATION

#### YOLO algorithm:

A pre-trained YOLO network has been used for object detection (generating a bounding box around them), and its output is fed to a Pix2Pix's generator that has learned how to fill holes in the center of images, using the images without holes as a reference:

1. YOLO detects the objects.
2. A subimage of every object is taken, adding the pixels around it.
3. Out of every subimage, the center pixels are removed (replaced by ones) and the result is sent generator, whose task is to fill it with the surrounding pixels.

YOLO algorithm works using the following three techniques:

- Residual blocks
- Bounding box regression
- Intersection Over Union (IOU)

Residual blocks:

First, the image is divided into various grids. Each grid has a dimension of  $S \times S$ . The following image shows how an input image is divided into grids.

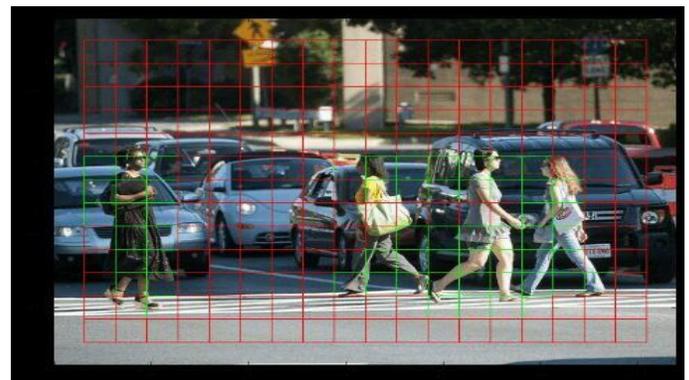
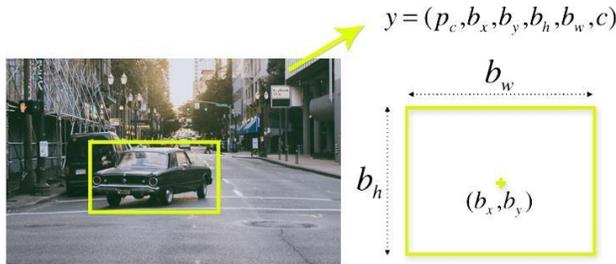


Fig 2 : Input image divided into grids

**Bounding box regression:**

A bounding box is an outline that highlights an object in an image. Every bounding box in the image consists of the following attributes:

- Width (bw).
- Height (bh).
- Class (for example, person, car, traffic light, etc.)- This is represented by the letter c.
- Bounding box center (bx,by).



**Intersection over union (IOU):**

Intersection over union (IOU) is a phenomenon in object detection that describes how boxes overlap. YOLO uses IOU to provide an output box that surrounds the objects perfectly. Each grid cell is responsible for predicting the bounding boxes and their confidence scores. The IOU is equal to 1 if the predicted bounding box is the same as the real box. This mechanism eliminates bounding boxes that are not equal to the real box.

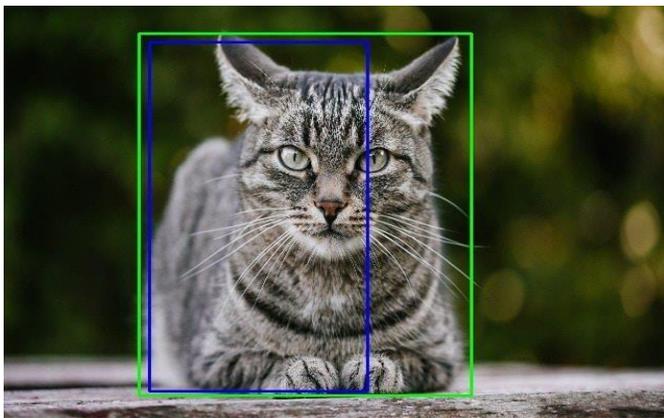


Fig 3 : output

**VIII. RESULTS**

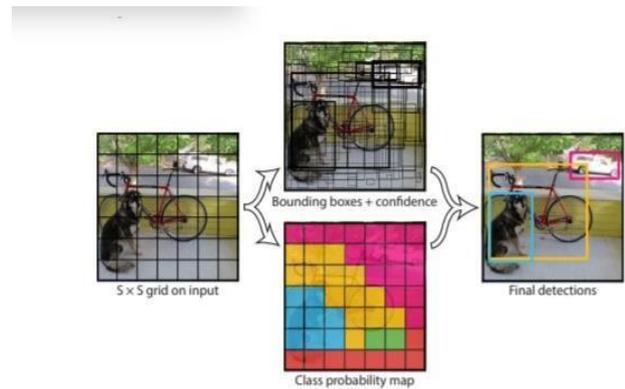


Fig 4 : Combition of Algorithm

**IX. CONCLUSION AND FUTURE SCOPE**

The proposed project can perform automatically detecting and removing unwanted background people from photographs that is able to achieve comparable results to hand-crafted manual target selection. The system is able to fill the gaps using neighboring pixels automatically. Overall the system performs as intended and can produce exceptional results.

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