The Office

Generate High resolution images from Low Resolution image using Generative Adversarial Network

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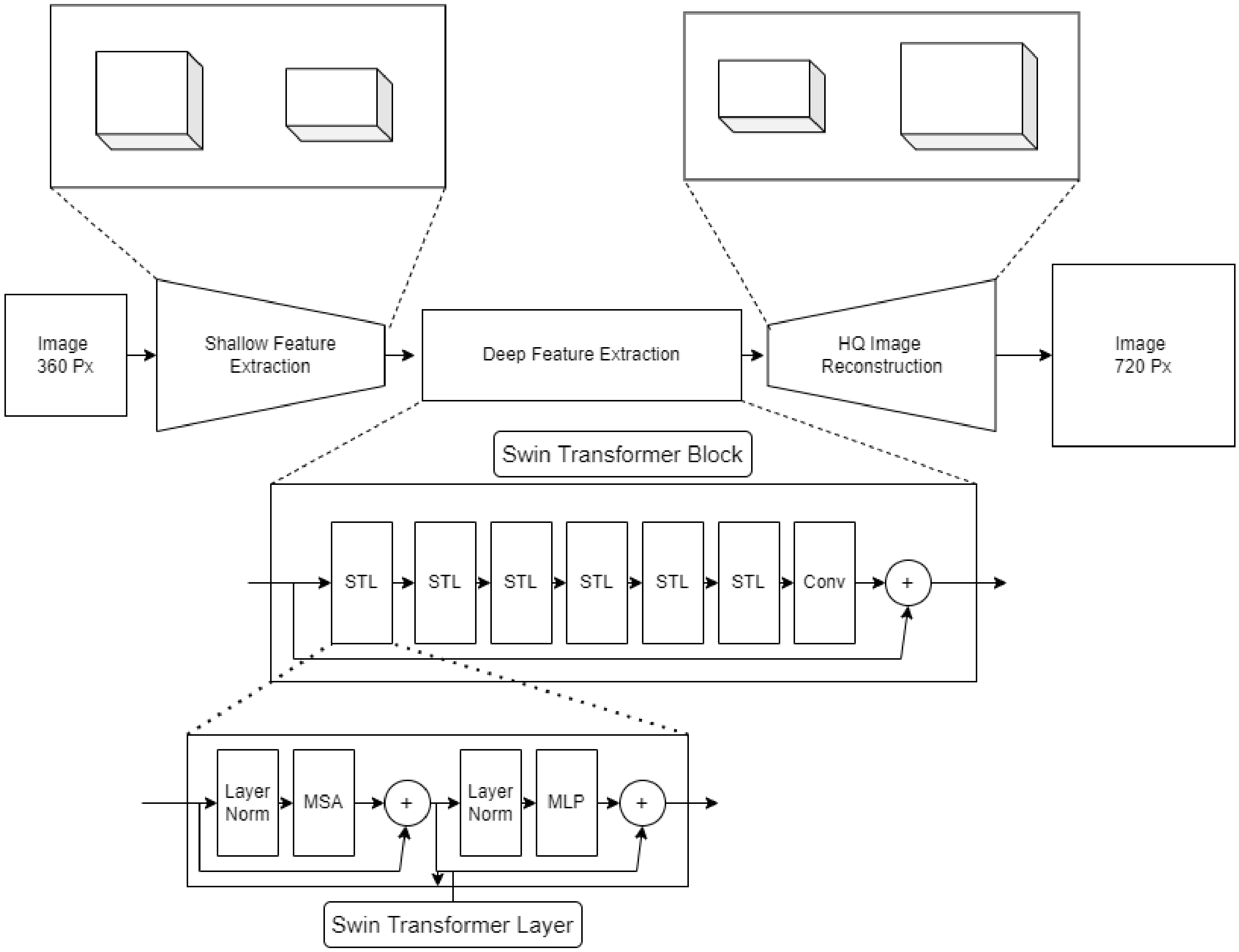
- We have made the below model which we are going to implement in our project.
- There are mainly 3 parts in our model: 1) Shallow Feature Extraction
  2) Deep feature Extraction
  3) HQ Image reconstruction
- In this week, we have implemented the Shallow feature Extraction part completely, SWIN Transformer Layer.
- In Shallow Feature Extraction, we used Convolution method with 3*3 kernel.
- For implementation of SWIN transformer layer we used attention mechanism.
- There we get 3 vectors Q : query vector, K: Key vector and V : value vector . Then basic attention formula
  Attention(Q, K, V) = SoftMax(QKT/√d + B) * V

- Then there was simple Malti layer perceptron layer which was simple implemented which nn.LinearLayer(in,out)

```python
class WindowAttention(nn.Module):
    r""" Window based multi-head self attention (W-MSA) module with relative position bias.
    It supports both of shifted and non-shifted window.

    Args:
        dim (int): Number of input channels.
        window_size (tuple[int]): The height and width of the window.
        num_heads (int): Number of attention heads.
        qkv_bias (bool, optional):  If True, add a learnable bias to query, key, value. Default: True
        qk_scale (float | None, optional): Override default qk scale of head_dim ** -0.5 if set
        attn_drop (float, optional): Dropout ratio of attention weight. Default: 0.0
        proj_drop (float, optional): Dropout ratio of output. Default: 0.0
    """

    def __init__(self, dim, window_size, num_heads, qkv_bias=True, qk_scale=None, attn_drop=0., proj_drop=0.):

        super().__init__()
        self.dim = dim
        self.window_size = window_size  # Wh, Ww
        self.num_heads = num_heads
        head_dim = dim // num_heads
        self.scale = qk_scale or head_dim ** -0.5

        # define a parameter table of relative position bias
        self.relative_position_bias_table = nn.Parameter(
            torch.zeros((2 * window_size[0] - 1) * (2 * window_size[1] - 1), num_heads))  # 2*Wh-1 * 2*Ww-1, nH

        # get pair-wise relative position index for each token inside the window
        coords_h = torch.arange(self.window_size[0])
        coords_w = torch.arange(self.window_size[1])
        coords = torch.stack(torch.meshgrid([coords_h, coords_w]))  # 2, Wh, Ww
        coords_flatten = torch.flatten(coords, 1)  # 2, Wh*Ww
        relative_coords = coords_flatten[:, :, None] - coords_flatten[:, None, :]  # 2, Wh*Ww, Wh*Ww
        relative_coords = relative_coords.permute(1, 2, 0).contiguous()  # Wh*Ww, Wh*Ww, 2
        relative_coords[:, :, 0] += self.window_size[0] - 1  # shift to start from 0
        relative_coords[:, :, 1] += self.window_size[1] - 1
        relative_coords[:, :, 0] *= 2 * self.window_size[1] - 1
        relative_position_index = relative_coords.sum(-1)  # Wh*Ww, Wh*Ww
        self.register_buffer("relative_position_index", relative_position_index)

        self.qkv = nn.Linear(dim, dim * 3, bias=qkv_bias)
        self.attn_drop = nn.Dropout(attn_drop)
        self.proj = nn.Linear(dim, dim)
```



Generative Network