TT-GAN: A *Talinum triangulare* Hydroponic Growth Dataset and VAE-GAN-Based Simulation Framework with IoT Monitoring

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***Abstract*—**

***Index Terms*—Talinum triangulare, Hydroponics, GAN, VAE-GAN, Synthetic Data, IoT, Smart Agriculture**

I. Introduction

Agricultural productivity and food security remain critical challenges in many developing regions, particularly across sub-Saharan Africa, where indigenous crops play a central role in nutrition and income. Despite their importance, many of these crops remain underrepresented in modern data driven agricultural research, especially in the context of machine learning and generative modelling [1]. This lack of structured and high-quality datasets limits the application of artificial intelligence (AI) techniques for growth analysis, simulation and decision making in indigenous farming systems.

Recent advances in deep generative models, particularly Generative Adversarial Networks (GANs) and Variational Auto encoders (VAEs), have demonstrated capabilities in learning complex data distributions and synthesizing realistic samples across domains such as computer vision, medical imaging and simulation environments [2], [3]. However, the majority of existing applications rely on large scale, well curated datasets derived from controlled laboratories, industrial farms or Western crop varieties. As a result, the potential of generative modelling remains untapped for indigenous African crops grown under locally relevant conditions.

Talinum triangulare, commonly known as waterleaf, is a widely consumed leafy vegetable across West and Central Africa. It is an herbaceous, perennial and glabrous plant widely grown in tropical regions as a leaf vegetable with high moisture content of almost 90.8 g per 100 gm of edible leaf [4]. It is an erect perennial herb with swollen roots and succulent stems, 30-100 cm tall. The branches have two lateral basal buds. The leaves are spirally arranged to nearly opposite, often crowded at the top of the stem. It is valued for its rapid growth cycle, nutritional content and adaptability to diverse environments [4]. Despite its agricultural and socioeconomic relevance, publicly available datasets capturing its growth dynamics, particularly under controlled and sensor-monitored conditions, are virtually nonexistent. This data gap presents a significant barrier to the development of AI-driven tools for simulation, monitoring and optimization of its cultivation.

Fig. 1. *Talinum triangulare* [5]

Hydroponic farming systems offer a controlled growth environment that is well suited for systematic data acquisition. By minimizing soil-related variability and enabling precise regulation of water availability, hydroponics provides a repeatable experimental platform for studying plant growth patterns. When integrated with Internet of Things (IoT) sensors, such systems enable continuous monitoring of environmental parameters, improving data reliability and reproducibility [**?**]. In particular, water level sensors play a critical role in hydroponic setups as water availability directly influences nutrient uptake and plant development.

Fig. 2. Hydroponics plant growth [10]

Generative modelling techniques have evolved beyond single architectures toward hybrid architectures that combine the strengths of multiple models. Variational Autoencoders (VAE) offer structured latent representations and stable training but often suffer from blurry outputs while Generative Adversarial Networks (GAN) are capable of producing clear images but may exhibit training instability [11]. Hybrid VAE-GAN architectures address these limitations by jointly learning meaningful latent spaces and adversarial realism thus making them well suited for simulation tasks where explanation and clearity is needed.

Building on these observations, this work introduces *TT-GAN*, a novel dataset and simulation framework centred on the hydroponic growth of *Talinum triangulare*. The proposed system integrates an IoT monitored hydroponic setup for structured image acquisition with a VAE-GAN based generative model trained to simulate plant growth patterns. Unlike prior works that focus solely on model performance, this study emphasizes dataset creation and reproducibility as primary research contributions.

The main objectives of this research are to:

- Design and deploy a low-cost IoT-enabled hydroponic system for controlled growth monitoring of *Talinum triangulare*.
- Capture, curate and publish a structured image dataset documenting hydroponic growth stages.
- Develop a VAE-GAN architecture from scratch for growth pattern simulation and image synthesis.
- Evaluate the generative performance of the proposed model using appropriate evaluation metrics.

The contributions of this paper are threefold: (i) the introduction of a publicly documented hydroponic growth image dataset for *Talinum triangulare*, (ii) the development of a reproducible IoT-based data acquisition pipeline and (iii) the implementation of a hybrid VAE-GAN framework for plant growth simulation. By bridging gaps in indigenous crop research, IoT-based monitoring and generative AI, this work aims to provide a foundation for future studies in data-driven agriculture.

II. Literature Review

A. Talinum triangulare: Biological and Agricultural Relevance

Talinum triangulare, commonly referred to as waterleaf, is a fast-growing leafy vegetable widely cultivated and consumed across West Africa. The plant is valued for its high moisture content, rich mineral composition and nutritional benefits including significant levels of vitamins, antioxidants and dietary fiber [6]. Due to its short growth cycle and adaptability, *Talinum triangulare* plays an important role in household food security and small-scale farming systems. Despite its agricultural relevance, existing scientific studies on *Talinum triangulare* are largely limited to nutritional analysis, traditional cultivation methods and medicinal properties [7], [8]. There is a notable absence of publicly available datasets documenting its growth patterns. This lack of structured data limits the application of machine learning and computer vision for growth analysis and simulation of this indigenous crop.

B. Hydroponic Farming and Controlled Environment Agriculture

Hydroponic farming is a soil-less cultivation method in which plants are grown using nutrient-enriched water solutions. By eliminating soil-related variability, hydroponics enables precise control of environmental parameters such as water availability, nutrient concentration, and growth conditions [**?**]. These characteristics make hydroponic systems particularly suitable for experimental studies and reproducible data collection.

In recent years, hydroponic systems have been increasingly adopted in controlled environment agriculture, both for commercial production and research purposes [12]. Studies have demonstrated that hydroponics can enhance growth consistency and facilitate continuous monitoring when integrated with sensing technologies [13]. Hydroponics provides a stable platform for isolating specific growth factors thereby improving the reliability of collected datasets.

C. Variational Autoencoders

Variational Autoencoders (VAEs) are probabilistic generative models that learn latent representations of data through variational inference [3]. Unlike normal autoencoders, VAEs arrange their hidden features in an orderly way. This makes it easy to smoothly move between data points and create new data. That is why VAEs are good for learning patterns and generating new data.

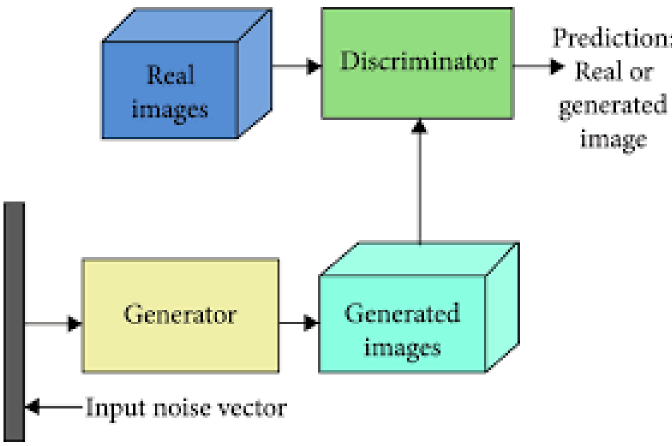
VAEs have been applied across a range of domains, including image synthesis, anomaly detection and data modelling [16], [17]. However, VAEs often have a problem as the images they generate can look too smooth or blurry, especially when the images are complex [14] . This limitation has motivated the development of hybrid architectures that combine VAEs with adversarial learning mechanisms to improve output realism [15].

D. Generative Adversarial Networks

Generative Adversarial Networks (GANs), introduced by Goodfellow *et al.* [2], consist of a generator and a discriminator trained in an adversarial framework. GANs have demonstrated remarkable success in generating high-fidelity images and handling complicated data patterns, leading to widespread adoption in computer vision and generative AI applications.

Despite their strengths, GANs are known to have problems during training such as training unstability, producing limited types of outputs and being very sensitive to hyperparameters [18], [19] . Numerous variants have been proposed to address these challenges, including conditional GANs, Wasserstein GANs and architectural refinements [20], [21], [22]. GANs excel at making realistic images but their hidden features are not well organized. This makes it harder to understand them and to control the images they generate [23], [24], [25] .

An image of a basic Generative Adversarial Network is illustrated in Fig. II-D describing the interaction of Generator and Discriminator in adversarial learning through which the Discriminator aims to predict real or generated images.



Basic diagram of Generative Adversarial Network [26]

E. Hybrid VAE–GAN Architectures

Hybrid architectures combining VAEs and GANs have been proposed to leverage the complementary strengths of both models. One of the earliest and most influential approaches is the VAE–GAN framework introduced by Larsen *et al.* [11], which integrates adversarial training into the VAE reconstruction process. This approach enables the learning of structured latent representations while improving the perceptual quality of generated samples.

Subsequent studies tried combining VAEs and GANs in different ways. These hybrids showed better training stability, produced more diverse outputs and created more realistic images than using VAEs or GANs alone [27], [28], [29]. These properties make VAE–GAN architectures particularly suitable for simulation tasks, where both consistency and realistic output are required. However, their application to agricultural growth simulation and indigenous crop datasets remains largely unexplored.

F. IoT Monitoring in Agriculture

The integration of Internet of Things (IoT) technologies into agriculture has enabled real-time monitoring, data-driven decision-making and improved resource management [30], [31]. IoT-based agricultural systems typically employ sensor networks to collect environmental data such as temperature, humidity, water level, and nutrient conditions [32].

In hydroponic setups, sensors play a critical role in ensuring stable growth conditions and generating reliable datasets. Water-level monitoring is essential for maintaining nutrient availability and preventing stress conditions that may affect plant development [33]. IoT-enabled monitoring improves data traceability which is crucial for reproducible machine learning research.

G. Datasets and Data Scarcity in Agricultural AI

High-quality datasets are a foundational requirement for the development and evaluation of machine learning models. In agricultural AI, the majority of publicly available datasets focus on plant disease detection, yield estimation or large-scale commercial crops [34]. Indigenous crops and small-scale farming systems remain under represented particularly in developing regions.

Several studies have highlighted data scarcity as a major barrier to AI adoption in agriculture across Africa and other developing regions [35], [36]. Liang et al. [37] highlights the importance of careful dataset design and curation in building trustworthy AI systems, emphasizing strategies to ensure data quality, diversity and representativeness while addressing biases and ethical considerations. The creation and publication of a domain specific dataset have therefore been recognized as valuable research contributions in their own right. By addressing this gap, dataset-centric studies enable reproducibility, benchmarking and future methodological advancements.

H. Summary and Research Gap

The reviewed literature highlights significant advances in generative modelling, controlled environment agriculture and IoT-based monitoring systems. However, a clear gap exists at the intersection of these domains. Existing works rarely combine indigenous crop datasets, sensor-aligned hydroponic growth monitoring and hybrid generative models within a unified framework. In particular, no publicly documented dataset or generative simulation framework currently exists for the hydroponic growth of *Talinum triangulare*.

This work addresses these gaps by introducing a novel dataset and VAE–GAN-based simulation framework grounded in IoT-monitored hydroponic cultivation, thereby extending generative modelling research into an under explored but agriculturally significant domain.

III. Methodology

This section explains the full experimental process employed in this study, including the hydroponic setup, the IoT monitoring system, how the dataset was collected and prepared and how the VAE-GAN model was designed and trained. The methodology is presented to ensure reproducibility and to clearly separate data acquisition from model development.

A. Overview of the Experimental Pipeline

The proposed methodology follows a four-stage pipeline:

1) Controlled hydroponic cultivation of *Talinum triangulare* using stem cutting.
2) IoT-based monitoring of water level using a water-level sensing system.
3) Image dataset acquisition and curation building a structured hydroponic growth dataset.
4) Development and training of a VAE-GAN architecture for growth pattern simulation.

An overview of the complete system architecture is illustrated in Fig. 3.

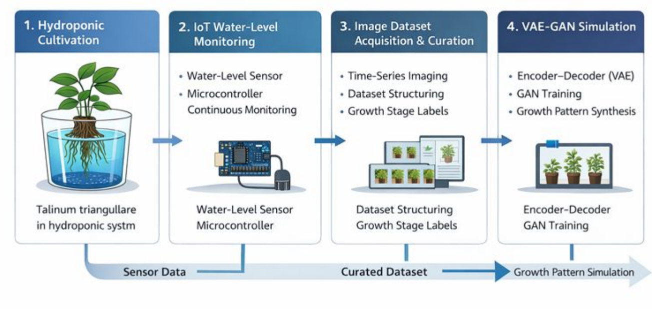


Fig. 3. Complete System Architecture

B. Hydroponic Growth Setup for Talinum triangulare

1) Plant Material and Propagation Method: Talinum triangulare was propagated using a stem cutting obtained from a mature and healthy parent plant. Stem cutting was selected due to it's widespread use in traditional cultivation and suitability for rapid vegetative propagation. The stem cutting measured 14 cm in length with a distance of 10.3 cm from basal end of stem to the first node. Multiple nodes were retained to ensure successful rooting and early growth initiation. The cutting was allowed a healing delay of 60 minutes post cutting to minimize the risk of rot.

Prior to placement in the hydroponic system, the cutting was visually inspected to ensure no damage. No chemical rooting agents were applied, allowing the growth process to reflect natural propagation behaviour under controlled water conditions.

Fig. 4 illustrates the freshly prepared stem cutting, highlighting the presence of seven (7) nodes.

Fig. 4. Stem Cutting of *Talinum triangulare*

2) Hydroponic System Design: A hydroponic setup was employed to minimize system complexity while maintaining controlled growth conditions. The system consisted of a transparent container measuring 12 cm in length partially filled to 10 cm with tap water, supporting the plant stem such that the basal end was submerged while the leaves remained above the water surface.

This configuration enabled direct observation of root development and ensured consistent water exposure across growth stages. The use of a transparent container also facilitated visual inspection and image capture without disturbing the plant. This is illustrated in Fig. 5.

Fig. 5. Hydroponics Setup

Hydroponics was selected as the cultivation method due to its ability to:

- Eliminate soil-induced variability.
- Enable repeatable experimental conditions.
- Support sensor-based monitoring.

C. IoT-Based Water-Level Monitoring System

1) Sensor Selection and Hardware Components: To monitor water availability within the hydroponic system, a water-level sensor was integrated into the setup. The sensor was interfaced with an Arduino Uno R3 microcontroller, which served as the central data acquisition and processing unit. The sensor continuously measured changes in water level and, based on a threshold value of 600, activated a visual indicator: the green LED illuminated when the reading was 600, while the red LED was triggered for readings 599. Simultaneously, the exact water level was displayed in real time on an LCD screen thus allowing continuous monitoring of the hydroponic system.

Primary hardware components included:

- Arduino Uno R3
- Water level sensor
- Battery pack with four AA batteries
- Green and red LEDs
- 220 Ω and 10 kΩ resistors
- Jumper wires
- 16x2 LCD I2C

The water-level sensor was positioned vertically at a slight angle within the hydroponic container maintaining a safe distance from the plant stem to avoid interference with growth. The sensor plates were fully submerged while the electronic components remained above the water level preventing water damage and ensuring sensor longevity. This configuration minimized fluctuations in readings caused by water movement or surface ripples, providing stable monitoring of water level throughout the growth period.

The wiring diagram of the hydroponic monitoring system, illustrated in Fig. 6, depicts the interconnection of all system components. The water-level sensor is connected to the analog input pin of the Arduino Uno R3 allowing continuous measurement of the water level. The green and red LEDs are connected to digital output pins via 220 current limiting resistors, enabling the Arduino to control the visual indicators based on sensor readings. The LCD display is interfaced with the Arduino using I2C communication lines, providing real-time water-level information. Power is supplied to the Arduino from a standard 5V source which also powers the LEDs and LCD.

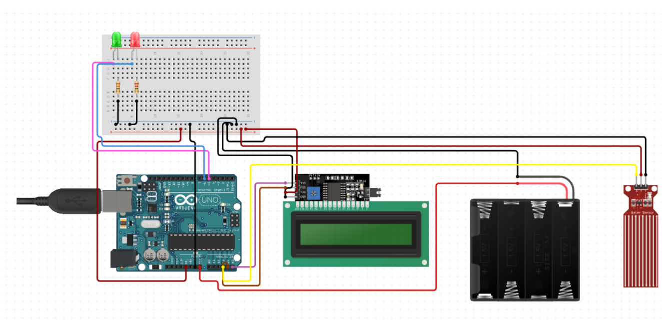


Fig. 6. Wiring Diagram for the IoT based Water Level Monitoring System

2) Data Acquisition and Logging: The microcontroller continuously monitored the water level sensor with readings transmitted via a serial connection to a connected computer for real-time recording. Each measurement was logged with a timestamp enabling continuous tracking of water-level fluctuations throughout the plant growth period. The recorded data were regularly reviewed to verify proper sensor operation and ensure data integrity. While the primary focus of this study was on acquiring images of plant growth for dataset construction, the inclusion of water-level monitoring provided additional environmental context enhancing the completeness of the dataset.

A sample serial monitoring output is shown in Fig. **??**.

D. Image Dataset Acquisition and Curation

1) Image Capture Protocol: Images of *Talinum triangulare* were captured daily at regular intervals throughout the hydroponic growth period using a smartphone camera. Image acquisition was conducted under natural daylight conditions with consistent camera positioning to minimize variability unrelated to plant growth. The camera distance was kept as uniform as possible across all capture sessions to ensure consistency within the dataset.

Image capture was performed over a period of 30 days with photographs taken from four viewpoints: front view, top view and two side views. This multi-angle strategy was employed to capture comprehensive visual information on plant morphology and structural development over time. In total, 120 images were collected and curated to form the final growth dataset.

2) Dataset Scope and Structure: Each image was carefully checked to make sure it was clear, useful and properly framed. Images with blur, blocked views or poor lighting were removed from the dataset.

Representative dataset samples are shown in Fig. 7.

Fig. 7. Dataset Samples

3) Dataset Storage and Publication: Each image was saved in JPEG (.jpg) format and organized within a folder structure. The complete dataset has been uploaded to a public repository on Kaggle for accessibility and reproducibility. It is also available for download at charlesekanem.com.ng/datasets.html

E. VAE-GAN Architecture Design

The proposed generative model adopts a hybrid Variational Autoencoder–Generative Adversarial Network (VAE-GAN) architecture. This design combines the structured latent space learning of VAEs with the adversarial training mechanism of GANs to generate realistic hydroponic growth images.

The architecture consists of three primary components:

- Encoder network,
- Decoder/generator network,
- Discriminator network.

The implemented VAE–GAN architecture operates on RGB images resized to 64×64 pixels and normalized to a fixed intensity range, consistent with the preprocessing pipeline used during training. Each input image is processed through a convolutional feature extraction pathway that progressively reduces spatial resolution while increasing channel depth. This hierarchical encoding captures salient visual characteristics of *Talinum triangulare*, including leaf contours, venation patterns and texture variations.

Instead of producing a single deterministic representation, the encoder maps extracted features into a latent probability distribution configured by a mean vector and a logarithmic variance vector. During training, a latent sample is obtained by injecting controlled stochastic noise into this distribution enabling probabilistic sampling while maintaining gradient stability through the reparameterization mechanism. This approach enforces continuity in the latent space and promotes generalization beyond individual training samples.

The sampled latent vector is subsequently projected back into image space through a fully connected expansion layer, followed by a sequence of transposed convolutional layers. This decoding pathway mirrors the encoder's downsampling operations, gradually restoring spatial resolution until a full-sized RGB image is reconstructed. ReLU activations are used between layers for non-linearity, and a Tanh activation is applied at the output layer to bound pixel values within the normalized intensity range of [1,1].

In parallel, an adversarial evaluation pathway processes both real input images and reconstructed or randomly generated images produced by the decoder. This pathway employs convolutional layers with progressively increasing feature depth to learn discriminative representations capable of distinguishing authentic plant images from synthetic outputs. The adversarial signal is computed using a binary classification objective, thereby encouraging the generative pathway to produce images that are indistinguishable from real samples.

Training is performed using alternating optimization steps between the adversarial pathway and the variational–generative pathway. The adversarial pathway is optimized to correctly classify real images as authentic and generated images as synthetic, while the variational–generative pathway is optimized using a composite objective function. This objective balances three components: pixel-level reconstruction fidelity, latent-space regularization to enforce distributional continuity and prevent overfitting, and adversarial feedback to enhance perceptual realism.

Training dynamics are quantitatively monitored using image quality metrics computed from reconstructed samples, including peak signal-to-noise ratio and structural similarity index. These metrics provide insight into reconstruction accuracy and perceptual consistency across training epochs, complementing loss-based diagnostics. In addition, visual samples are periodically generated and saved to enable qualitative assessment of convergence behavior, texture sharpness, and structural coherence.

After convergence, the architecture supports both reconstruction-based evaluation, in which input images are reconstructed to assess representational quality, and generative sampling, where new latent vectors are drawn to synthesize novel yet plausible waterleaf images. This dual capability aligns with the intended use of the architecture as both a reconstruction-driven representation model and a specialized image generator tailored to small-scale botanical datasets.

A schematic diagram of the architecture is provided in Fig. 8. where in the VAE-GAN hybrid: an input image is encoded into a latent vector via the Encoder, then reconstructed by the Decoder/Generator. The Discriminator evaluates both real and generated images, providing adversarial feedback, while three losses: KL divergence, feature reconstruction and adversarial loss guide training.

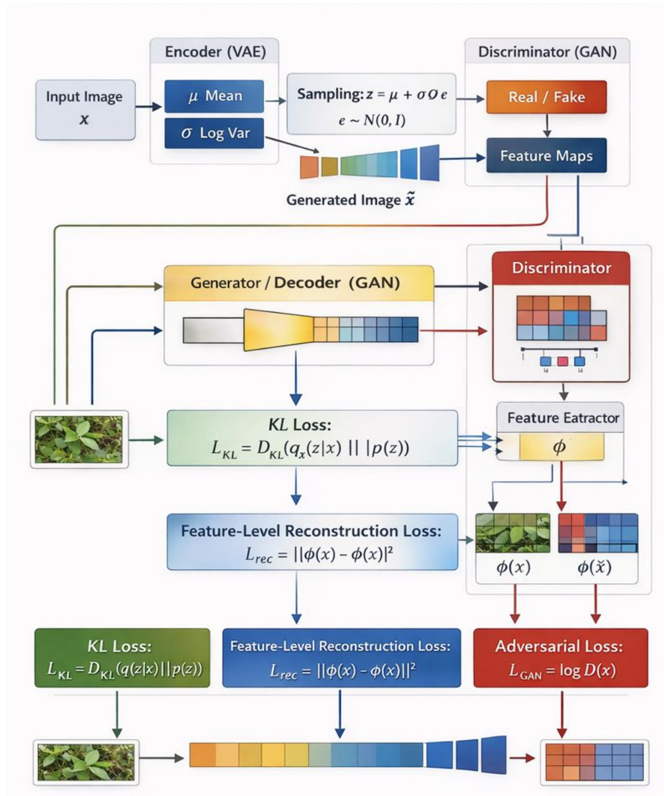


Fig. 8. VAE-GAN Architecture

F. Training Strategy and Loss Functions

The variational autoencoder (VAE) component was trained using a composite loss consisting of a reconstruction loss and a Kullback–Leibler (KL) divergence term. The reconstruction loss enforces pixel-wise similarity between the input image x and its reconstruction $\hat{x}$:

$$L_{\text{rec}} = \sum_{i,j,k} (x_{i,j,k} - \hat{x}_{i,j,k})^2 \tag{1}$$

The KL divergence regularizes the latent space by constraining the learned distribution toward a unit Gaussian prior. If the latent vector has dimension d with mean μ_i and standard deviation σ_i, the KL divergence is:

$$L_{\text{KL}} = -\frac{1}{2} \sum_{i=1}^{d} \left(1 + \log(\sigma_i^2) - \mu_i^2 - \sigma_i^2\right) \tag{2}$$

The adversarial (GAN) component employs a discriminator D to distinguish real images from generated samples $G(z)$, where z is a latent vector. The adversarial loss is:

$$L_{\text{adv}} = \frac{1}{N} \sum_{n=1}^{N} \left[\log D(x^{(n)}) + \log(1 - D(G(z^{(n)}))) \right] \tag{3}$$

The total training loss combines all three components:

$$L_{\text{total}} = L_{\text{rec}} + \beta L_{\text{KL}} + \gamma L_{\text{adv}} \tag{4}$$

Here, β and γ are weighting coefficients that balance the contributions of latent-space regularization and adversarial realism. Training was performed for 1000 epochs, with intermediate outputs sampled every 10 epochs to monitor convergence and visual quality.

G. Evaluation Metrics

The performance of the proposed VAE–GAN model was measured using both numbers and visual checks. For the numerical evaluation, we looked at how accurately the model could reconstruct images and how the losses changed during training. For the visual evaluation, we examined the generated images and compared them side by side with real plant images. Using both types of evaluation allowed us ensure the model performs well both mathematically and visually.

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