

**Table .** Comparison of Methods for fMRI Decoding and Visual Image Reconstruction

| Category                          | Representative Method                                | Dataset  | Innovation  | Advantages  | Disadvantages   | Results  |
|-----------------------------------|--|----------|---|---|---|--|
| Traditional Methods               | Gabor-wavelet RF Model [9]                           | Vim-1    | Early visual features are mapped.                                       | Preset image sets can be recognized.                        | Pixel reconstruction cannot be performed.                             | Category recognition is achieved.  |
|                                   | Bayesian CCA Model [10]                              | Vim-1    | Sparse mappings are extracted.  | Simple pixel images can be reconstructed.                   | Reconstruction is limited by fine lines and high noise.               | Rough image reconstruction is obtained.                                      |
| Deep Learning (Non-generative)    | Voxels $\rightarrow$ Pixels Bidirectional Model [15] | GOD      | Unlabeled data are used for training.                                   | Rough structures can be reconstructed.                      | Rough structures are the only ones reconstructed.                     | Shape similarity is achieved.  |
|                                   | NEI-GNN Multi-scale [16]                             | GOD      | Structural details are optimized.                                       | Good texture can be obtained.                               | Semantic consistency is lacking.                                      | Accurate structure reconstruction is achieved.                               |
| Generative (Encoder-Decoder type) | Foreground-Attention & Loop-Enc-Dec [20]             | GOD      | A visual attention mechanism for guidance is introduced.                | Attended regions can be effectively reconstructed.          | Generalization is limited by dataset diversity.                       | Clear structure with limited scene coverage is obtained.                     |
| Generative (GAN type)             | Dual-guided Brain Diffusion Model [35]               | NSD      | Multi-stage guidance control is applied.                                | Randomness and blur can be improved.                        | Performance is slightly worse in complex scenes.                      | High semantic consistency is achieved.                                       |
| Generative (Diffusion Models)     | MindDiffuser[34]                                     | NSD      | Dual guidance for semantics and structure is applied.                   | Randomness and blur can be improved.                        | Regularization adaptability is insufficient.                          | Good detail in simple scenes is achieved.                                    |
|                                   | STTM[41]   | NSD, GOD | Cross-subject transfer and high/low-level joint learning are performed. | Cross-subject adaptation transfer can be realized.          | Structural fidelity still needs improvement.                          | Good results in both low-level pixels and high-level semantics are obtained. |
|                                   | LDM[44]  | NSD      | Simple linear mapping for reconstruction is applied.                    | High resolution and high semantic fidelity can be achieved. | Reconstructed visual images lack natural appearance.                  | High-resolution reconstruction is obtained.                                  |
|                                   | MindEye2[45]   | NSD      | A short training period for good reconstruction is required.            | Cross-subject shared model can be applied.                  | Reconstruction is limited to natural scenes and susceptible to noise. | High precision with few samples is achieved.                                 |