# X Results and Discussions

The ESPCN++ model we've proposed shows impressive advancements in single-image super-resolution (SISR) for higher scale factors (×2, ×4, ×6), all while keeping computational complexity low. This section anayzes the model’s performance, both quantitatively and qualitatively, comparing it to with state-of-the-art methods and discussing the effects of key methodological choices.

**X.1 Quantitative Evaluation**  
We assessed the model using benchmark datasets like Urban100, B100, SET5, SET14, and DIV2K, focusing on PSNR and SSIM metrics. As illustrated in Table 1, ESPCN++ surpasses baseline models such as VDSR, SRCNN, and EDSR at higher scale factors. For example, on the Urban100 dataset with a ×6 scale, ESPCN++ achieves a PSNR of 31.89 dB and an SSIM of 0.7846, [while previous studies did not report these results for x6 scale, indicating limitations in their ability to handle such scale factors. The lightweight architecture, with only 20,236 parameters, also boosts efficiency, as shown in Table 2, which highlights a remarkable 99% reduction in parameters compared to EDSR’s hefty 43.6M.

**X.2 Impact of Patch-Based Processing**  
Using a patch-based approach (patch size: 10×10, stride: 5) allowed for localized feature extraction, helping to preserve high-frequency details that often get lost in full-image processing. The overlapping patches added some redundancy, which improved contextual understanding. For instance, in Fig. 4, the image upscaled at ×6 retains sharper edges and textures compared to EDSR’s output (Fig. Mention EDSR’s output), which suffers from blurring. However, too much overlap in patches might slow down computation time, indicating a trade-off between performance and efficiency.

**X.3 Role of Residual Blocks and Pixel Attention**  
The use of residual blocks helped reduce information loss by maintaining identity mappings, as shown by the lower MSE (Graph 3) that converges to 0.0004 in just 6 epochs. Additionally, the pixel attention mechanism boosted performance by focusing on important pixels.

## Limitations and Future Work

While ESPCN++ excels at higher scales, extreme degradation (e.g., ×8 or ×10) still poses challenges. Excessive compression in intermediate layers, or loss of frequency-rich components, can lead to irreversible degradation—posing a barrier to perfect reconstruction. Too much loss of information can lead to problems in reconstruction, especially for complex images with nuanced textures like ancient paintings or carvings. Future work could explore hybrid architectures combining patch-based methods with multi-scale attention to address this. Additionally, training on diverse degradation models (e.g., noise, motion blur) and scaling to 8x or higher super-resolution can be explored to further strengthen the model's robustness.