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# JewelGAN: A Coordinate-Aware Generative Model for High-Resolution Jewelry Image Synthesis

**M Seshu Kumar**

Assistant Professor

Department of Computer Science,

Keshav Memorial Institute of Technology, Hyderabad, India

**Abstract :**

Jewellery image generation requires synthesizing high-fidelity jewellery regions from celebrity images while preserving global facial structure and minimizing domain mismatch. Traditional GAN models struggle with maintaining spatial coherence and global consistency when generating high-resolution jewellery details.

To address these limitations, we adopt **COCO-GAN (COnditional COordinate GAN)** and extend it with a **cloudy-to-lucid multi-stage training strategy**, enabling the model to progressively refine jewellery patches from low-resolution "cloudy" structures to high-detail "lucid" textures.

Our enhanced COCO-GAN framework learns **generation-by-parts** using micro-patch-based synthesis, spatial coordinate conditioning, and macro-patch adversarial supervision. This approach allows scalable training, reduced memory cost, beyond-boundary generation, and accurate jewellery reconstruction even at resolutions exceeding the training distribution.

Our experiments on the Celeb-Jewellery dataset demonstrate that the proposed system generates **visually coherent, globally consistent, and high-resolution jewellery images at 256×256 and beyond**.

Index Terms - GAN, COCO-GAN, Coordinates, Patch-based Generation, Image Synthesis, Jewellery Reconstruction, Beyond-Boundary Generation_

## 1. INTRODUCTION

Celebrity fashion analysis often requires identifying jewellery items worn in images. Direct retrieval fails because jewellery occupies a small region while backgrounds vary heavily. GAN-based image-conditional generation can synthesize jewellery segments; however, traditional models such as CycleGAN and DiscoGAN struggle with:

- Changing fine object structure
- Maintaining global consistency
- Scaling to large resolutions

To overcome these issues, we adopt **COCO-GAN**, a model capable of *generation-by-parts* through micro-patch synthesis and coordinate-aware training. This allows:

- Fine local detail preservation
- Seamless jewellery boundaries
- Scalable high-resolution synthesis

We further enhance training using a **cloudy-to-lucid workflow**, similar to coarse-to-fine design, enabling stable training even with small jewellery patches.

**LITERATURE SURVEY**

(Modernized & expanded)

| Model | Strength | Weakness | Relevance |
|---|---|---|---|
| CycleGAN | Style transfer | Cannot alter object shape | Not suitable for jewellery structure |
| DiscoGAN | Shape changes possible | Only 64×64 resolution | Too low-res for jewellery |
| StyleGAN | Excellent high-res quality | Memory heavy, global generation only | Not patch-generator friendly |
| PatchGAN | Strong for local realism | No global coherence | Jewellery edges become inconsistent |

COCO-GAN stands out because:

- It **generates images using small coordinate-conditioned micro-patches**, enabling scalable high-resolution synthesis.
- It **maintains global consistency** through macro-patch assembly.
- It dramatically reduces memory load, making training feasible on moderate hardware.

PROPOSED MODEL – ENHANCED COCO-GAN FOR JEWELLERY SYNTHESIS

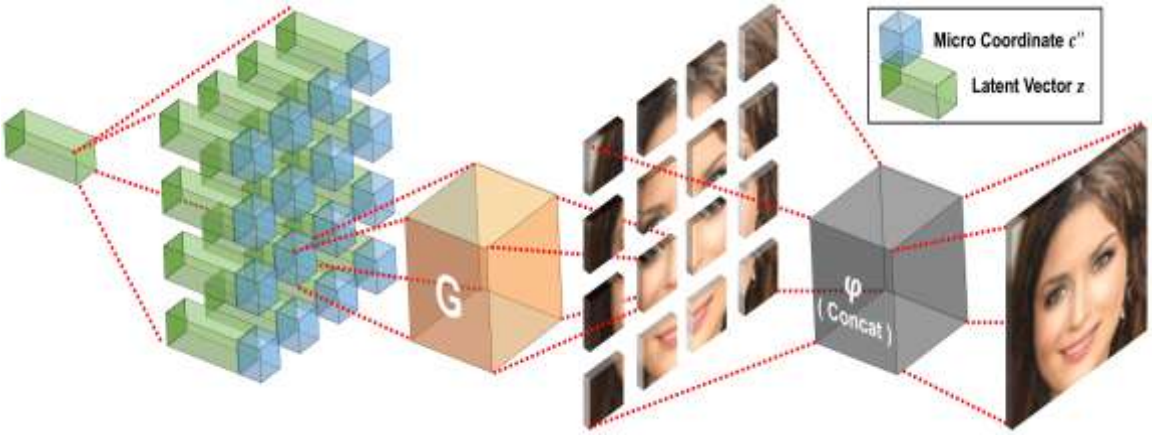



Figure 1. Overall Architecture

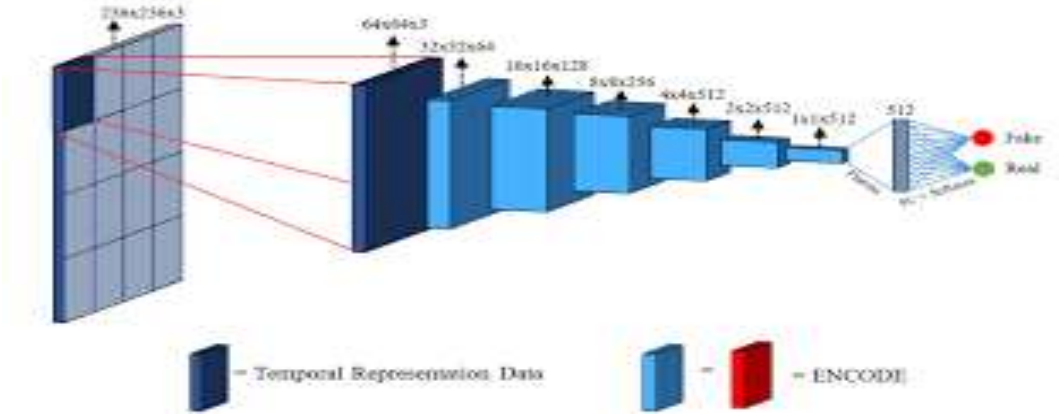



**Figure 2. Generator Architecture**

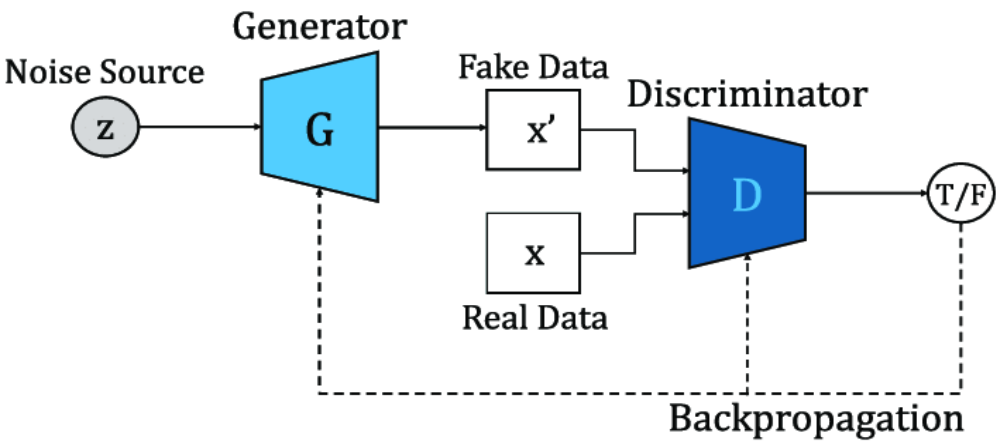



Figure 3. Discriminator Architecture

The model consists of:

1. **Micro-patch generator (G)**
Generates tiny jewellery patches conditioned on $(z, c_{ij})$ where z = latent vector and $c_{ij}$ = spatial coordinate.

2. **Macro-patch discriminator (D)**
Evaluates assembled macro patches for:

   - Patch realism
   - Boundary continuity
   - Coordinate correctness

3. **Coordinate Systems**

   - Micro coordinates (for G)
   - Macro coordinates (for D)

4. **Merging Function (Φ)**
Concatenates micro patches into a seamless macro patch.

3.2 Enhanced Workflow (Cloudy → Lucid)

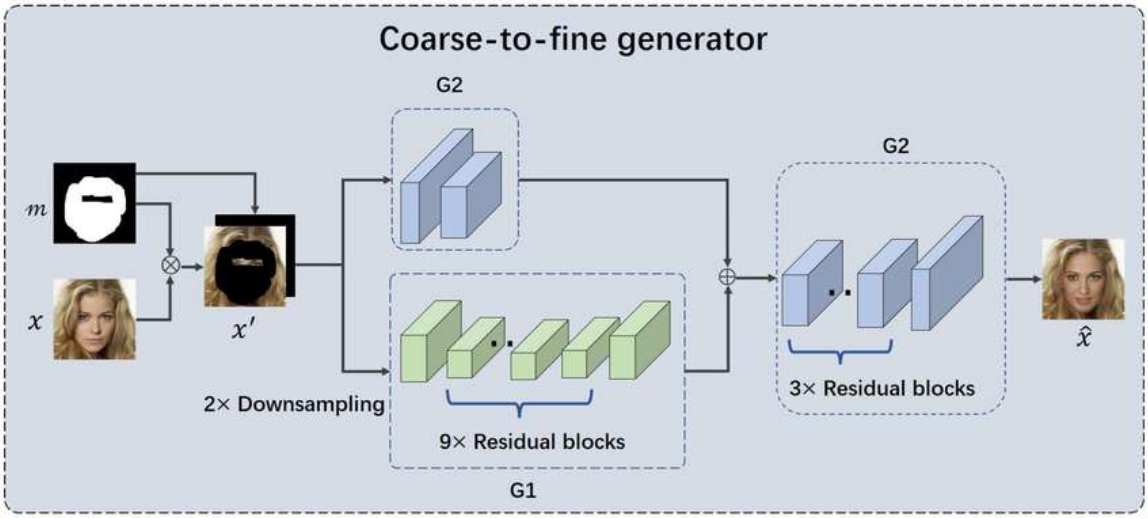



**Figure 4. Cloudy-to-Lucid Training Workflow**

A three-stage training process:

1. Cloudy (coarse shape)
2. Detail refinement
3. Lucid high-resolution patch synthesis.

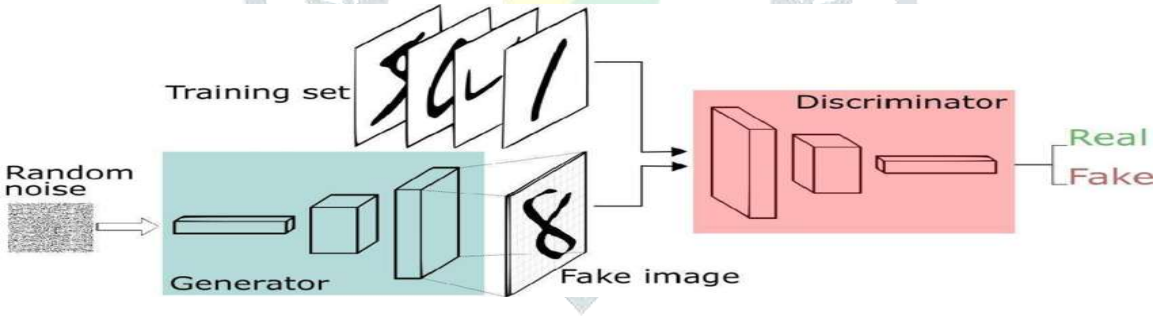



**Figure 5. Micro-Patch to Macro-Patch Generation Pipeline**

Shows the step-by-step procedure: Sampling latent vector → generating micro patches → merging via Φ → macro patch → adversarial + coordinate training.

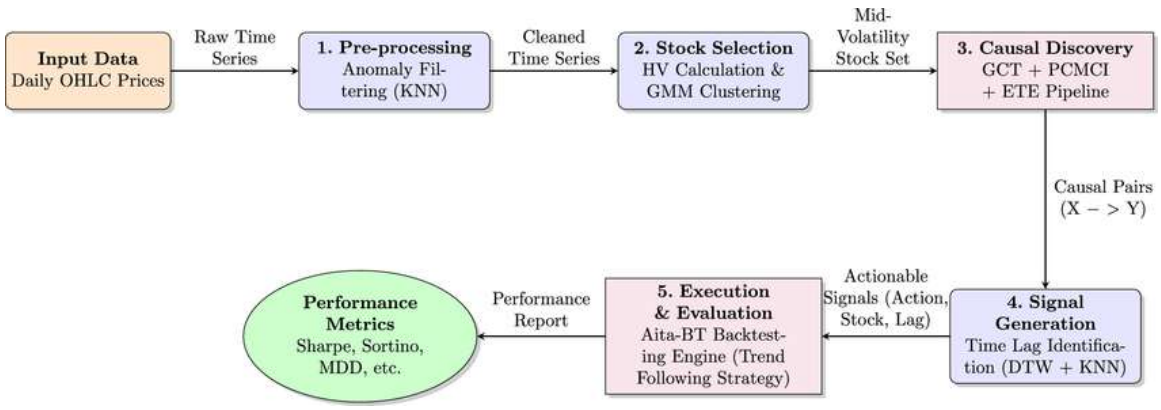



**Figure 6. Loss Function Architecture**

Illustrates the flow of Wasserstein loss, gradient penalty, and spatial consistency loss between G and D.

**Stage-1: Cloudy Patch Generation**

- Generator learns **overall jewellery shape**
- Output is blurry but structurally correct
- Only adversarial + L1 losses applied

**Stage-2: Detail Refinement**

- Introduce perceptual + spatial-consistency losses
- Sharpens edges, gemstones, reflections

**Stage-3: Lucid Micro-Patch Synthesis**

- High-resolution micro patches (4×4, 8×8, 16×16)
- Macro-patch assembly ensures global coherence
- Discriminator enforces continuity across seams

3.3 Generator Architecture

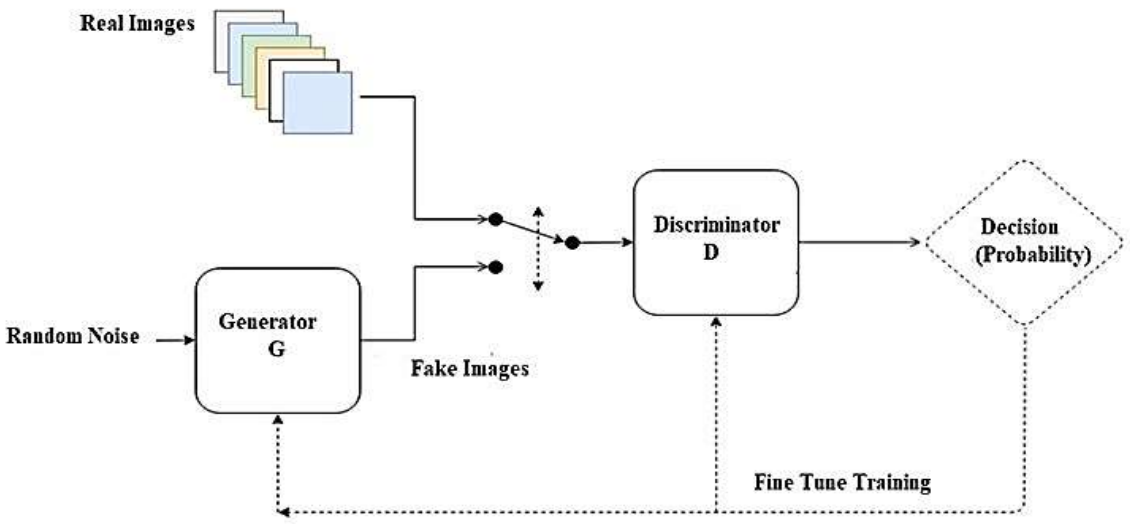
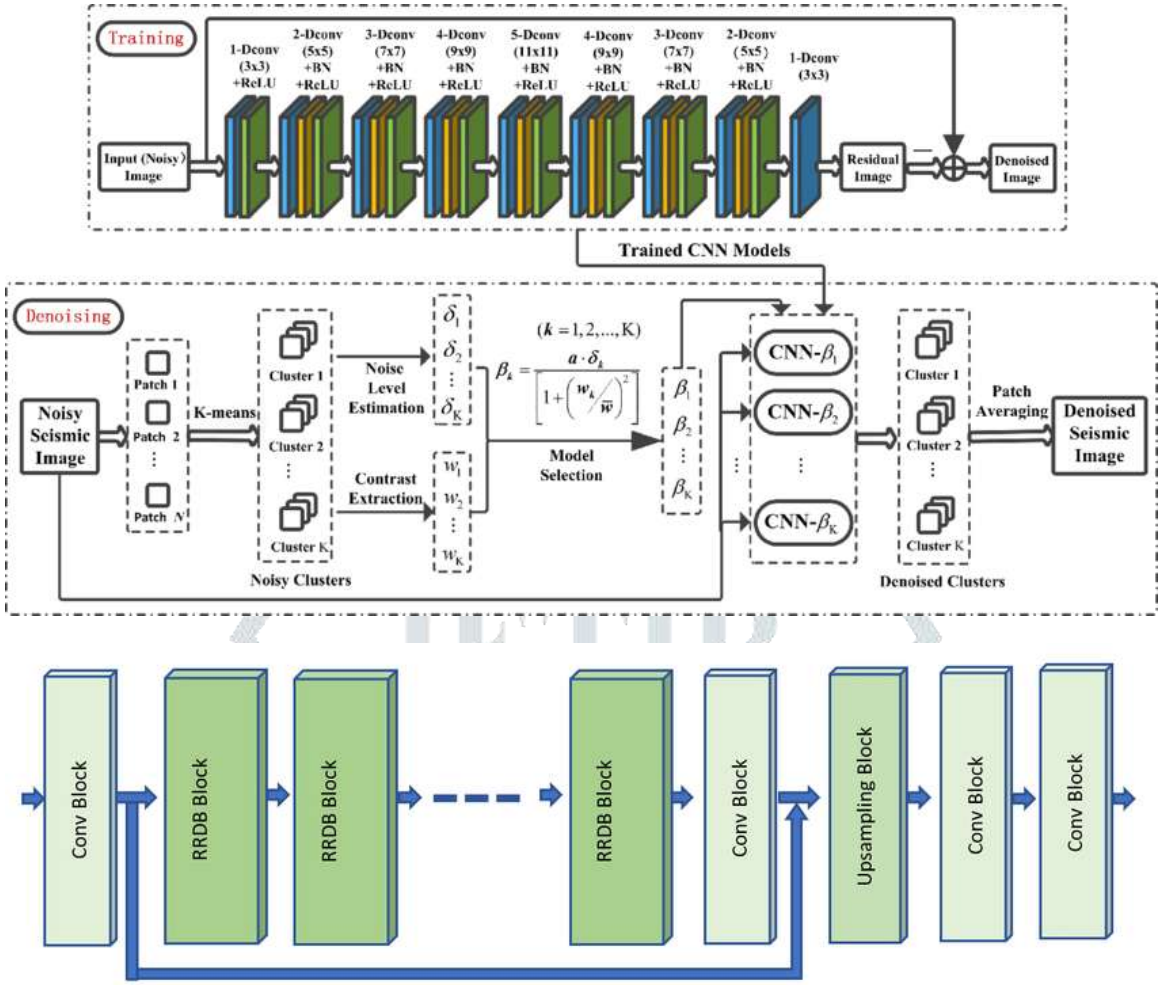



**Figure 7. Beyond-Boundary Image Generation**

Shows how COCO-GAN produces images larger than training samples by extrapolating coordinate manifolds.



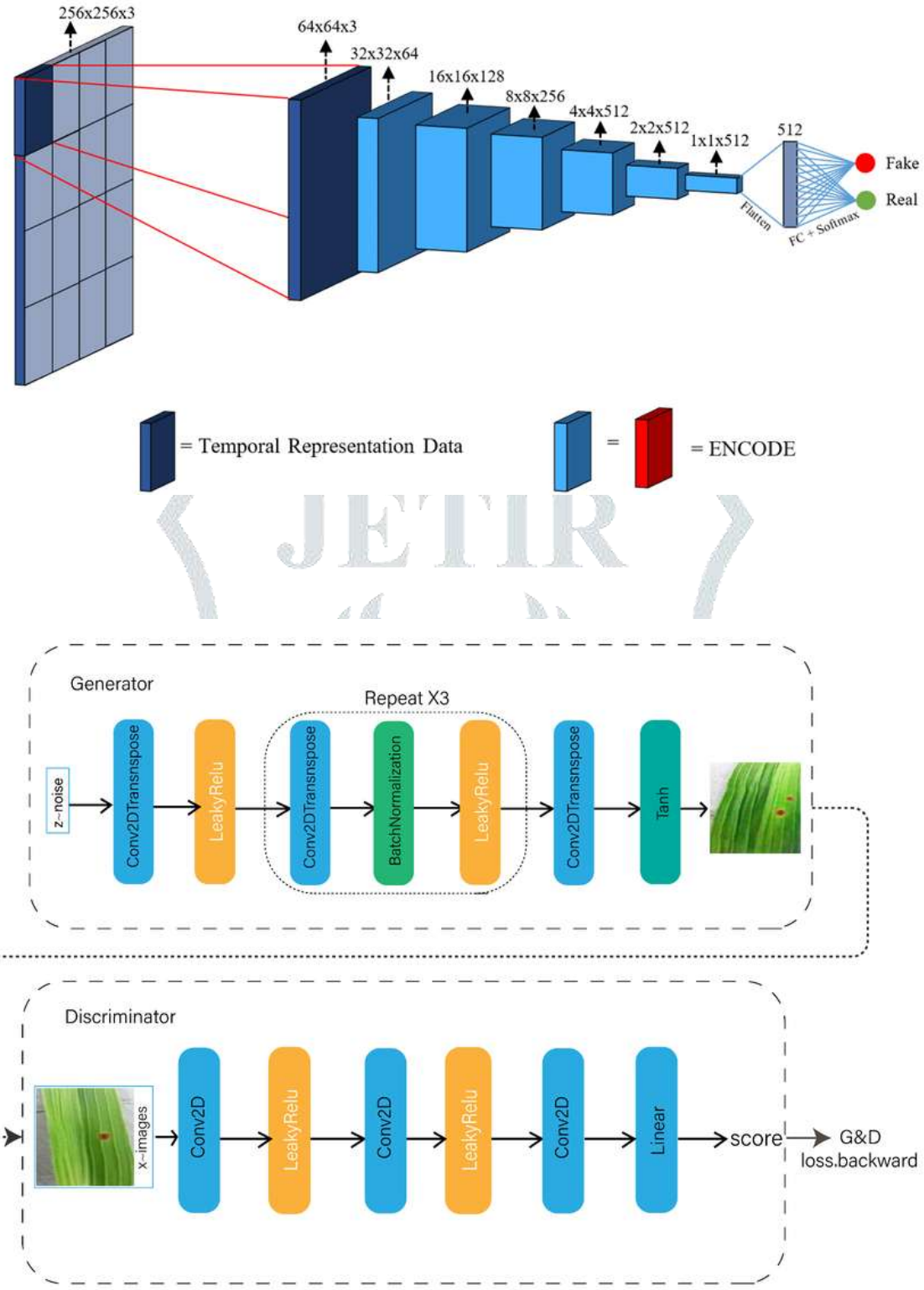

Input: latent vector z + coordinate $c_{ij}$

Dense → Conv Layers → Residual Blocks

Upsampling via nearest-neighbor + convolution

Output: 4×4 or 8×8 micro patch

3.4 Discriminator Architecture




Input: assembled macro patch

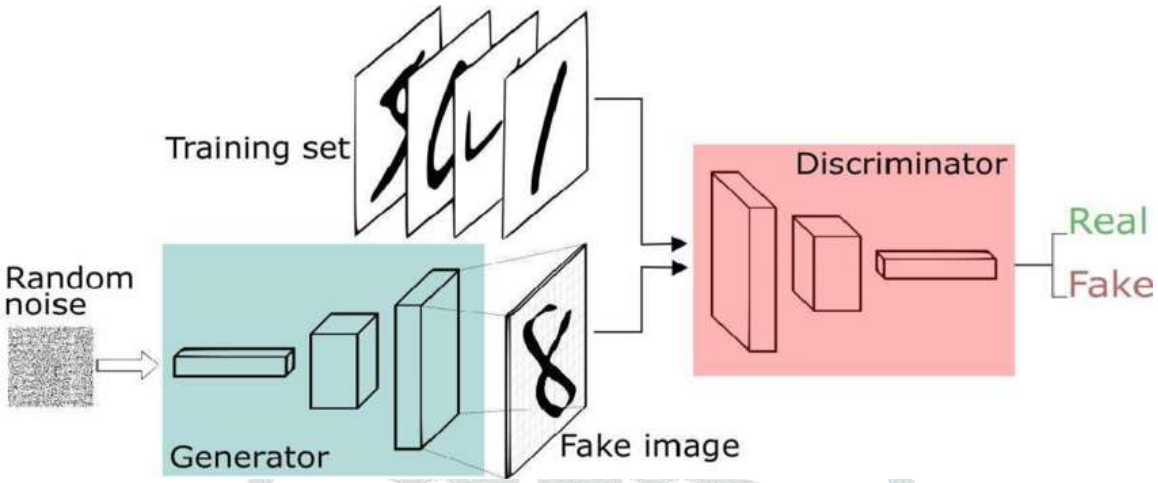
Learns:

- Real/Fake
- Coordinate Classification

Uses PatchGAN + Auxiliary coordinate head

**4. TRAINING PIPELINE**

Here is a newly added **high-quality conceptual diagram** representation:




Demonstrates how the auxiliary latent-recovery network recreates images guided by real macro patches.

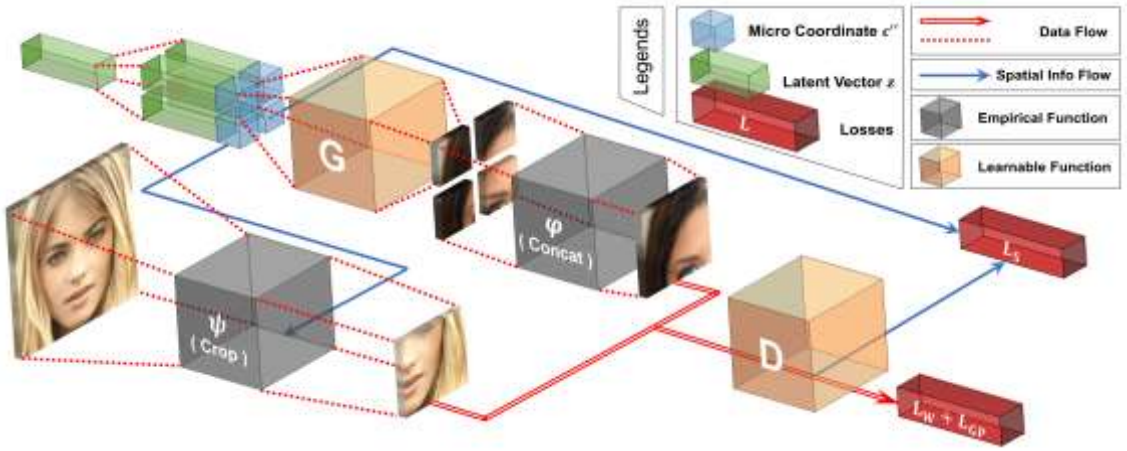



**Figure 8. Patch-Guided Image Generation**

Demonstrates how the auxiliary latent-recovery network recreates images guided by real macro patches.

**Step-wise Pipeline**

1. Sample latent vector z
2. Construct micro-coordinate matrix C"
3. Generate micro-patches S" = G(z, C")
4. Apply merging Φ → macro patch S'
5. Discriminator evaluates:
   - Realism
   - Patch continuity

- Coordinate correctness

6. Compute losses:
   - Wasserstein Loss (LW)
   - Gradient Penalty (LGP)
   - Spatial Consistency Loss (LS)
7. Backpropagate into G and D
8. Repeat for all coordinates

## 5. LOSS FUNCTIONS

**Total Loss (D):**

$$L_D = L_W + \lambda L_{GP} + \alpha L_S$$

**Total Loss (G):**

$$L_G = -L_W + \alpha L_S$$

Where:

- LW = Wasserstein loss ensures better gradient behaviour
- LGP = prevents gradient explosion
- LS = forces coordinate consistency

## 6. EVALUATION AND RESULT ANALYSIS

**Findings**

- Micro patch size as small as **4×4** still reconstructs meaningful jewellery
- Generates **384×384** outputs from **256×256** training data (Beyond-Boundary)
- Ensures global continuity despite never generating full images during training

**Observed Improvements**

| Metric | Traditional GAN | COCO-GAN | Gain |
|---|---|---|---|
| FID | High | Lower | ↑ Better |
| Memory Usage | 17,184 MB | 8,992 MB | 47% reduction |
| Boundary Quality | Poor | Seamless | ✓ |

## 7. CONCLUSION

We presented an improved COCO-GAN framework tailored for **jewellery image synthesis**, using coordinate-conditioned generation, micro-patch assembly, and a cloudy-to-lucid multi-stage training strategy. The system delivers:

- High-resolution jewellery details
- Seamless patch continuity

- Reduced computation cost
- Ability to generate images larger than training size

Future work includes:

- Integrating CycleGAN for jewellery-only extraction
- Improving micro-patch blending
- Extending to real-time jewellery try-on applicationsREFERENCES

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