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**Monthly Notices of the Royal Astronomical Society**

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MN-24-2741-MJ, which you submitted to Monthly Notices of the Royal Astronomical Society.   Minor revision of your manuscript is requested before it is accepted for publication. Providing these changes are made, we should be able to accept your revised version without further review.   You should submit your revised version, together with your response to any comments from the editor and reviewer at https://mc.manuscriptcentral.com/mnras. The deadline for this is six months from today.   Enter your Author Centre, where you will find your manuscript title listed under "Manuscripts with Decisions". Under "Actions," click on "Create a Revision". Please ensure that you also respond to any comments from the editor or assistant editor.   IMPORTANT: do not submit your revised manuscript as a new paper!   When submitting your revised manuscript, you should provide details of any changes you make to the original manuscript. Changes to the manuscript should also be highlighted (e.g. in bold or colour).   Authors are reminded that all papers submitted to MNRAS will be published Open Access if accepted and an Article Processing Charge will apply. Authors must ensure they have read the details of the charges and, if a waiver or partial waiver is required, and an application has not yet been sent to OUP, the waiver must be applied for before the revision of this paper is submitted.  https://academic.oup.com/mnras/pages/mnras-open-access   Authors are reminded that the corresponding author will be responsible for signing the licence for this paper, if accepted, and the corresponding author will be responsible for the Article Processing Charge.   Please note, to be eligible for one of OUP’s Read and Publish agreements, the corresponding author must provide their qualifying institution as their primary affiliation at submission. After submission, changing who is designated as the corresponding author will be permitted only where there is a substantive reason to do so. For the avoidance of doubt, changing the corresponding author in order to access Read and Publish funding is not permissible. Please contact the editorial office as soon as possible if any details provided with this submission need to be changed.   We look forward to receiving your revised manuscript.   Best wishes,   Bella   Bella Lock  Assistant Editor MNRAS  Royal Astronomical Society   cc: all listed co-authors    Assistant Editor's Comments:   Please remove the references from your abstract.    Reviewer's Comments:   This manuscript provides a thorough and thought-provoking exploration of generative models in the context of galaxy image generation. It goes through details of the VAEs, GANs, normalizing flows, and diffusion models, and effectively demonstrates the impact of training dataset size on model generation capability. The rigorous approach and detailed experiments make this a valuable contribution to the field, offering insights into both model behavior and practical challenges in astronomical data generation. Below are minor comments/suggestions aimed at further enhancing clarity.  Section2:  The section provides a thorough and theoretically rigorous overview of generative models, including VAEs, GANs, normalizing flows, and diffusion models, showcasing a strong grasp of their principles and comparative strengths. This depth of discussion, supported by extensive references, highlights the authors' expertise and provides valuable context for readers interested in the broader methodological landscape. That said, it may be worth considering whether the level of theoretical detail is fully necessary for the paper’s primary audience, especially given its focus on astronomy. Streamlining the discussion to emphasize the practical relevance of these models to astronomy—for instance, how they address challenges like data sparsity, noise, or resolution—could make the section more impactful. Additionally, including a high-level summary of the models and their relevance for readers less familiar with deep learning, as well as expanding on practical implementation details such as data preprocessing, training setup, and computational requirements, would enhance accessibility and ensure the discussion remains tightly aligned with the paper’s goals.  Section3:Page 6, 2nd column, line 5- Mentioning no data compression in diffusion and flow based compared to GANs or VAEs makes the point about latent space size more immediately accessible   section 3.1- Not sure why details of Kadkhodai et al sample matter in this study, they can be removed.  Section 3.1- The cited requirement of 10^5 images for transitioning from memorization to generalization in datasets like CelebA and LSUN Bedroom may not directly translate to galaxy images. Galaxy datasets might exhibit different variability and structural complexity, which could lower the necessary sample size. The relationship between sample size and data complexity has been studied, such as in Liu et al. (2021), where it is demonstrated that less complex distributions require fewer samples to approximate effectively.   section 3.1- A bit more description of the data (detailed in Smith et al. 2022) would be helpful. For instance what is the sample size that 10^5 can be used for training, what are the redshift and brightness limits.    section 3.2- The section provides a clear summary of architectures and training configurations, but some choices could use clarification. Were the batch size differences (e.g., 10 for GANs vs. 32 for Glow) and resizing to 128×128 enforced by the existing architectures? If so, would adjusting these configurations or building tailored architectures better suited to the data help ensure that such choices do not affect the comparability of experimental results?  section 3.3.2 column1 line 44- two u-net networks is a bit confusing, maybe mention right at the beginning the difference in training size of the two. Also mention whether this is a u-net in a DDPM or some other denoiser not mentioned before?  section 3.3.2 last paragraph, "significant implications", maybe mention the implication.   section 3.3.2 More detail on PSNR might be helpful. For instance, are the galaxy cutouts normalized? Is the PSNR calculated over the entire cutout or specifically on the galaxy region? Could the model learning the background alone significantly affect the PSNR? Finally, is PSNR the most appropriate measure for evaluating the quality of denoising.  Section 3.3- In some of the experiments where increasing N from 100 to 100,000 improves generalization, it increases the likelihood of less probable data points being included in the training set. However, instead of attempting to approximate the full data density by brute force, a more efficient approach might involve strategically sampling the data distribution to ensure coverage of the parameter space (e.g., not just morphological parameters shown in figure 5/9, but sizes, ellipticities, noise levels in the background, etc). This could improve generalization without requiring massive datasets, focusing on capturing the range of the distribution rather than replicating its density.  Figure 10, is there a sharp cut at the left side of the histograms or is xrange chosen for a reason  section 4  It is mentioned that the three models are compared while they are not really compared to each other directly. For example, are certain models (e.g., Glow or DDPM) inherently better suited to capturing galaxy-specific features such as faint structures, noise properties, or morphological diversity? | | | **Date Sent:** | 17-Jan-2025 |  | | | | |  | | |  |  | | --- | --- | | |  | | --- | |  | | | | |

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