Integrated bio-inspired Design by AI:

Using cell structure patterns to train an AI model to explore topology design ideas

P5

BUILDING TECHNOLOGY MASTER TRACK

Faculty of Architecture and the Built Environment

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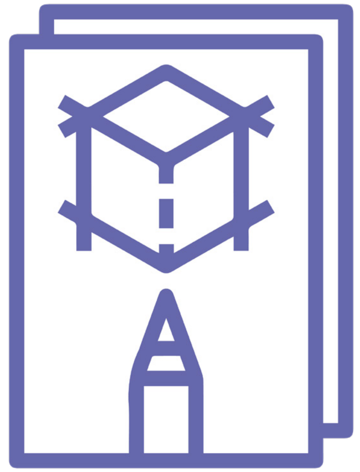
Faculty of Architecture
and the Built Environment

Content

Introduction

Design

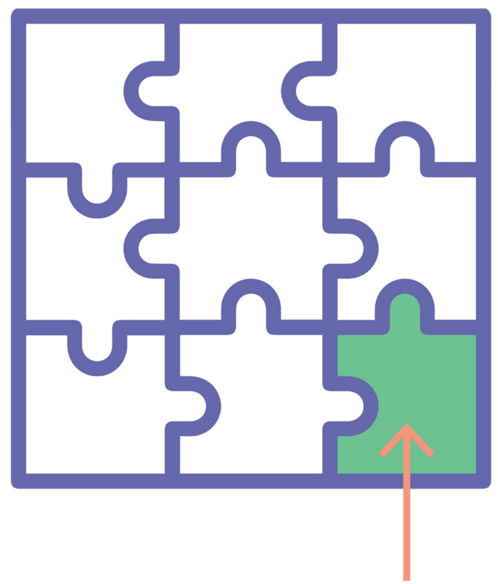
The major decisions regarding the building geometry, structure, massing are made during the **Conceptual Design**. These design decisions account for **75%** of the final product costs.



(Hsu, 2000)

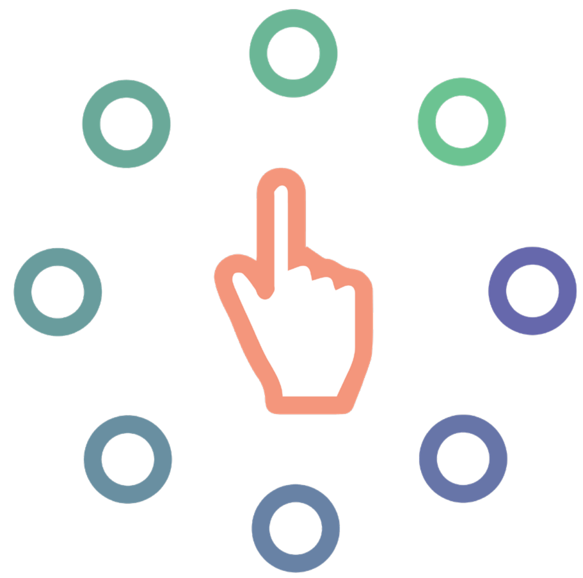
Design

Integrating the **structure** into the **Conceptual Design** phase can lead to several advantages, including reduced construction cost, architectural elegance, and is inherently safe.



Design

The computational tools have mainly been used for **analytical** purposes in **structural design**. Now, their role is becoming more versatile.



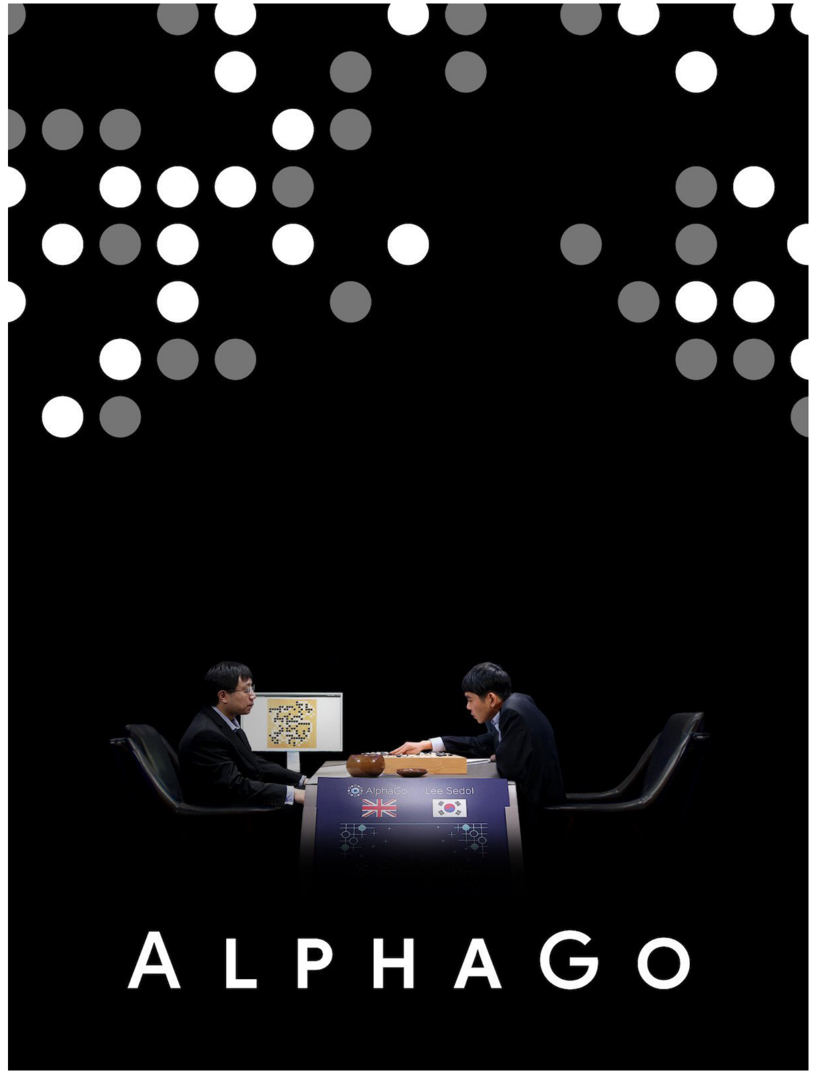
To aid the designers in the Conceptual Design phase, the computational tools must allow the exploration of a **variety** of solutions.

(Kicinger R. &., 2005)

Artificial Intelligence (AI)

“Artificial intelligence is that activity devoted to making machines ***intelligent****, and intelligence is that quality that enables an entity to function appropriately and with* ***foresight*** *in its environment.”*

(Nilsson, 2010)



DeepMind’s AlphaGo; was the first computer program to beat a professional Go player.

Source: https://www.amazon.com/AlphaGo-Lee-Sedol/dp/B077K9S2QH

Artificial Intelligence (AI)

Generative AI techniques can create new content by utilizing existing text, audio files, or images. With generative AI, computers detect the underlying pattern related to the input and produce similar content.

DALL.E; is a 12-billion parameter version of GPT-3 trained to generate images from text descriptions, using a dataset of text–image pairs.
Source: https://openai.com/blog/dall-e/

AI in Structural Design + Conceptual Design Phase

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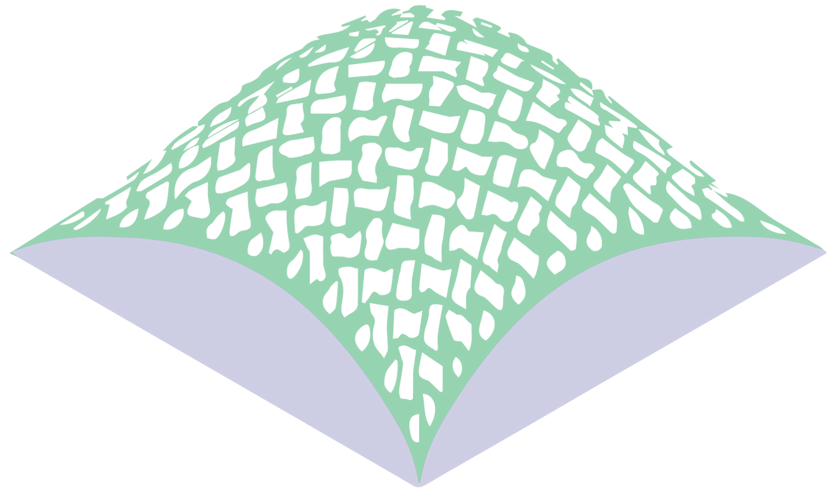
More Design Solutions to Explore?

Topology Exploration

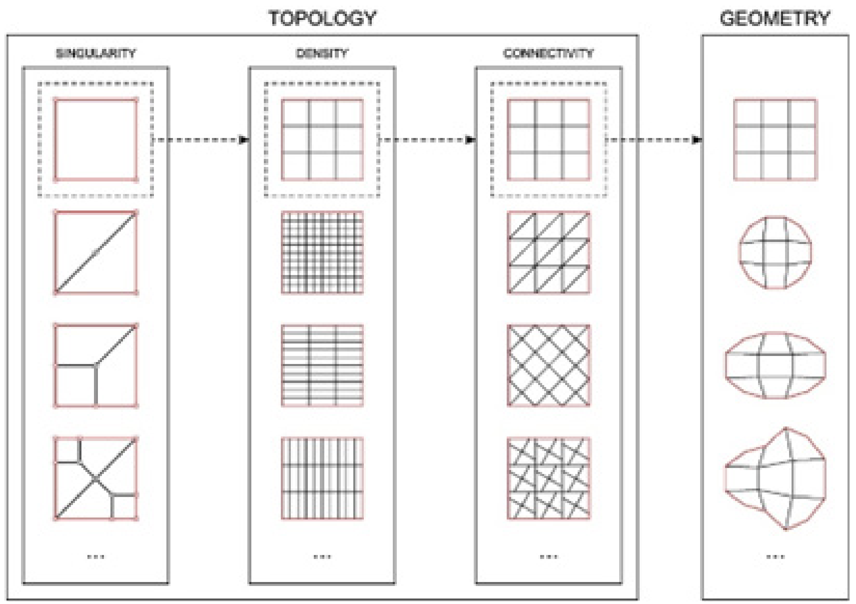
Topology in structure is the distribution of **material** in a space for a given set of constraints.

It only requires an **initial domain** - massing studies - to act upon, thus making it suitable for exploring and validating ideas in the early design Stages.

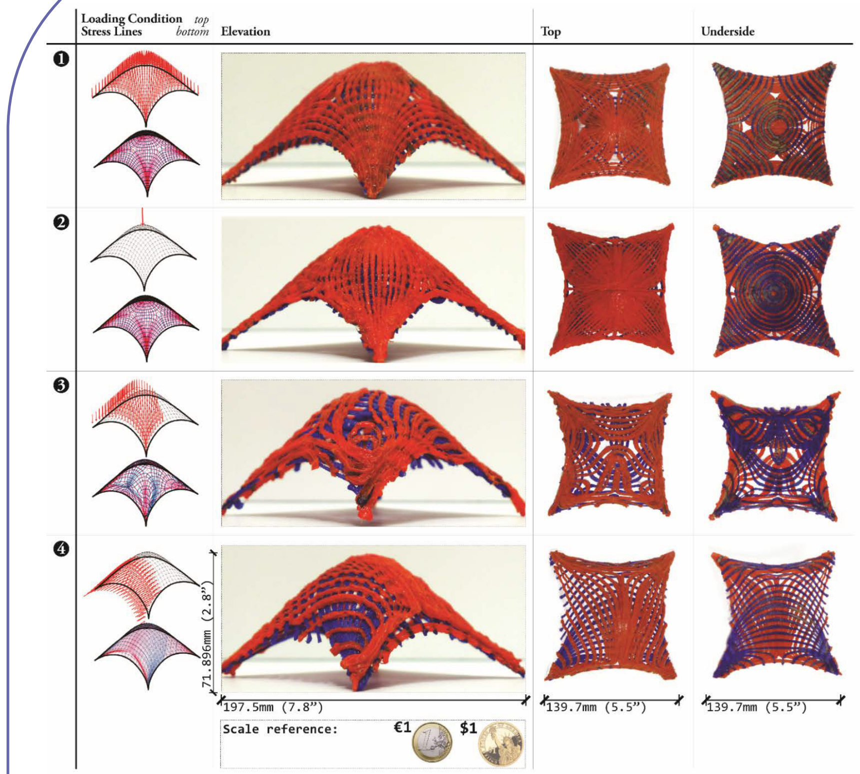


(Vinicius Mizobuti, 2019)

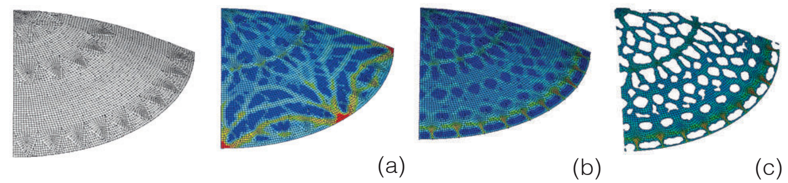
Topology in Shell Structures



Design space structure of a pattern's singularities, density, connectivity, and geometry, where each design space is defined by the design choices in the upstream spaces.
(Oval 2019)

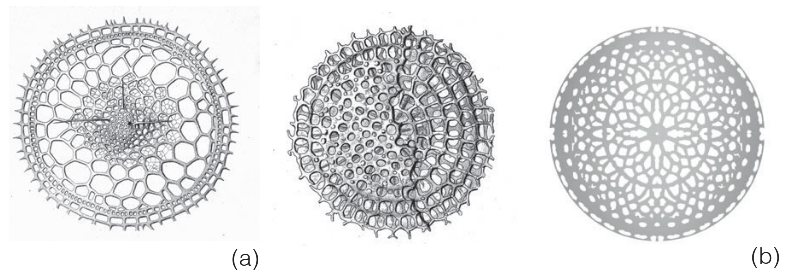


Fabrication results of stress-line-based topologies for various loading case: (1) Distributed load; (2) Central
point load; Asymmetrically distributed (3) vertical load and (4) lateral load (Kam-Ming Mark Tam, 2016)



Topology optimization of a circular shell structure with (a) highly
Discrete to (b) very dense point supports c) Choosing a density value

(Sigrid Adriaenssens, 2014)



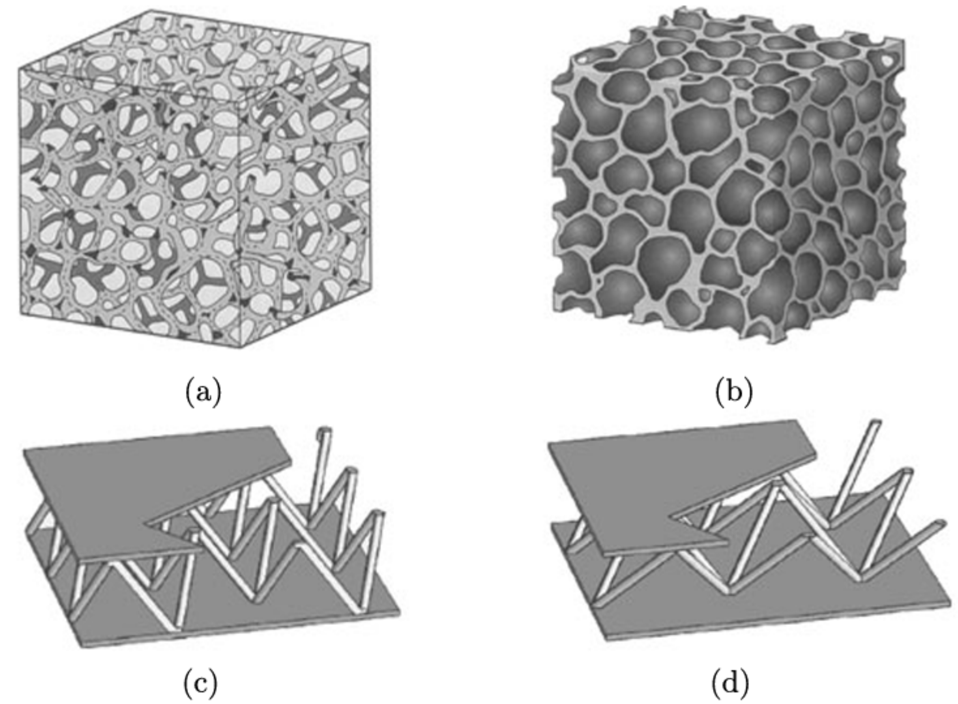
A resemblance between diatoms (Haeckel, 1904) (a) and the design proposal (b)

(Sigrid Adriaenssens, 2014)

Can we use Natural Patterns?

Nature shows us **optimized geometries**, determined by the necessity to develop **lightweight structures**.

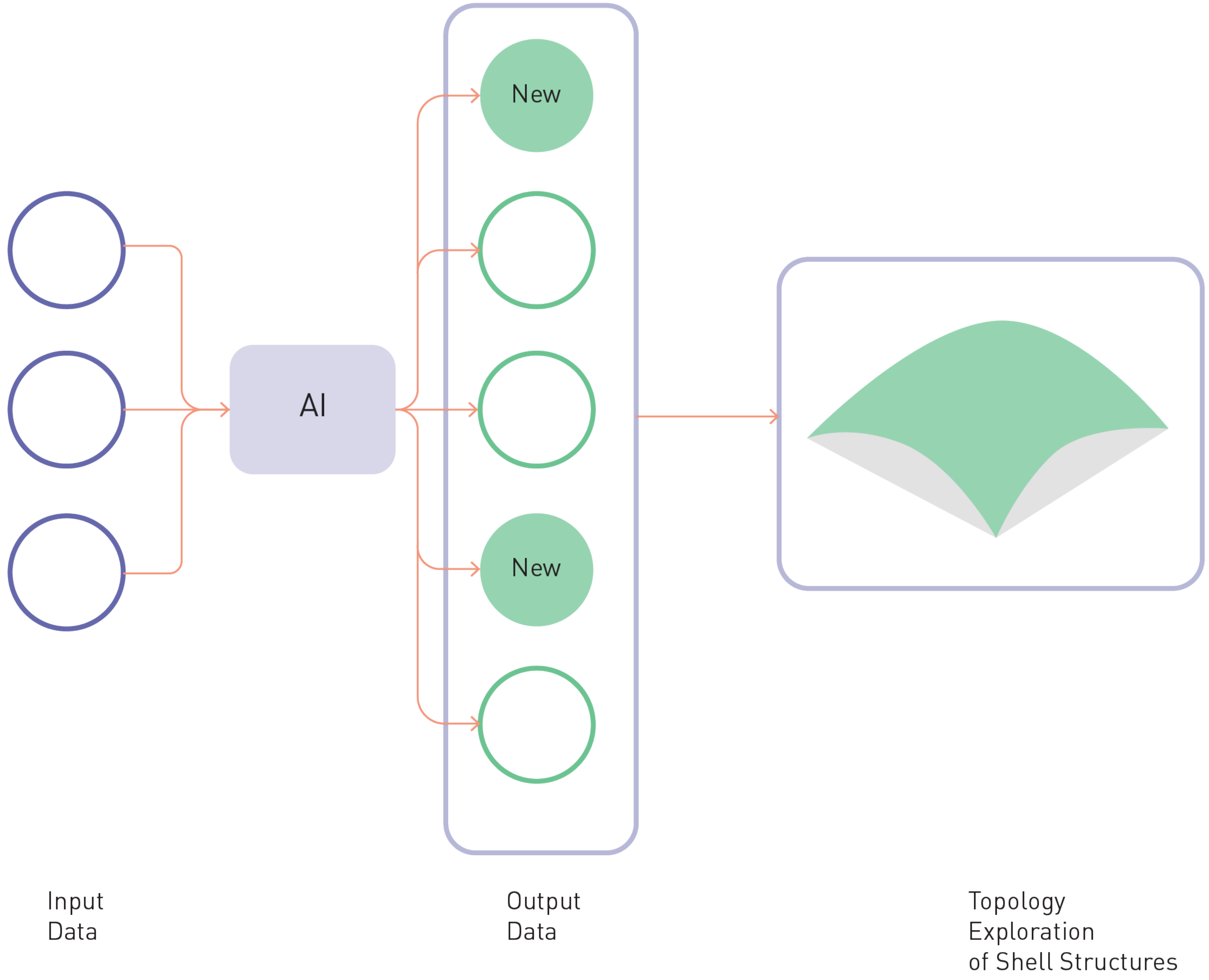
Many materials in nature are made up of **cellular solids**. Their cellular structure gives them unique properties that are exploited in a variety of applications.



Examples of different cellular solids: foams as (a) open-cell foams; (b) closed-cell foams; and periodic cellular solids (sandwich panels with core structures) as (c) tetrahedral lattice; (d) pyramidal lattice;

(Tian Jian Lu, 2013)

The Exploration



Main Research Question

How can AI extract useful information from a dataset of cellular solid structure patterns and reuse it to generate new patterns for structural design?

Research Sub-Question

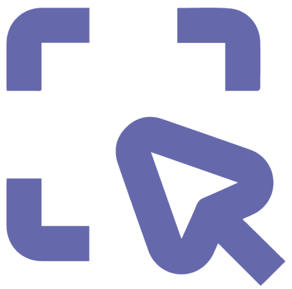
Sub Question 1: What are the selection criteria of the cellular solid patterns for creating the dataset?

Sub Question 2: How to artificially create a dataset?

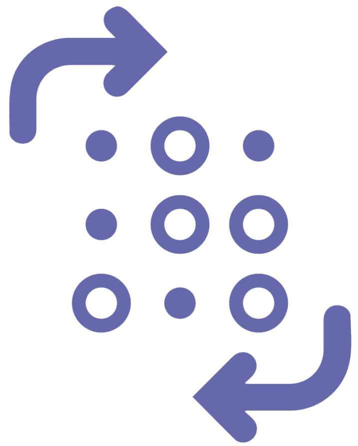
Sub Question 3: How can the AI-generated patterns be used to explore topology optimization design ideas? (Application)

Objectives

The workflow of the thesis can be used to explore **application of AI as a tool for generating conceptual design ideas**

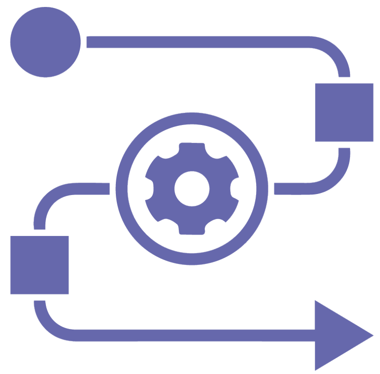


To select cellular solid patterns for creating the dataset to train the VAE model



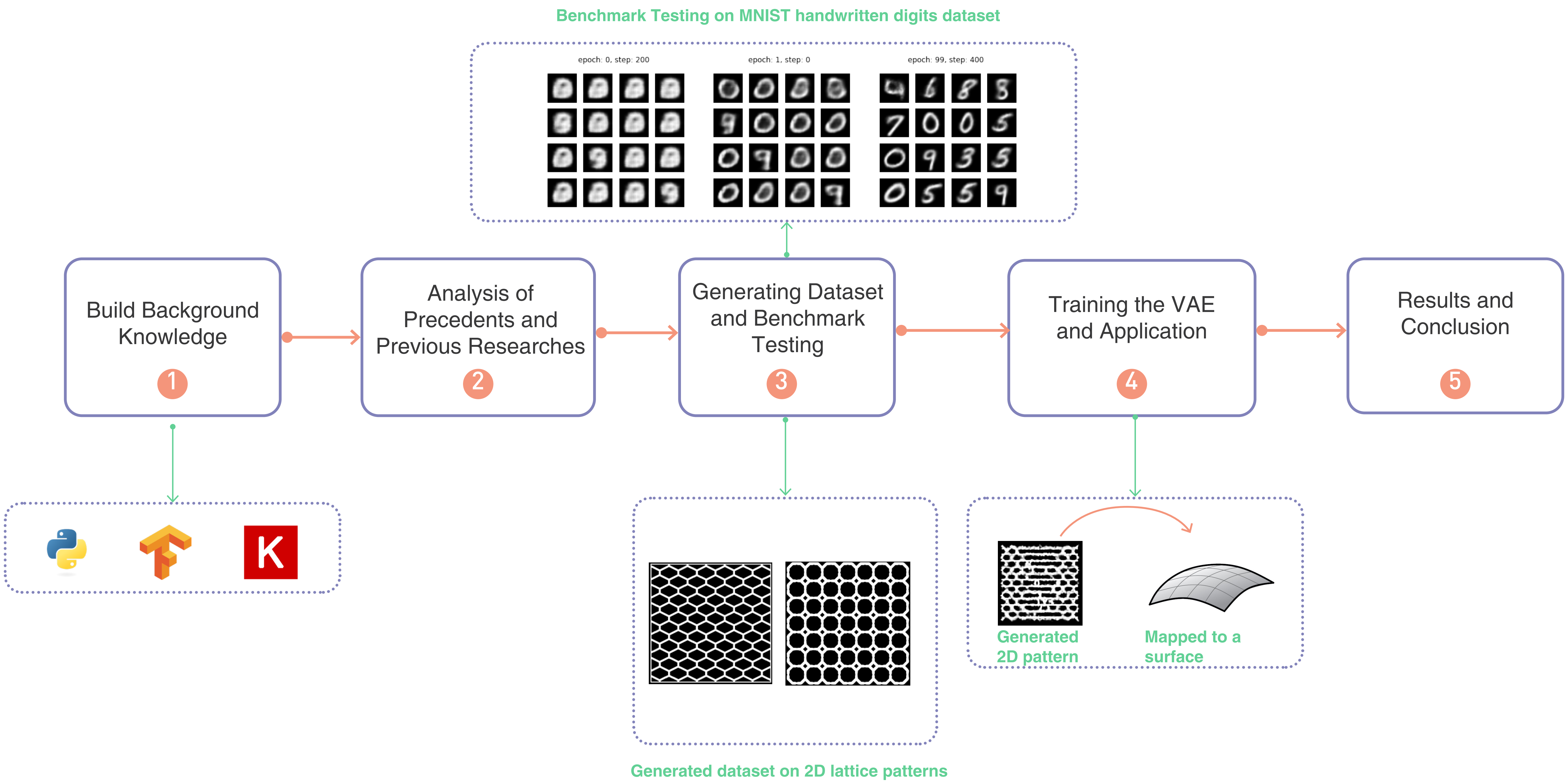
To generate a dataset of cellular solid structure patterns.

To train an VAE model on the generated dataset

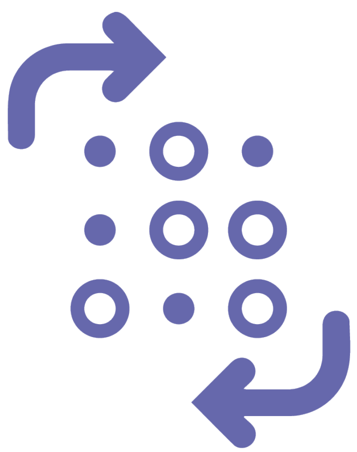


To create a workflow for application of the VAE as a design tool during conceptual   design for topology optimization.

Research Framework



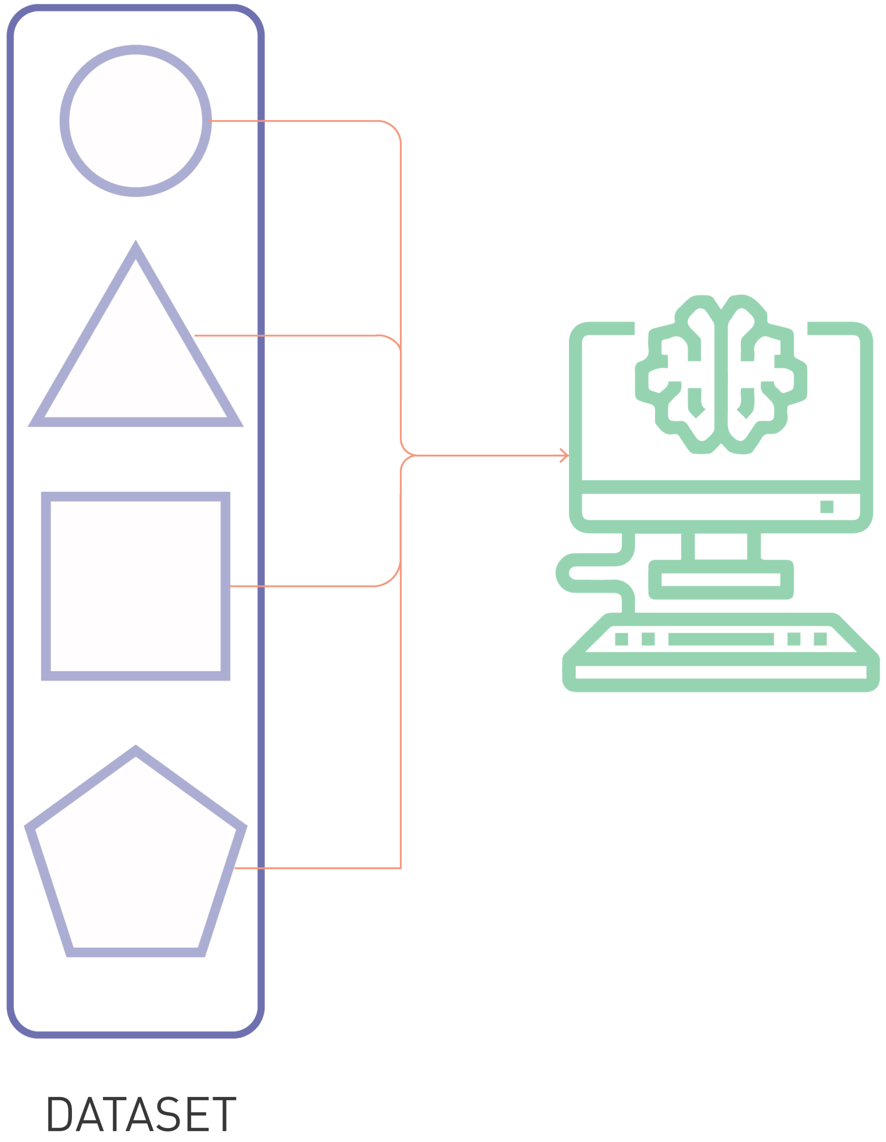
The workflow consists of 3 main stages



Dataset Generation → Training the VAE on the Dataset to generate new patterns → Application of the VAE as a design tool

Dataset Generation

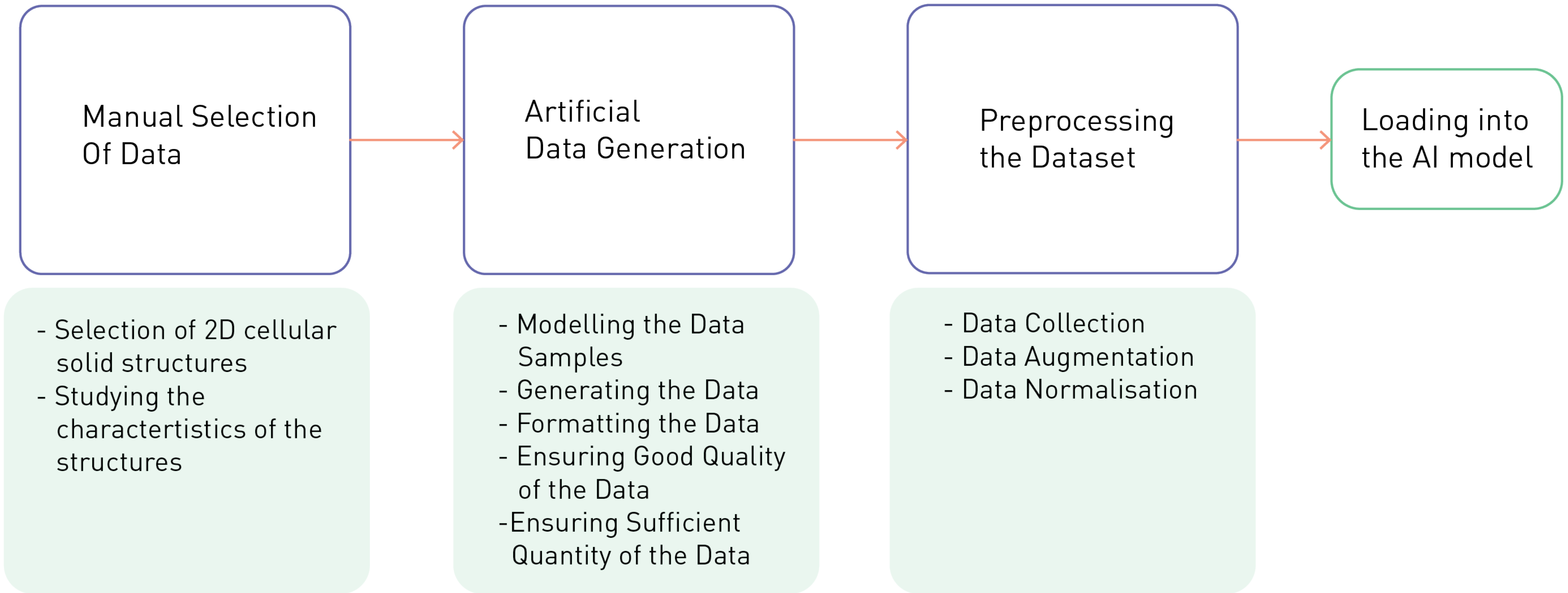
What is a Dataset?



Sources for Collecting Training Data

- Open Source
- Internet
- Artificial Data Generation

Stages in Dataset Generation



Manual Selection of Patterns

Cellular solid structures have been studied extensively in **shape morphing applications** as it provides stiffness to not deform under out-of-plane loads as well as flexibility.

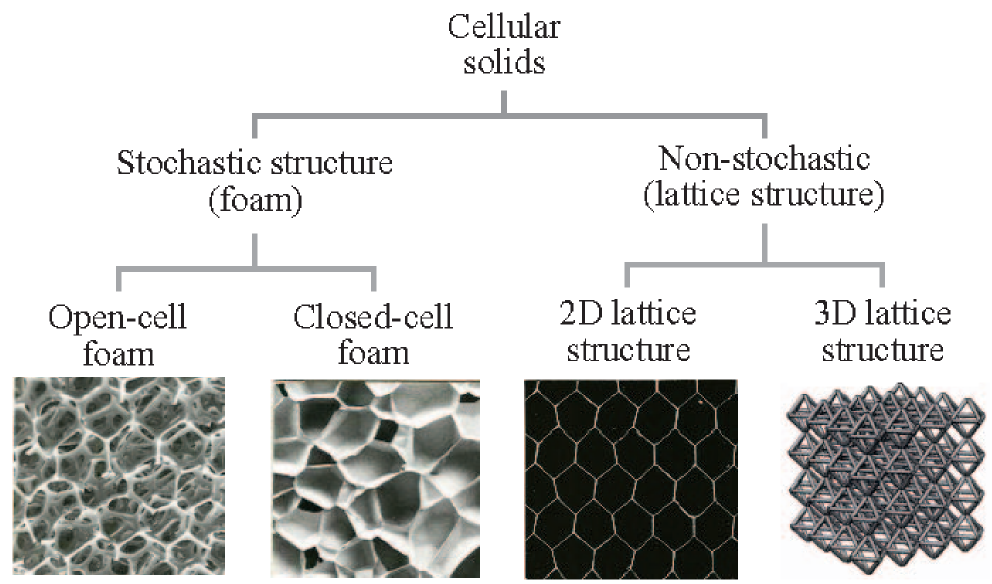
Timber gridshell with semi-regular kagome pattern of the center pompidou in Metz, France.
Source: https://www.flickr.com/photos/129231073@N06/24369656790

(Arredondo-Soto M, 2021)

Manual Selection of Patterns

Lattice materials are a subclass of cellular solids which are generated by tessellating a unit cell either in a plane or space.

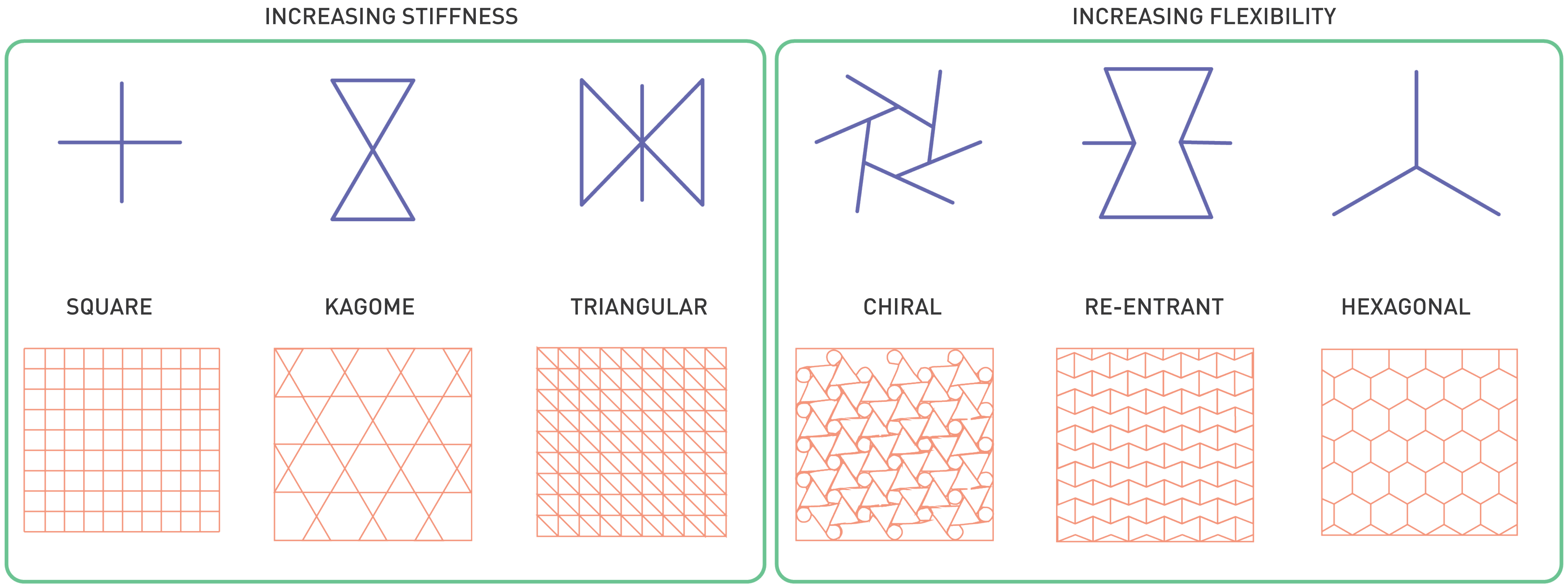
They have **high stiffness-weight ratio** because of which they have been extensively used in the lightweight applications and additive manufacturing.



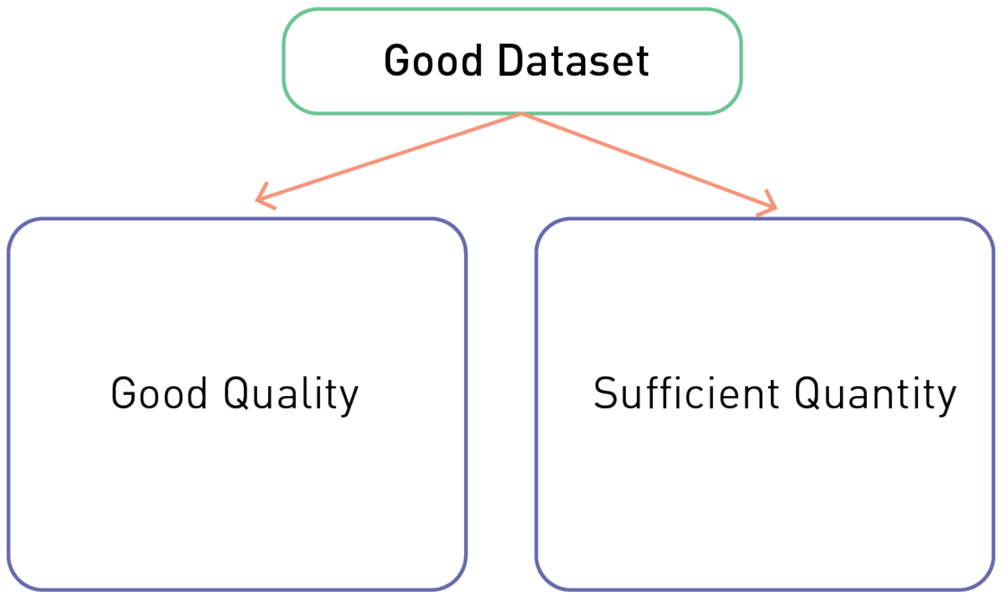
Categories of Cellular Solids.

Source: Design of lattice structure for additive manufacturing,
Wenjin Tao and Ming C. Leu, 2016,
International Symposium on Flexible Automation

Manual Selection of Patterns

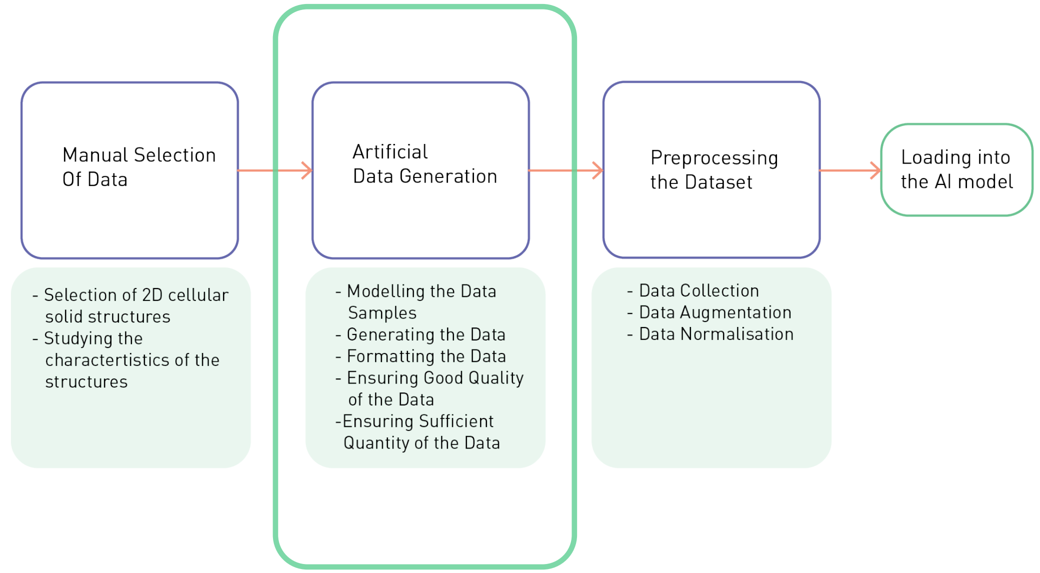


Model set-up for the Patterns



Model set-up for the Patterns

For a **good quality dataset** the data needs to be **continuous** (some recurring features in all the samples) and also **uniform** (Existence of similarity between some samples).
Generating a dataset from a parametric model ensures that those criteria are fulfilled.

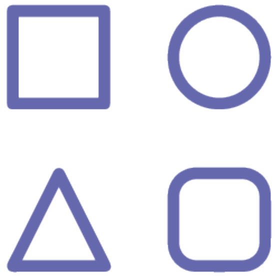
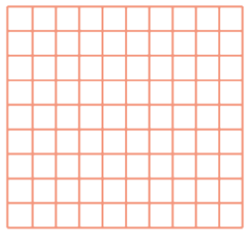
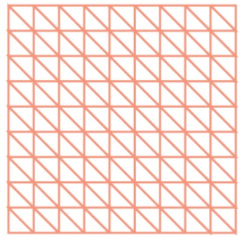
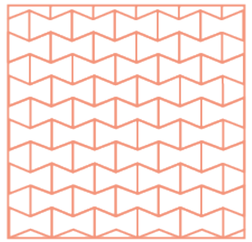
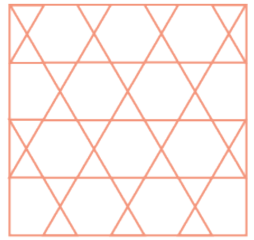
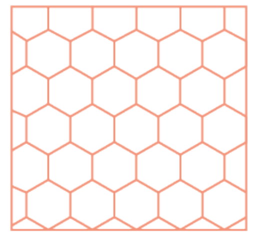


Model set-up for the Patterns

The first part of the parametric model set up was used to create the models bounded by the **range of variables** that were selected.

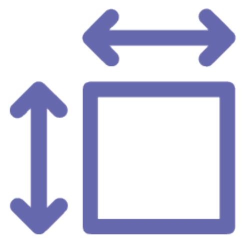
1. Type of the 2D lattice selected
2. The divisions of the patterns (size)
3. The thickness of the patterns
4. Transformation of the angle of the joints in the patterns

Model set-up for the Patterns

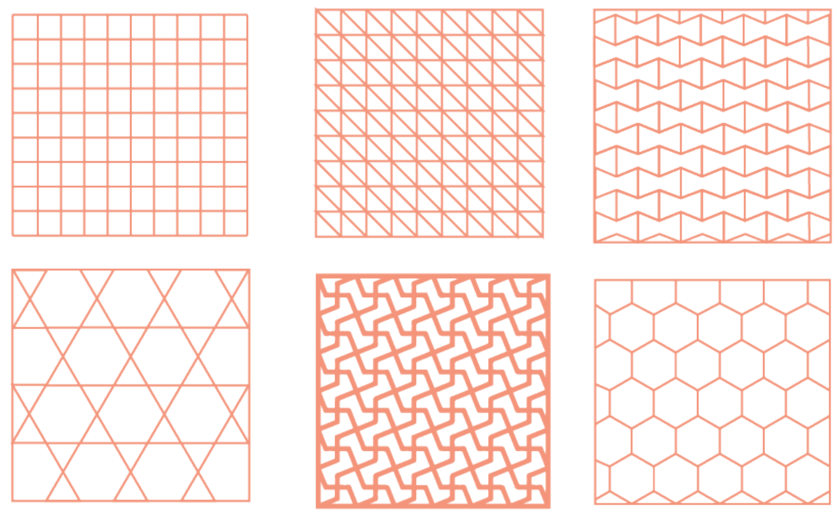
Variables	Application					
1) Types of patterns 	 Square	 Triangular	 Re-entrant	 Kagome	 Square-Chiral	 Hexagonal

Model set-up for the Patterns

2) Size of the Patterns



Patterns Applied to



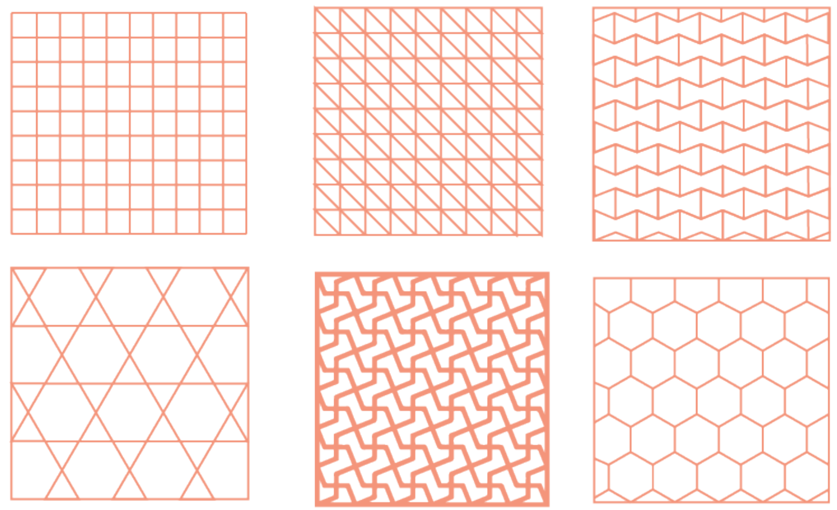
Variable		Domain
Square	U	[5, 10]
	V	[5, 10]
Triangular	U	[5, 10]
	V	[5, 10]
Re-entrant	U	[10,12]
	V	[10,12]
Kagome	U	[5, 8]
	V	[6, 9]
Square-Chiral	U	[8,10]
	V	[8,10]
Hexagonal	U	[8,10]
		[8,10]

The bounds of the variables were selected to control the total number of variations of the patterns for each unique pattern

Model set-up for the Patterns

3) Thickness

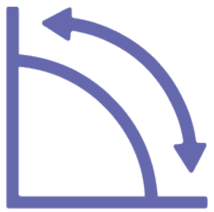
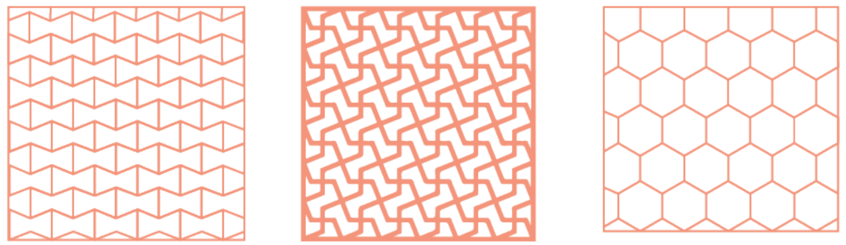
Patterns Applied to



Variable		Domain
Square	(t)	[50,60]mm
Triangular	(t)	[50,60]mm
Re-entrant	(t)	[50,60]mm
Kagome	(t)	[50,60]mm
Square-Chiral	(t)	[50,60]mm
Hexagonal	(t)	[50,60]mm

The bounds of the variables were selected to control the total number of variations of the patterns for each unique pattern

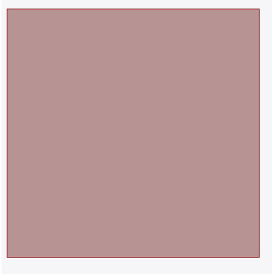
Model set-up for the Patterns

	Patterns Applied to	Variable		Domain
4) Parameter for Transformation 		Re-entrant	(a)	[0.6,0.7]
		Square-Chiral	(a)	[0.5,0.6]
		Hexagonal	(a)	[0.2,0.3]

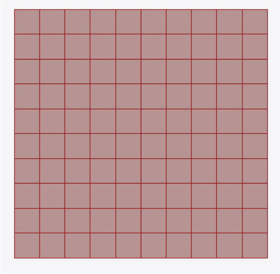
The bounds of the variables were selected to control the total number of variations of the patterns for each unique pattern

Model set-up for the Patterns

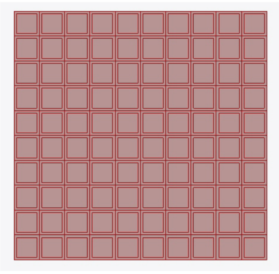
Square Lattice Patterns



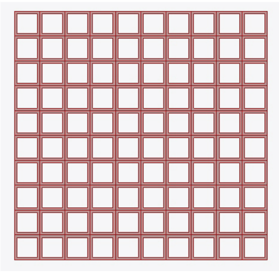
1. Creating a surface



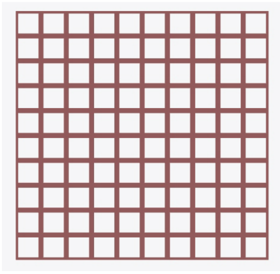
2. Creating Square Panels



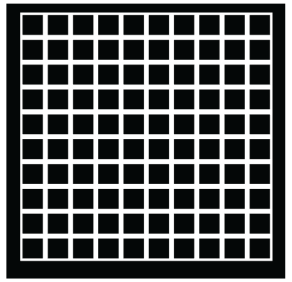
3. offset curve for Thickness



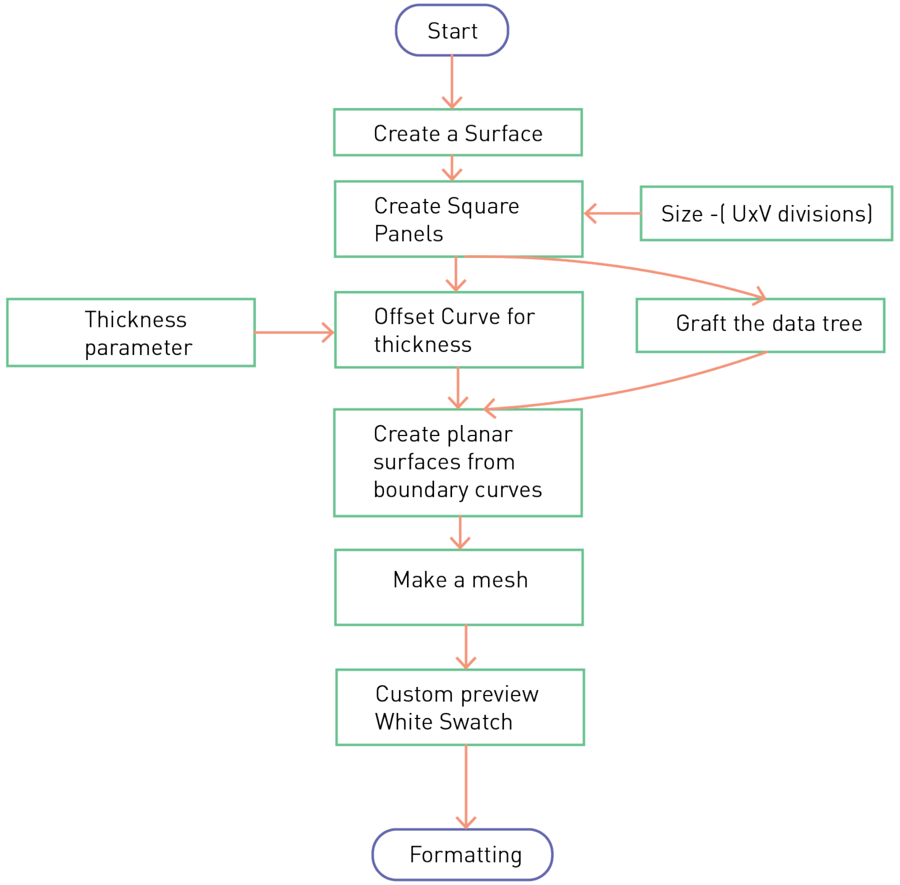
4. Create planar surfaces



5. Convert into a mesh

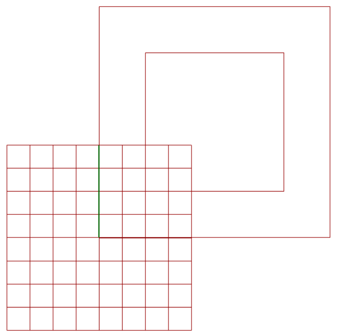


6. Visualise in
black and white



Model set-up for the Patterns

Square Chiral Lattice Patterns



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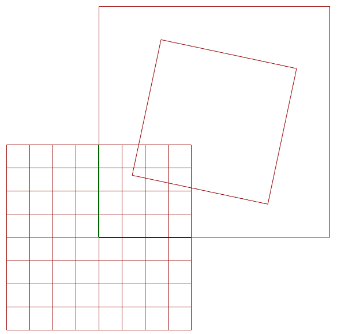

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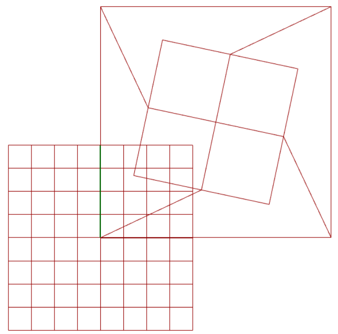

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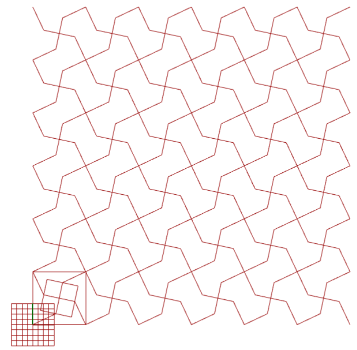

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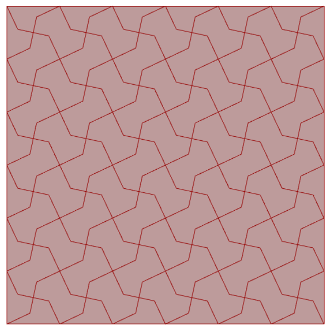

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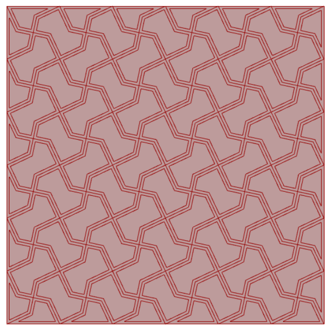

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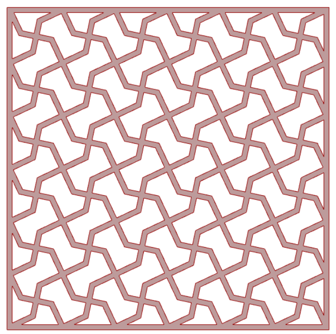

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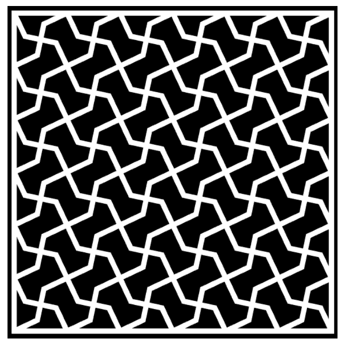

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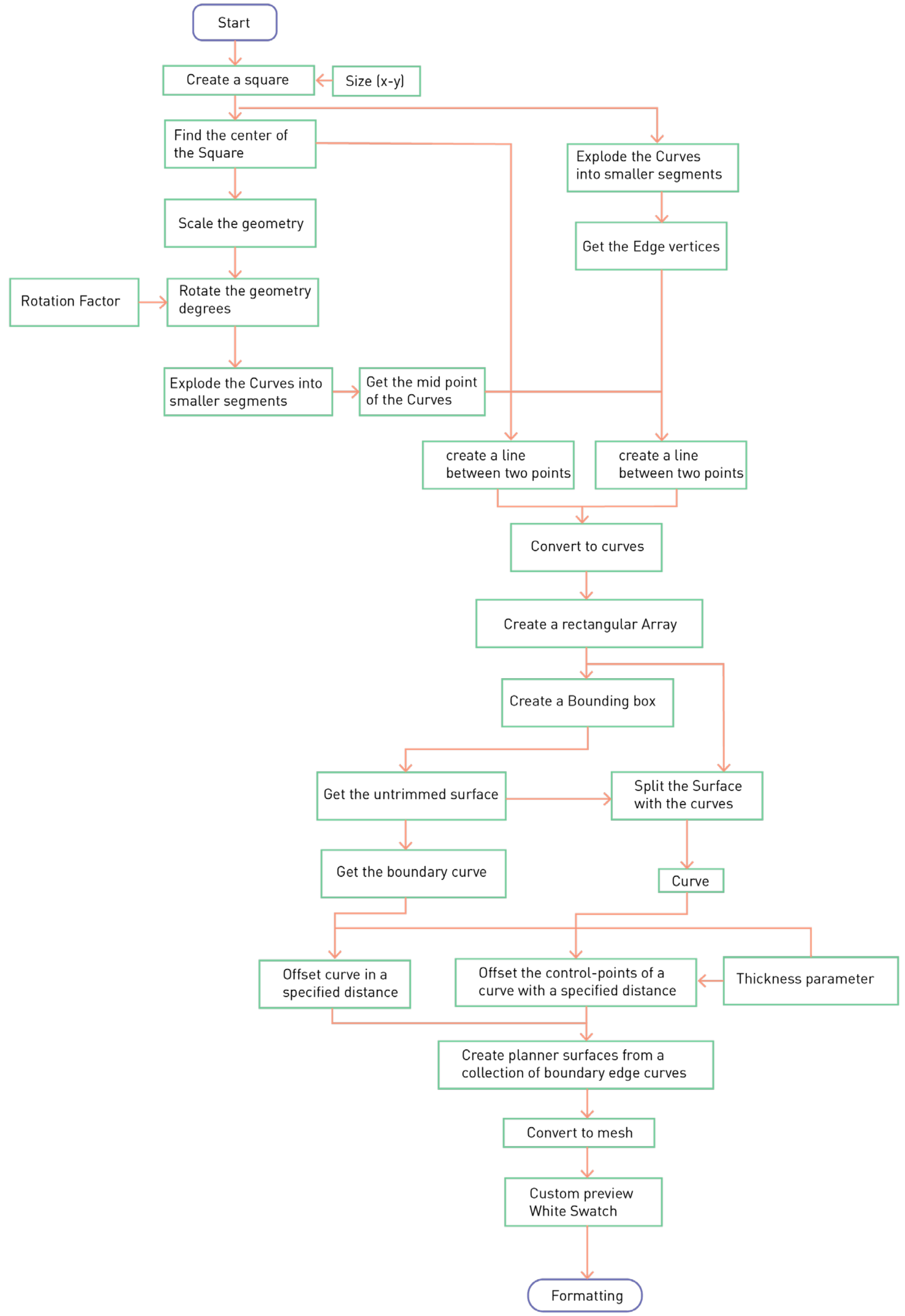
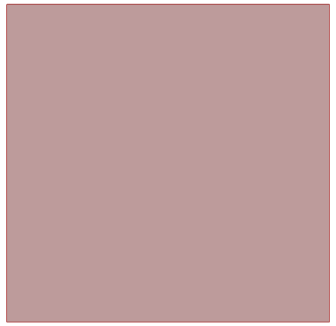


Model set-up for the Patterns

Kagome Lattice Patterns



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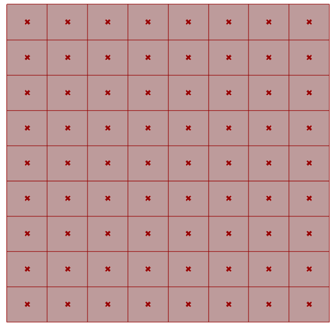

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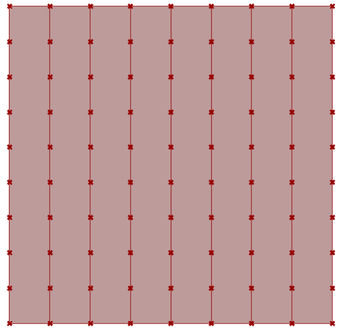

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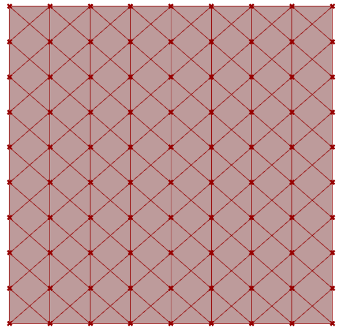

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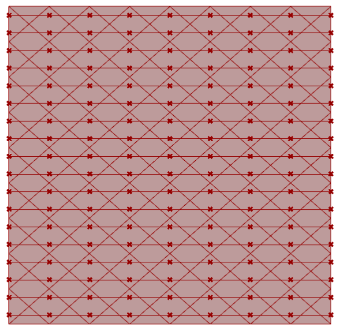

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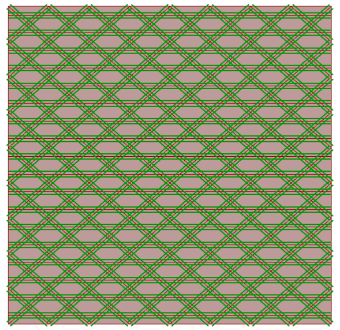

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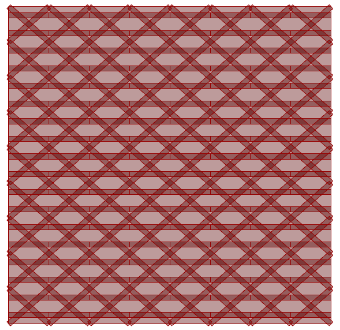
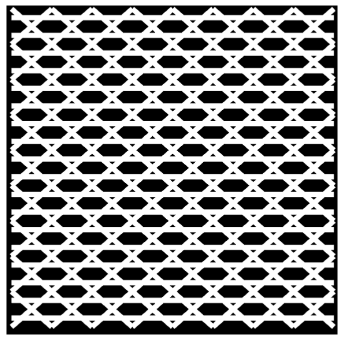
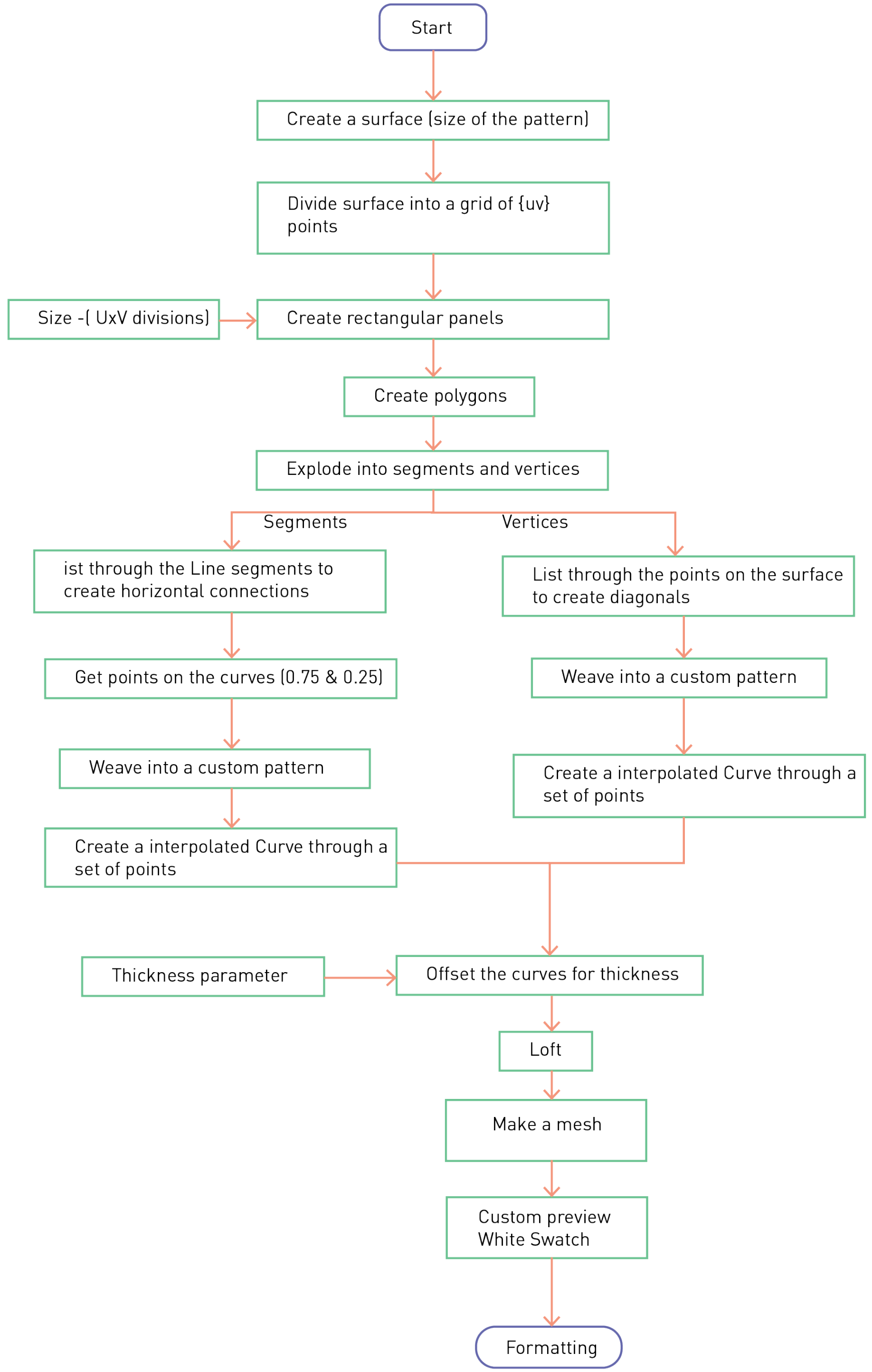


7

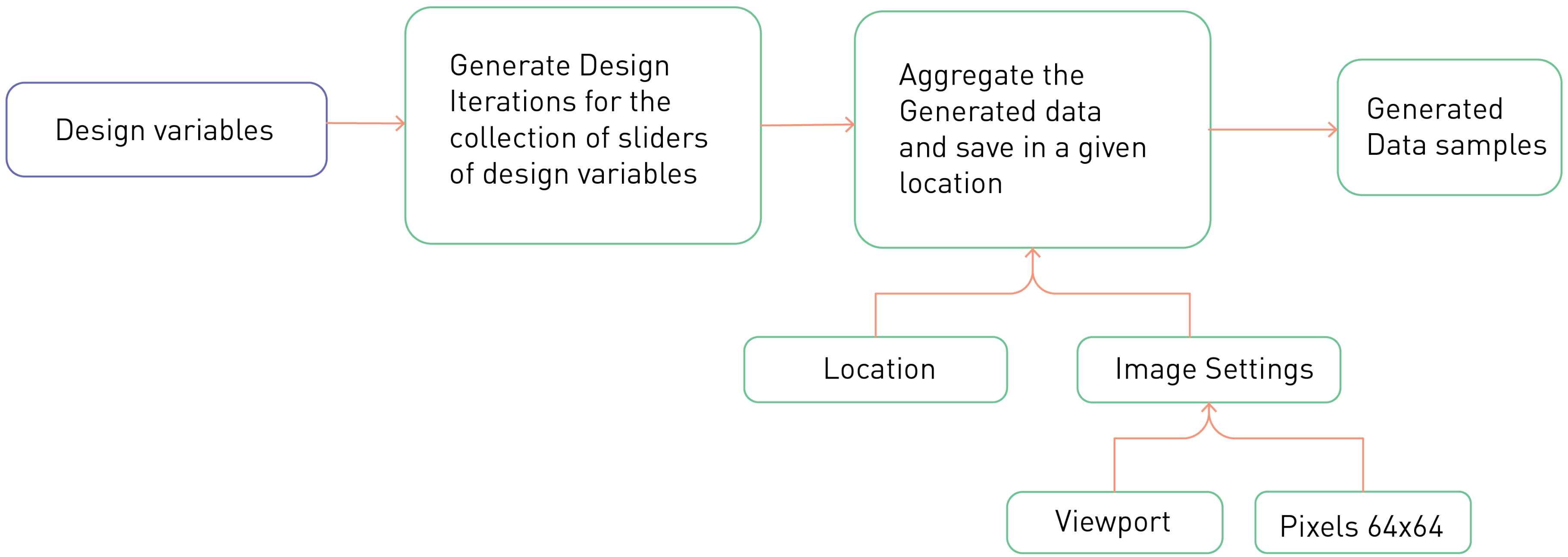


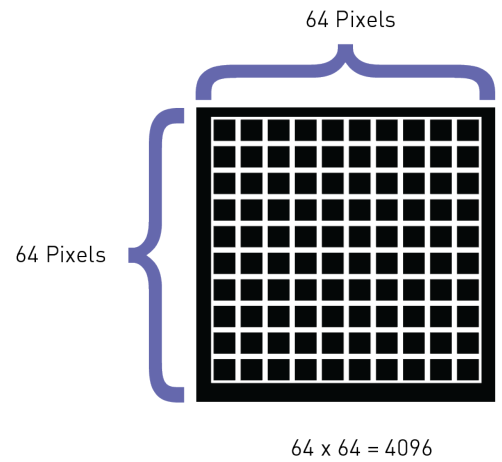
8



Model set-up for the Patterns

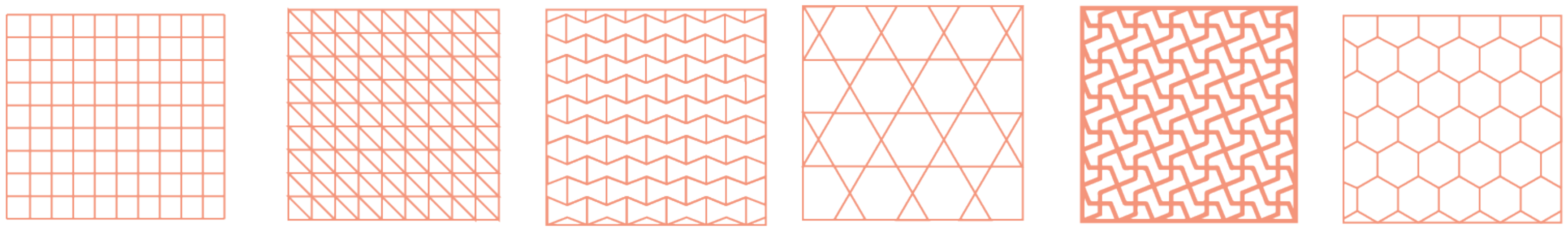
Formatting the Data Samples



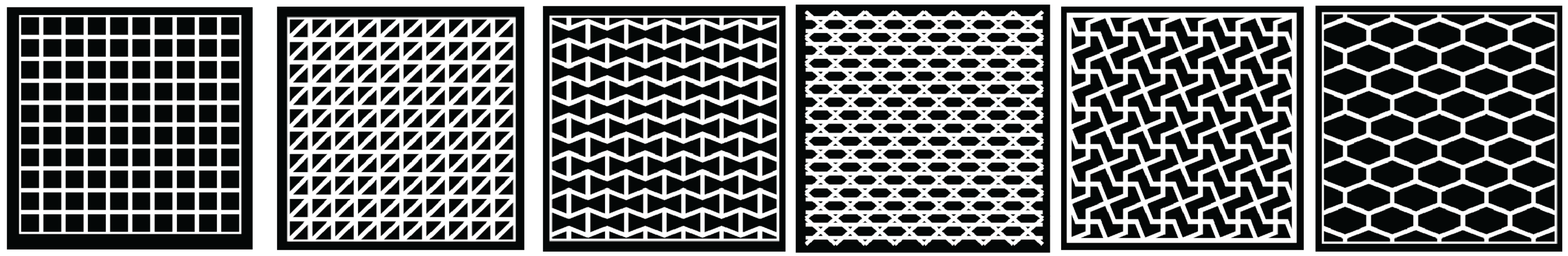


Model set-up for the Patterns

Formatting the Data Samples



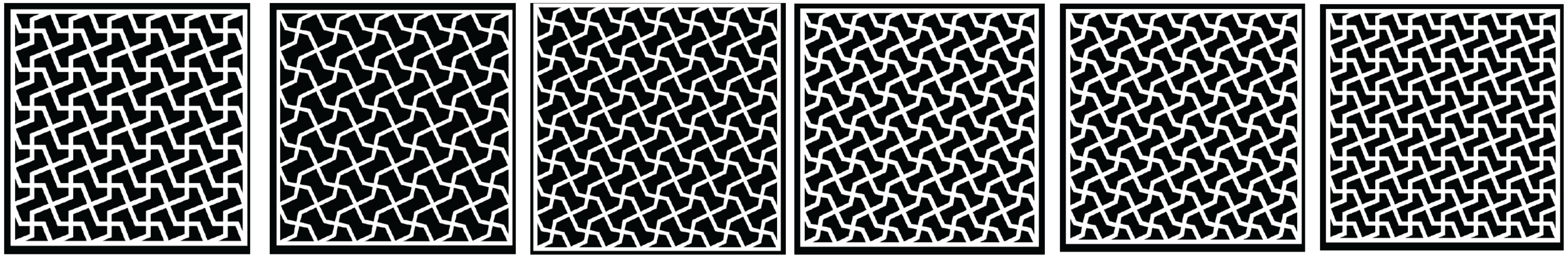
	Square	Triangular	Re-entrant	Kagome	Square-Chiral	Hexagonal
Total number of Iterations	126	126	198	176	198	198



examples of all the Lattice pattern exported as 64x64 resolution greyscale images

Model set-up for the Patterns

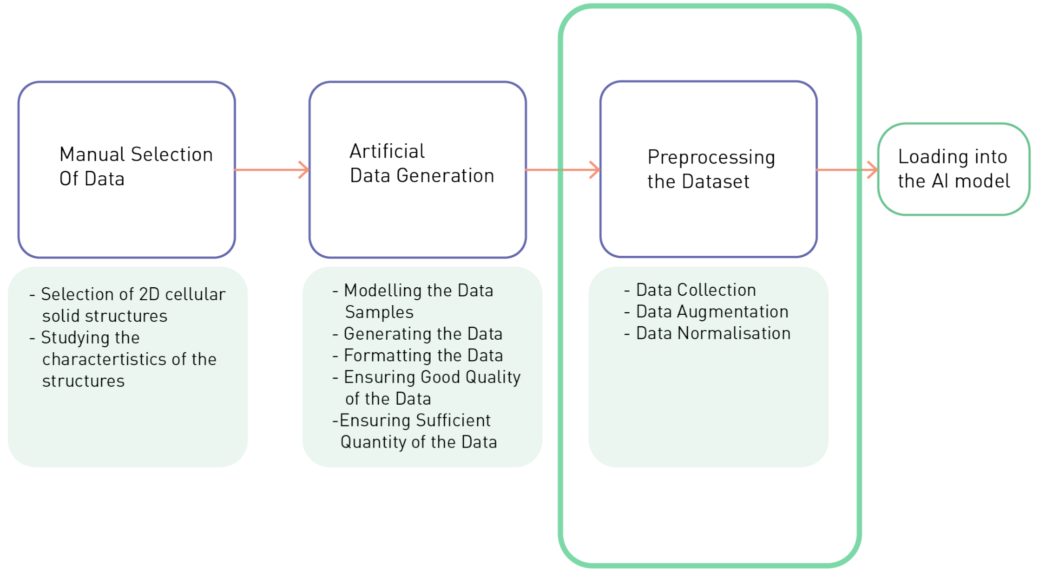
Formatting the Data Samples



A few Iterations of the Square-Chiral lattice pattern

Preprocessing the dataset

To have **sufficient quantity** of data in the dataset and to ensure that the AI can understand the data, the dataset needs to be **preprocessed.**

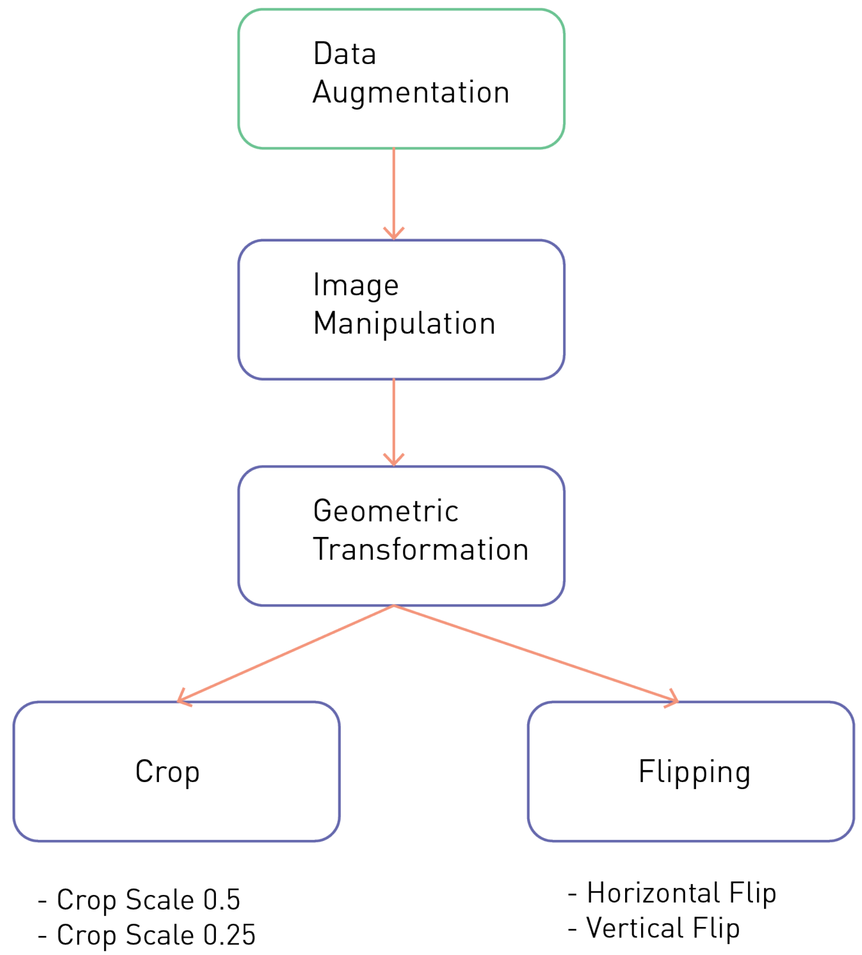


1. Data Augmentation
2. Data Reshaping
3. Data Normalisation
4. Splitting the dataset

Preprocessing the dataset

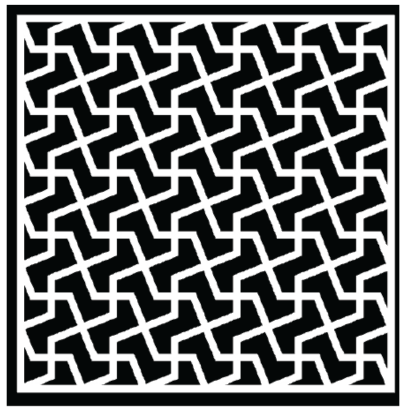
Data Augmentation

Data Augmentation provides a solution to the problem of limited data (Shorten 2019) by helping **increase the data population** though transformations.



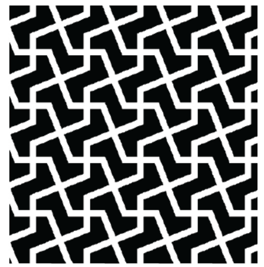
Preprocessing the dataset

Data Augmentation

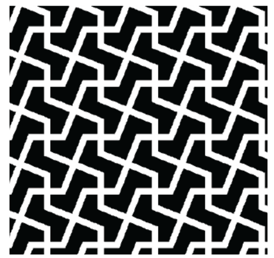


Original Data Sample

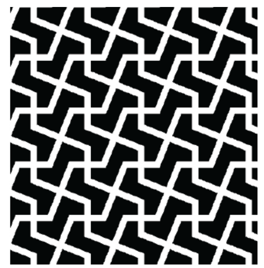
Crop 0.25



Crop 0.5



Flipped Horizontal



Flipped Vertical

Total Samples of original Dataset = 1022

Total Samples of Augmented Dataset = 4089

Preprocessing the dataset

Data Reshaping

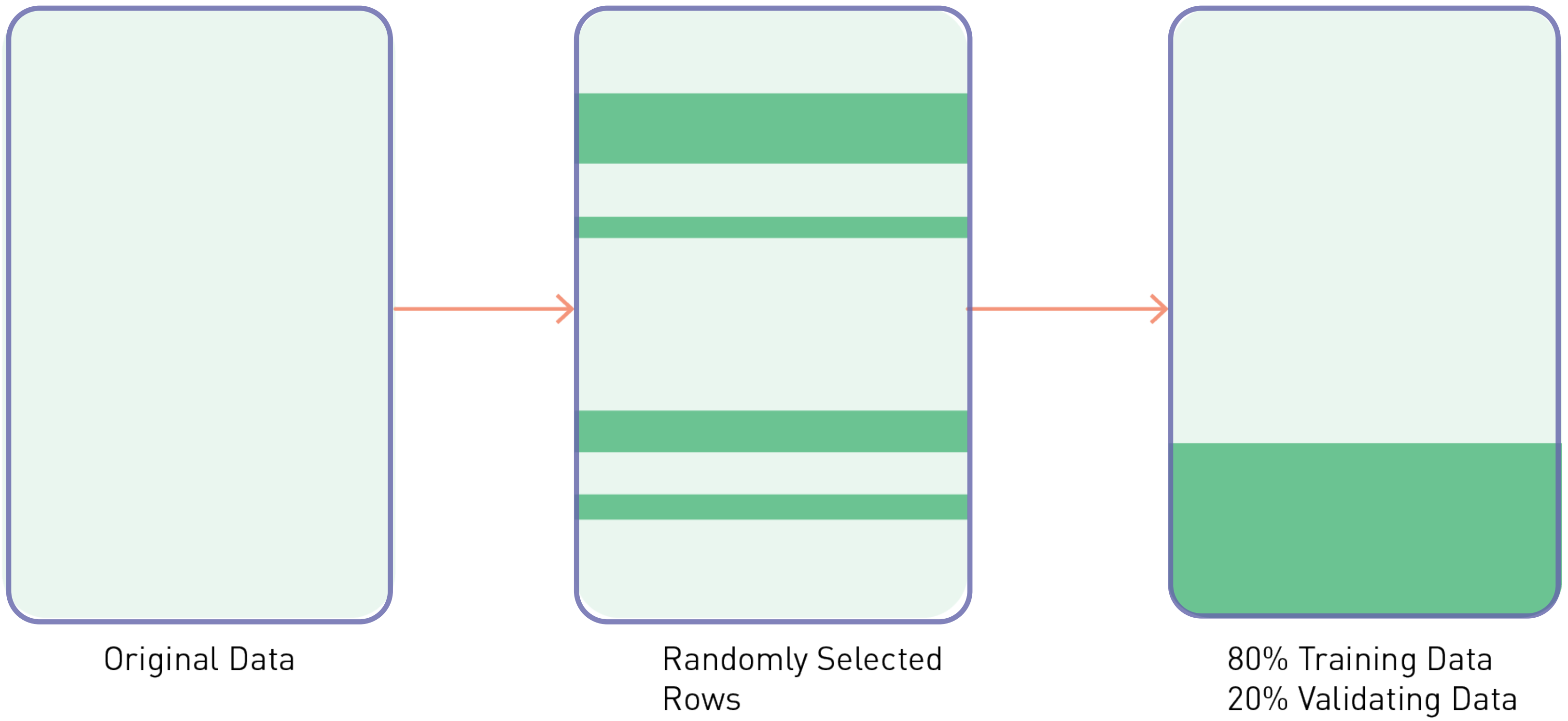
Dataset reshaped to a 4-dimensional NumPy array from a 3-dimensional array

Data Normalisation

Normalization is changing the range of pixel intensity values of the images.

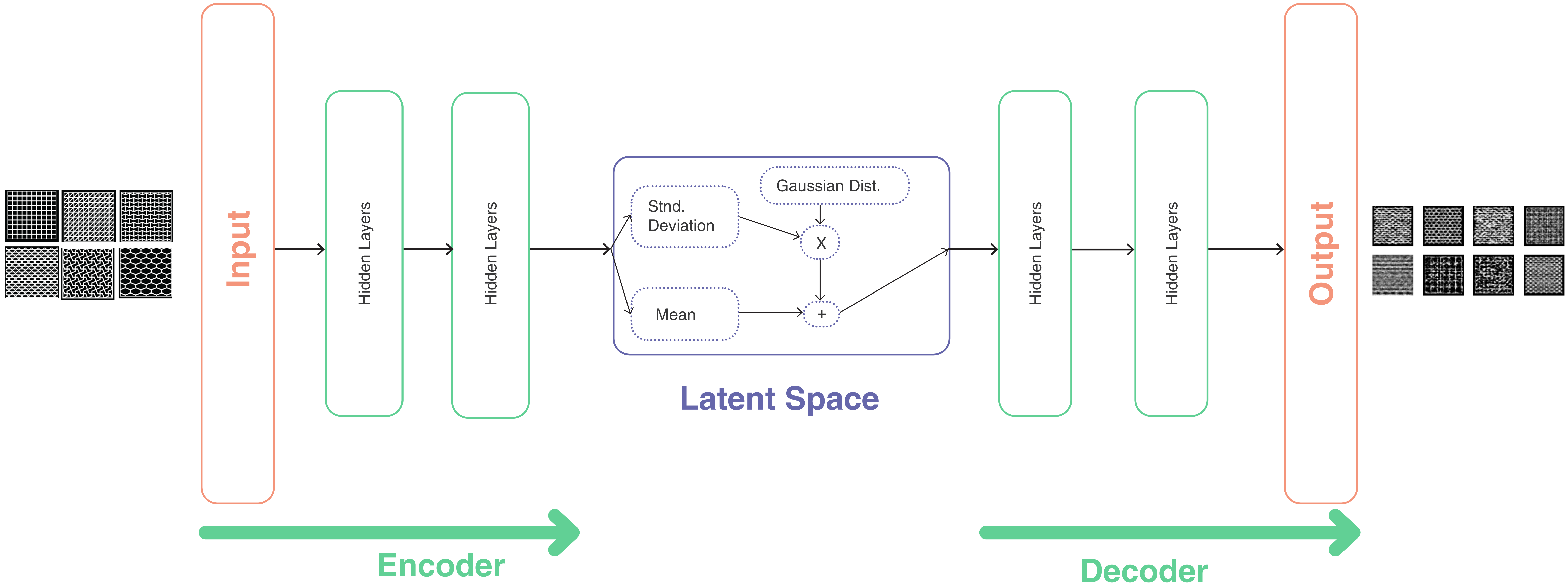
Preprocessing the dataset

Splitting the Dataset

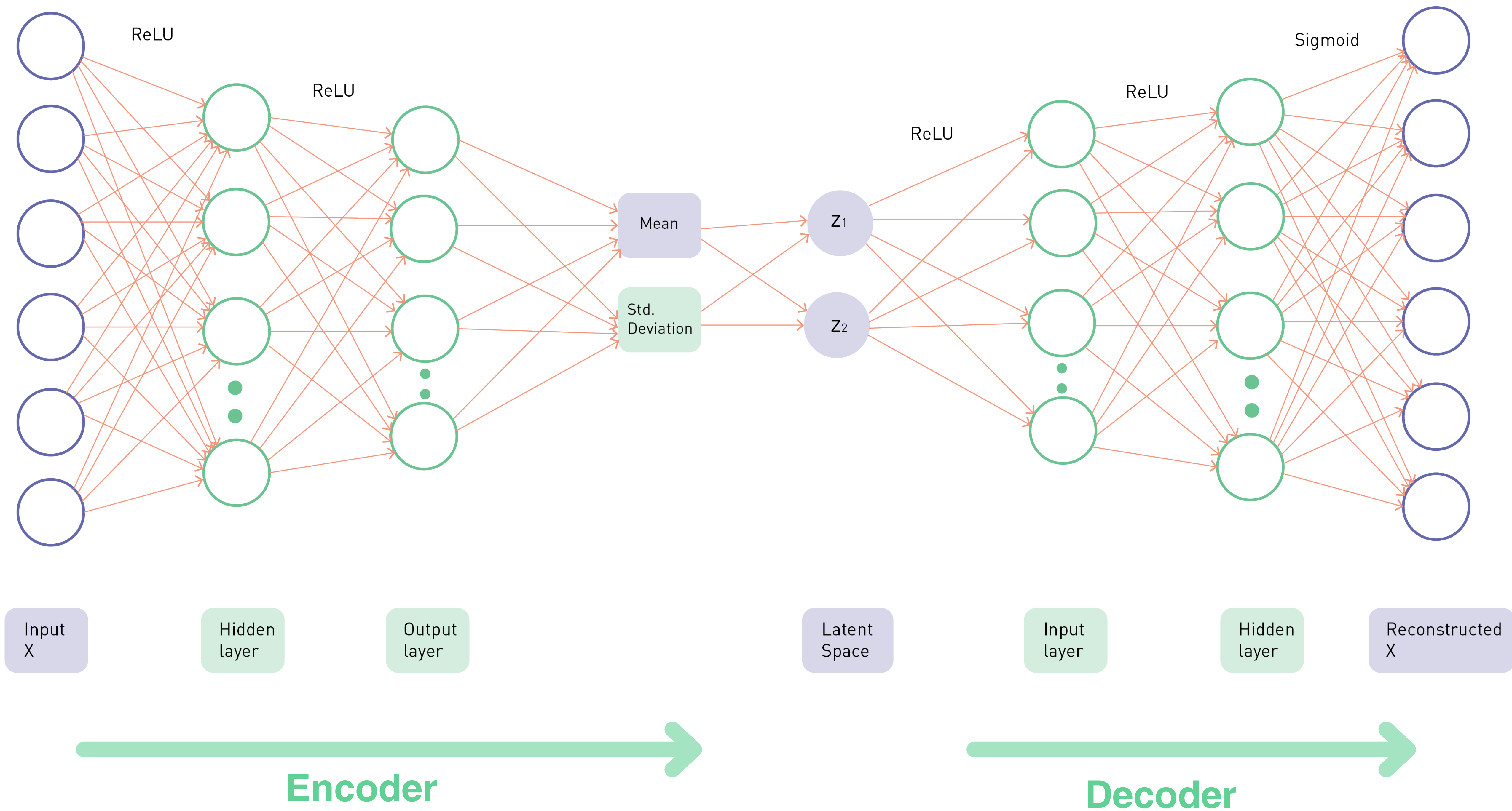


Training the VAE

VAE Architecture

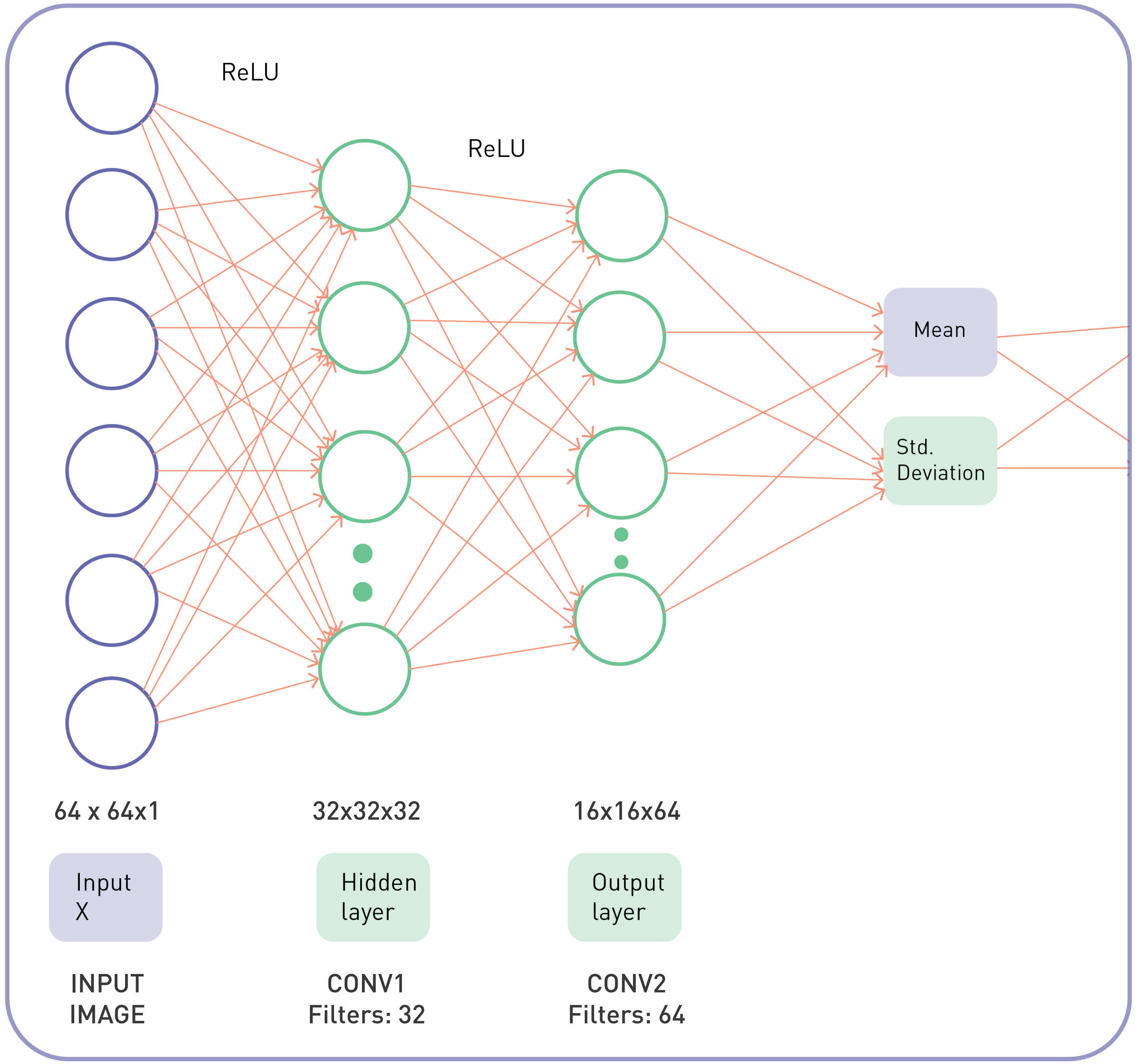


VAE Architecture

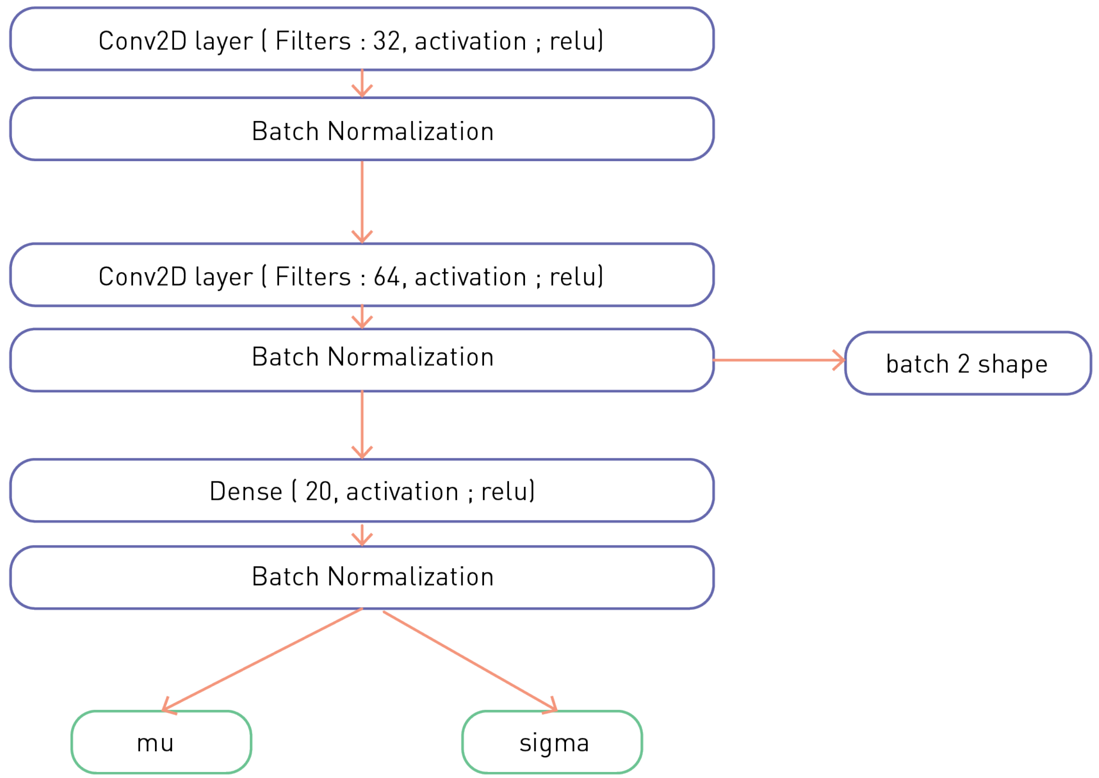


VAE

Encoder



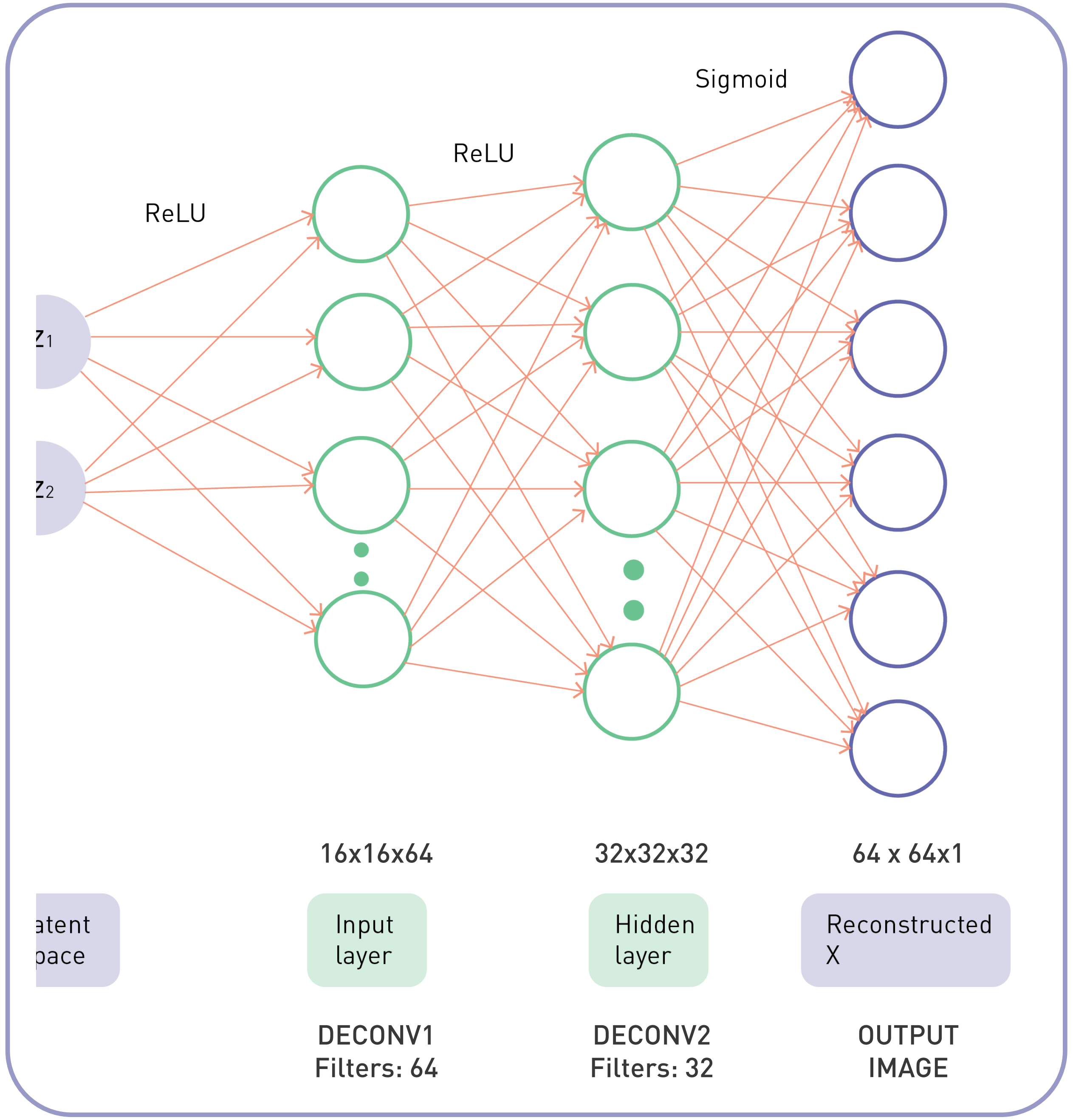
ReLU
ReLU
Mean
Std.
Deviation
64 x 64x1
32x32x32
16x16x64
Input
X
Hidden
layer
Output
layer
INPUT
IMAGE
CONV1
Filters: 32
CONV2
Filters: 64

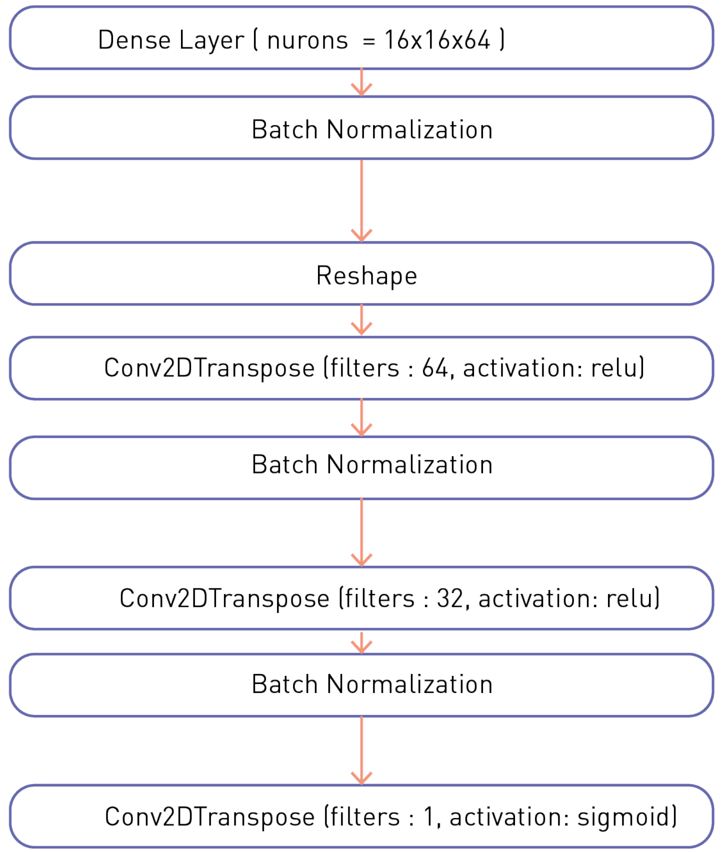


Conv2D layer (Filters : 32, activation ; relu)
Batch Normalization
Conv2D layer (Filters : 64, activation ; relu)
Batch Normalization
batch 2 shape
Dense (20, activation ; relu)
Batch Normalization
mu
sigma

VAE

Decoder


Sigmoid
ReLU
ReLU
z1
z2
16x16x64
32x32x32
64 x 64x1
atent
pace
Input
layer
Hidden
layer
Reconstructed
X
DECONV1
Filters: 64
DECONV2
Filters: 32
OUTPUT
IMAGE


Dense Layer (nurons = 16x16x64)
Batch Normalization
Reshape
Conv2DTranspose (filters : 64, activation: relu)
Batch Normalization
Conv2DTranspose (filters : 32, activation: relu)
Batch Normalization
Conv2DTranspose (filters : 1, activation: sigmoid)

VAE

Loss Function

To ensure that the Gaussian distribution that has been sampled aren't too far apart, a **regularization term** is added which is the Kullback-Leiber Divergence (KLD).

To measure the reconstruction loss of the VAE, **Binary-Cross Entropy** loss (BCE) has been used.

Both these terms are added to calculate the **total loss** of the model training

VAE

Training

After the Encoder, Sampling and the Decoder, the next step is to train the VAE model.
The **hyperparameters** such as **epochs** and **learning rate** , **batch size** of the model is controlled during this stage.

The number of **epochs** is the number of times the entire dataset will be passed through the VAE model.

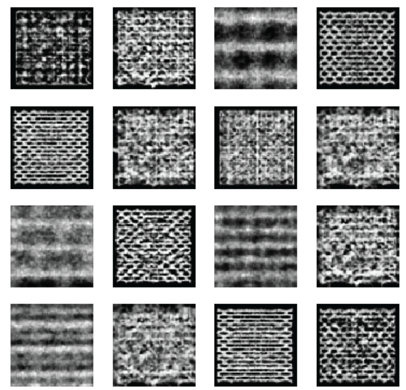
The optimizer is also specified with the learning rate of the model. **Learning rate** is the steps in which the model learns.

VAE

Training Results

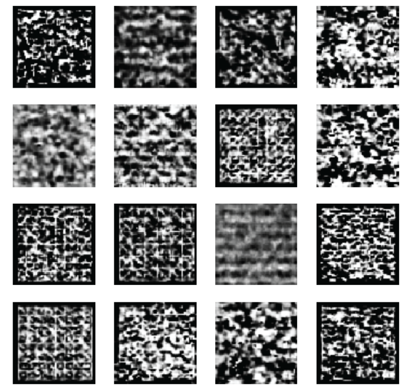
Iteration: Latent Dimension, Learning Rate

1



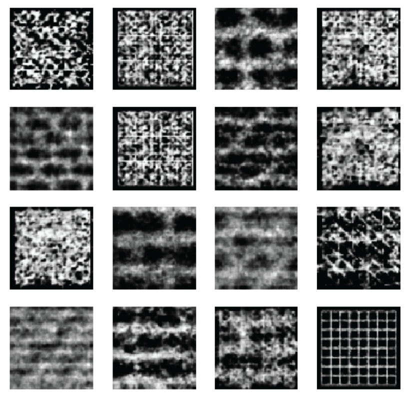
Latent Dimension (l_d) :2
Epochs (e) : 1000
Learning Rate (l_r) : 0.001
Total Loss : 1299

2



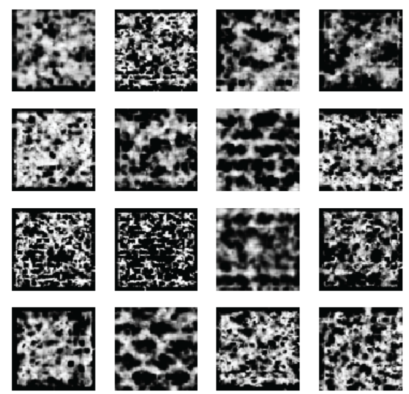
Latent Dimension (l_d) :2
Epochs (e) : 1000
Learning Rate (l_r) : 0.0005
Total Loss : 1271

3

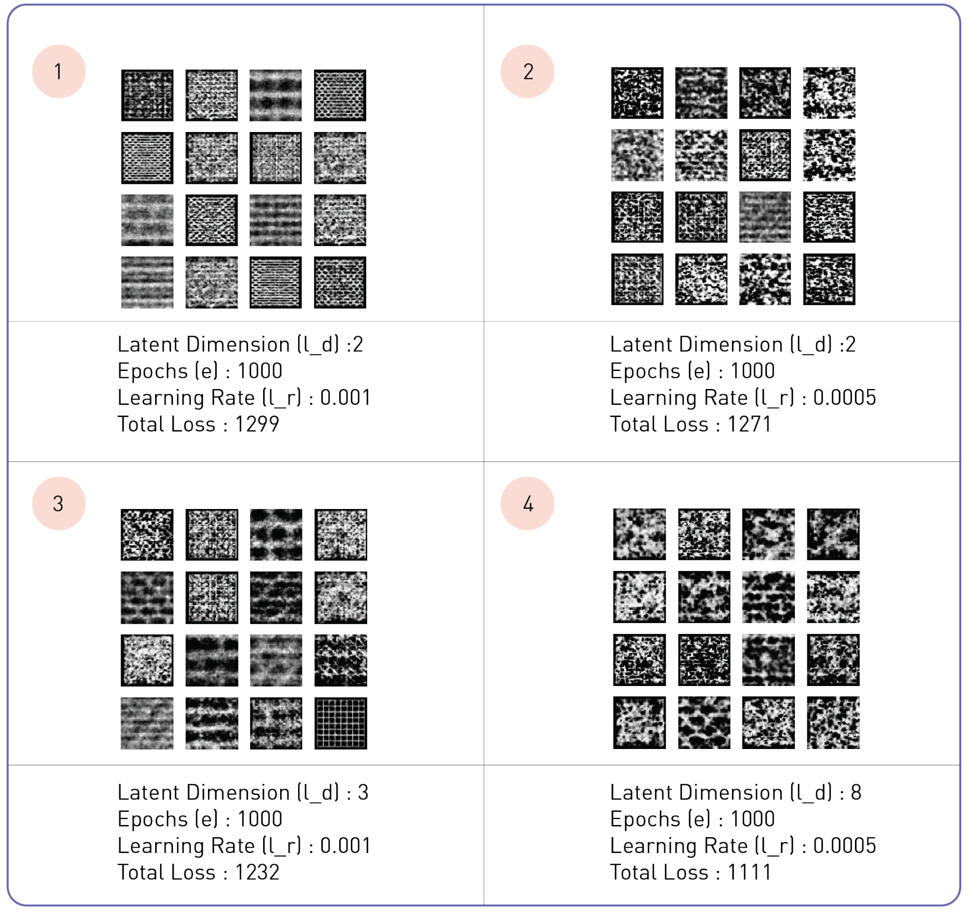


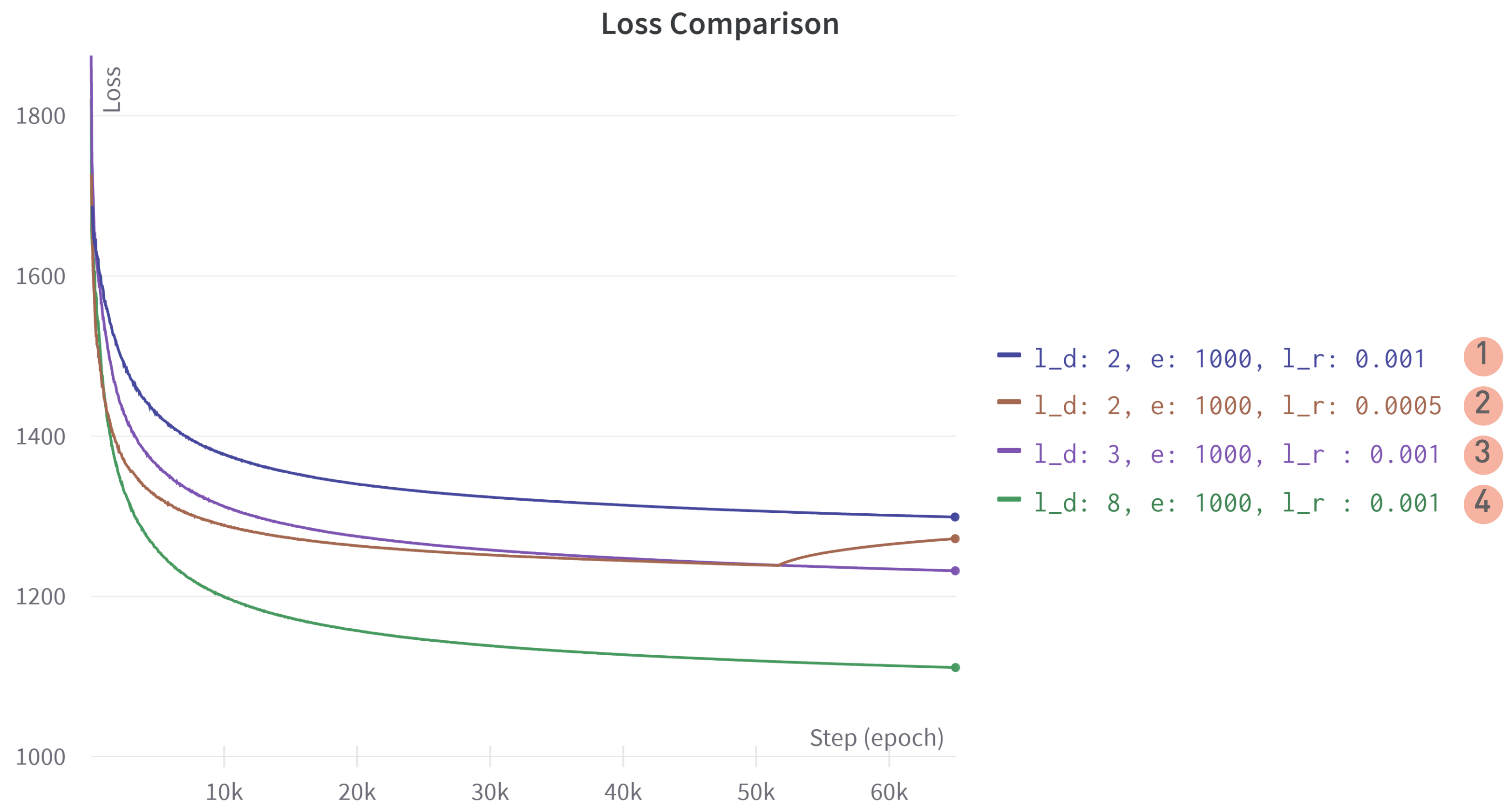
Latent Dimension (l_d) : 3
Epochs (e) : 1000
Learning Rate (l_r) : 0.001
Total Loss : 1232

4



Latent Dimension (l_d) : 8
Epochs (e) : 1000
Learning Rate (l_r) : 0.0005
Total Loss : 1111


1
Latent Dimension (l_d) :2
Epochs (e) : 1000
Learning Rate (l_r) : 0.001
Total Loss : 1299
2
Latent Dimension (l_d) :2
Epochs (e) : 1000
Learning Rate (l_r) : 0.0005
Total Loss : 1271
3
Latent Dimension (l_d) : 3
Epochs (e) : 1000
Learning Rate (l_r) : 0.001
Total Loss : 1232
4
Latent Dimension (l_d) : 8
Epochs (e) : 1000
Learning Rate (l_r) : 0.0005
Total Loss : 1111

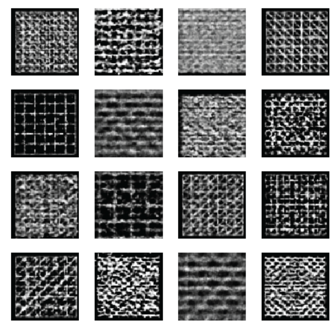

Loss Comparison
Loss
1800
1600
1400
1200
1000
Step (epoch)
10k
20k
30k
40k
50k
60k
l_d: 2, e: 1000, l_r: 0.001
1
l_d: 2, e: 1000, l_r: 0.0005
2
l_d: 3, e: 1000, l_r : 0.001
3
l_d: 8, e: 1000, l_r : 0.001
4

VAE

Training Results

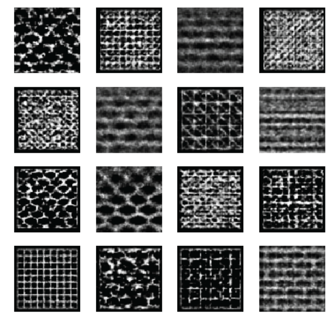
Iteration: Epochs, Batch size, Dense Layer

1



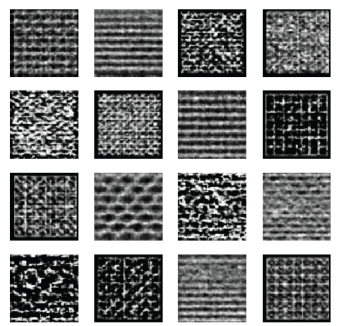
Latent Dimension (l_d) :2
Epochs (e) : 6000
Dense layer Filters (dl) : 60
Batch Size (b) : 64
Total Loss : 1249

2



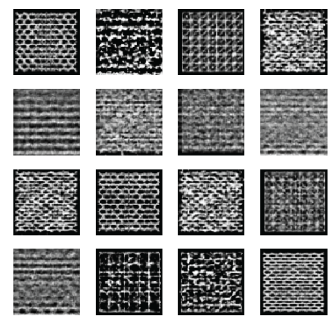
Latent Dimension (l_d) :2
Epochs (e) : 4000
Dense layer Filters (dl) : 20
Batch Size (b) : 64
Total Loss : 1324

3



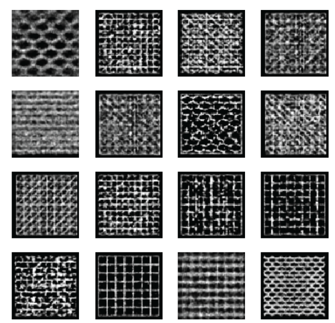
Latent Dimension (l_d) : 2
Epochs (e) : 4000
Dense layer Filters (dl) : 20
Batch Size (b) : 32
Total Loss : 1343

4



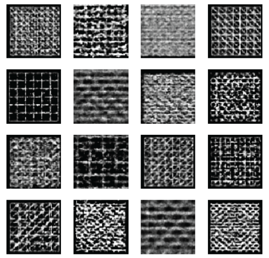
Latent Dimension (l_d) : 2
Epochs (e) : 4000
Dense layer Filters (dl) : 100
Batch Size (b) : 64
Total Loss : 1272

5



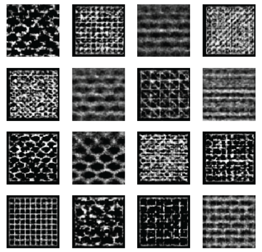
Latent Dimension (l_d) : 2
Epochs (e) : 4000
Dense layer Filters (dl) : 60
Batch Size (b) : 64
Total Loss : 1255

1



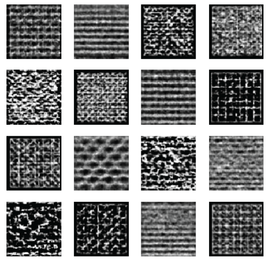
Latent Dimension (l_d) :2
Epochs (e) : 6000
Dense layer Filters (dl) : 60
Batch Size (b) : 64
Total Loss : 1249

2



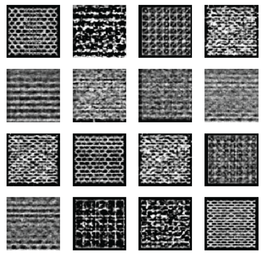
Latent Dimension (l_d) :2
Epochs (e) : 4000
Dense layer Filters (dl) : 20
Batch Size (b) : 64
Total Loss : 1324

3



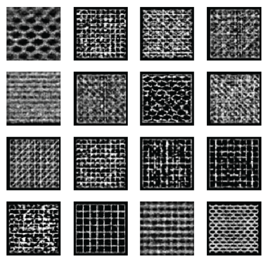
Latent Dimension (l_d) : 2
Epochs (e) : 4000
Dense layer Filters (dl) : 20
Batch Size (b) : 32
Total Loss : 1343

4



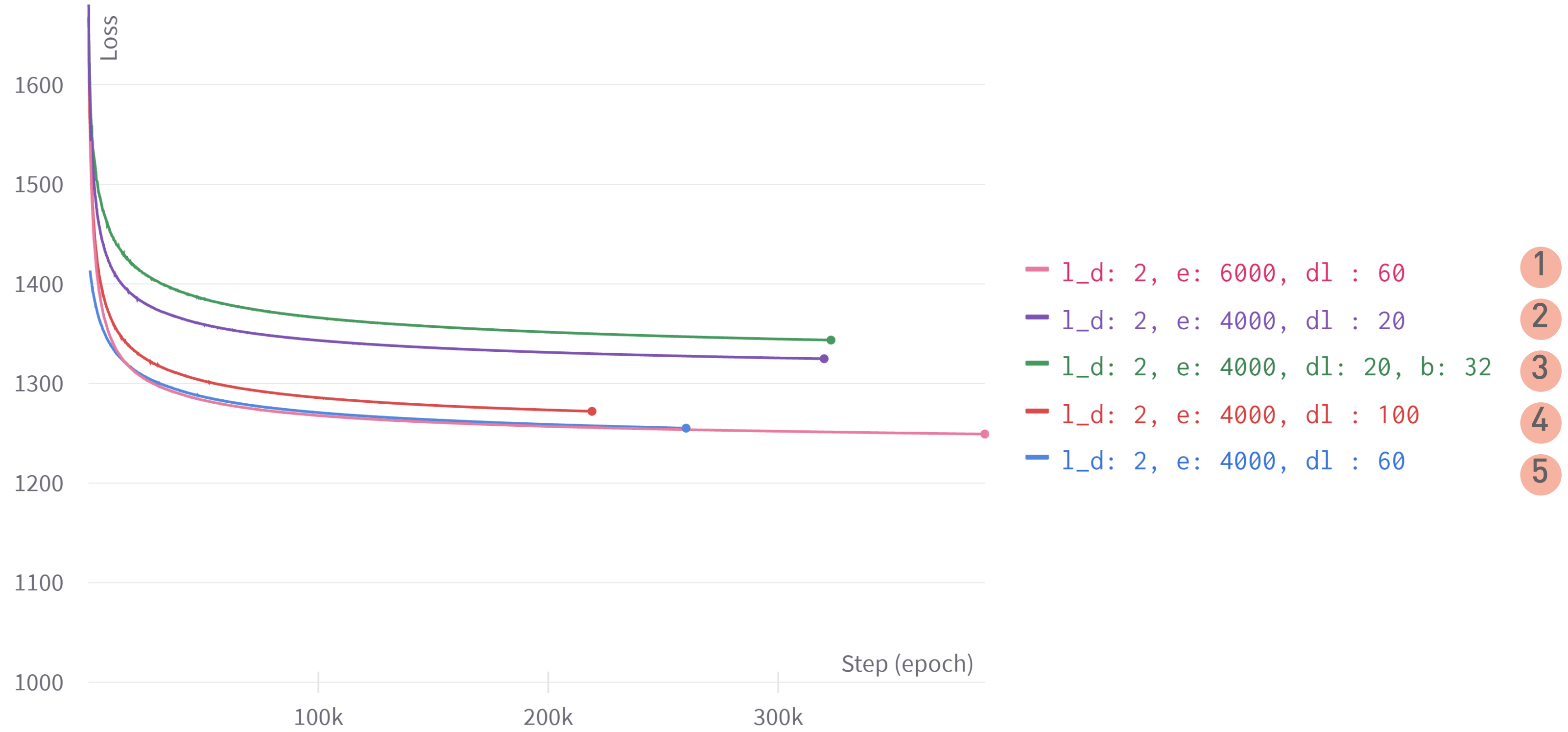
Latent Dimension (l_d) : 2
Epochs (e) : 4000
Dense layer Filters (dl) : 100
Batch Size (b) : 64
Total Loss : 1272

5



Latent Dimension (l_d) : 2
Epochs (e) : 4000
Dense layer Filters (dl) : 60
Batch Size (b) : 64
Total Loss : 1255

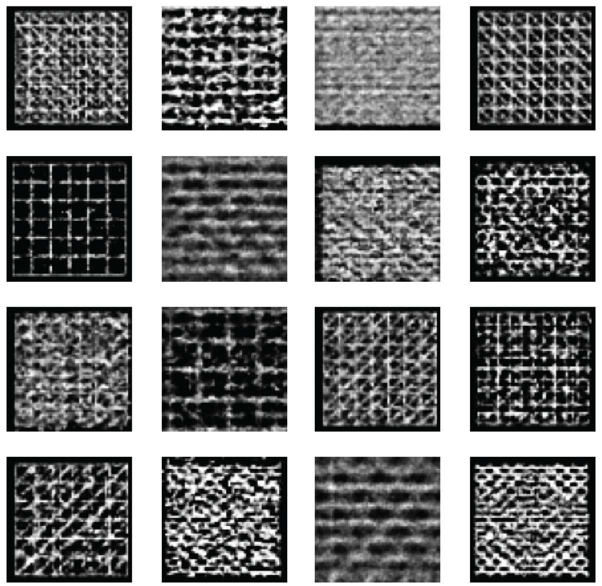
Loss Comparison for Latent dimension: 2 and Learning rate: 0.001



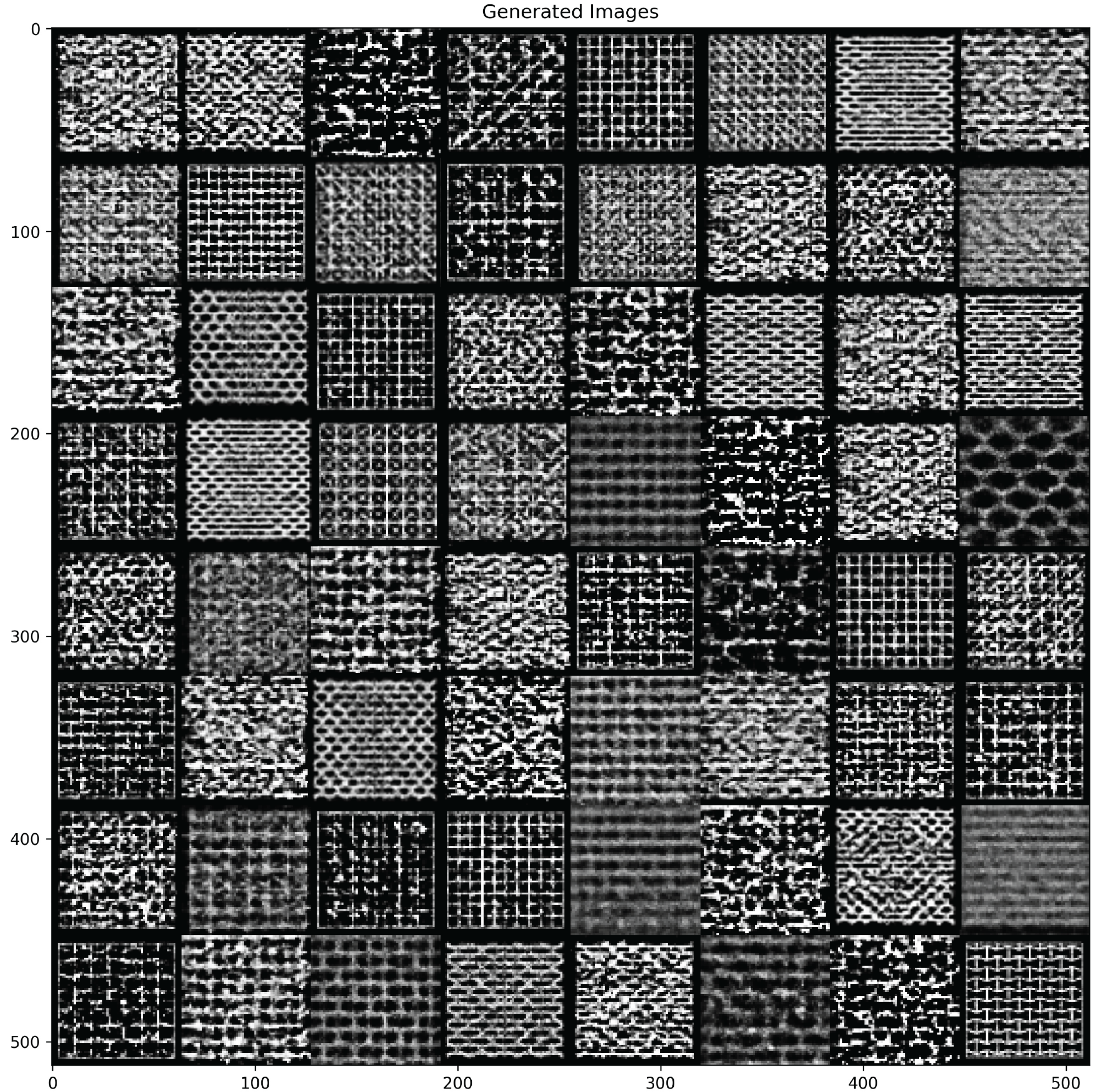
VAE

Training Results

1



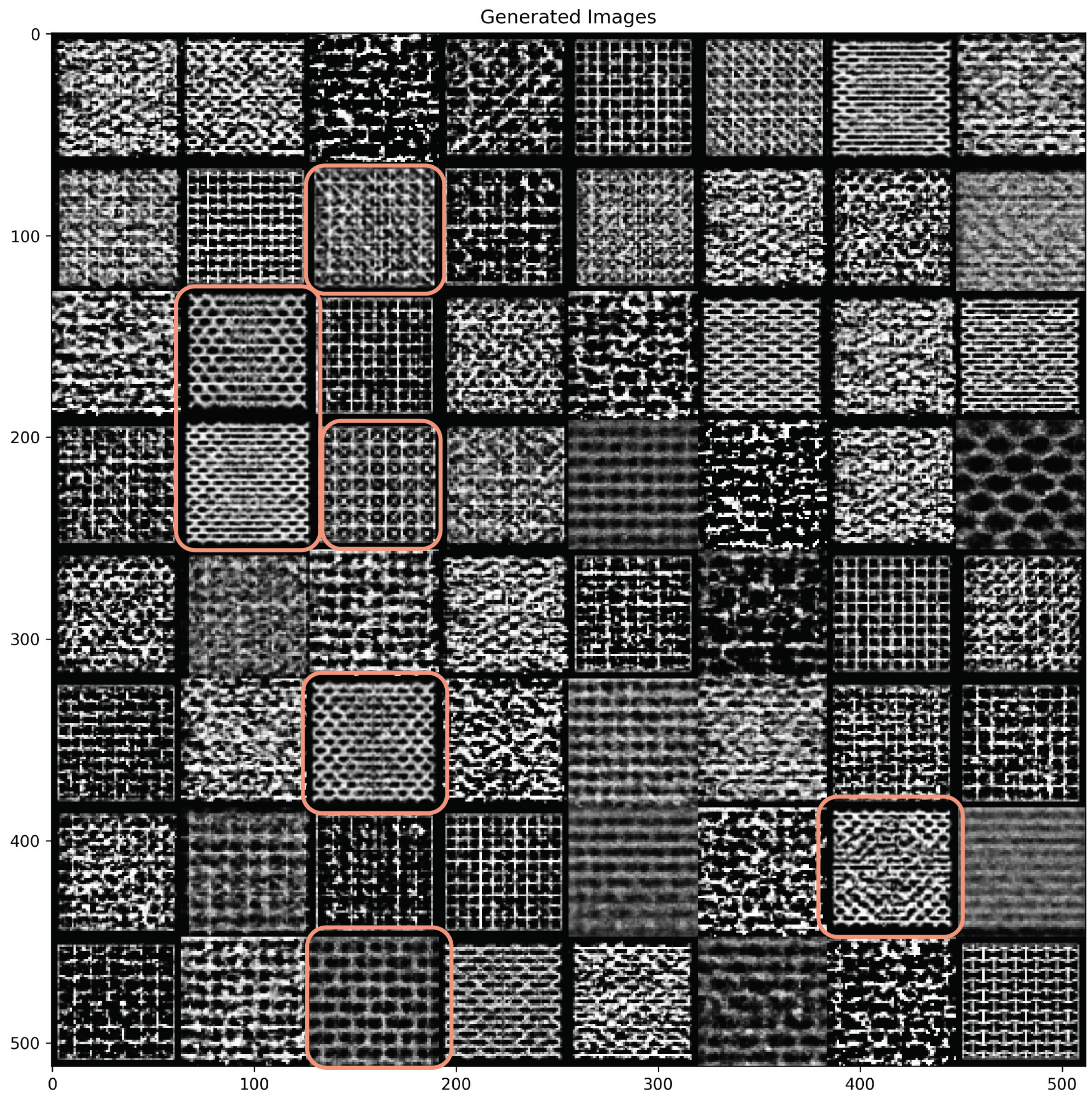
Latent Dimension (l_d) :2
Epochs (e) : 6000
Dense layer Filters (dl) : 60
Batch Size (b) : 64
Total Loss : 1249



VAE

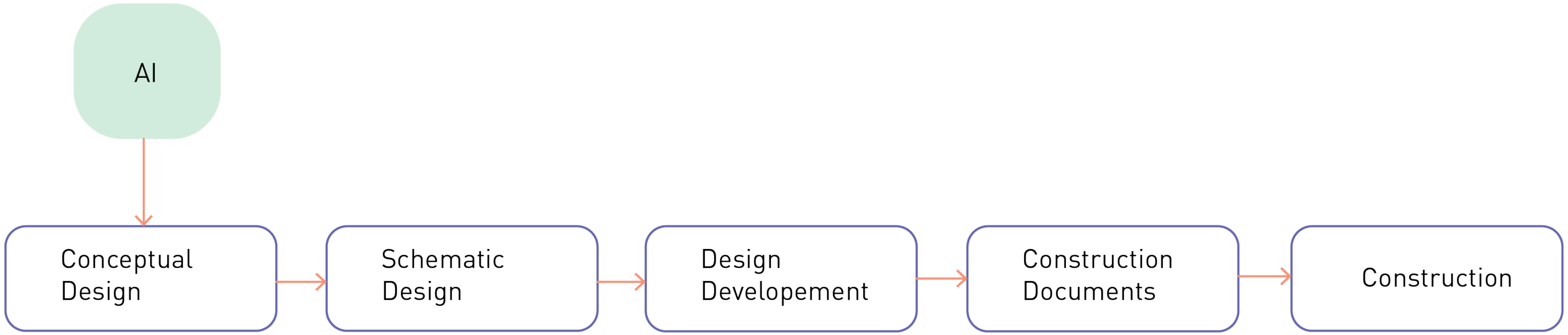
Training Results

Identifying **New generated patterns**

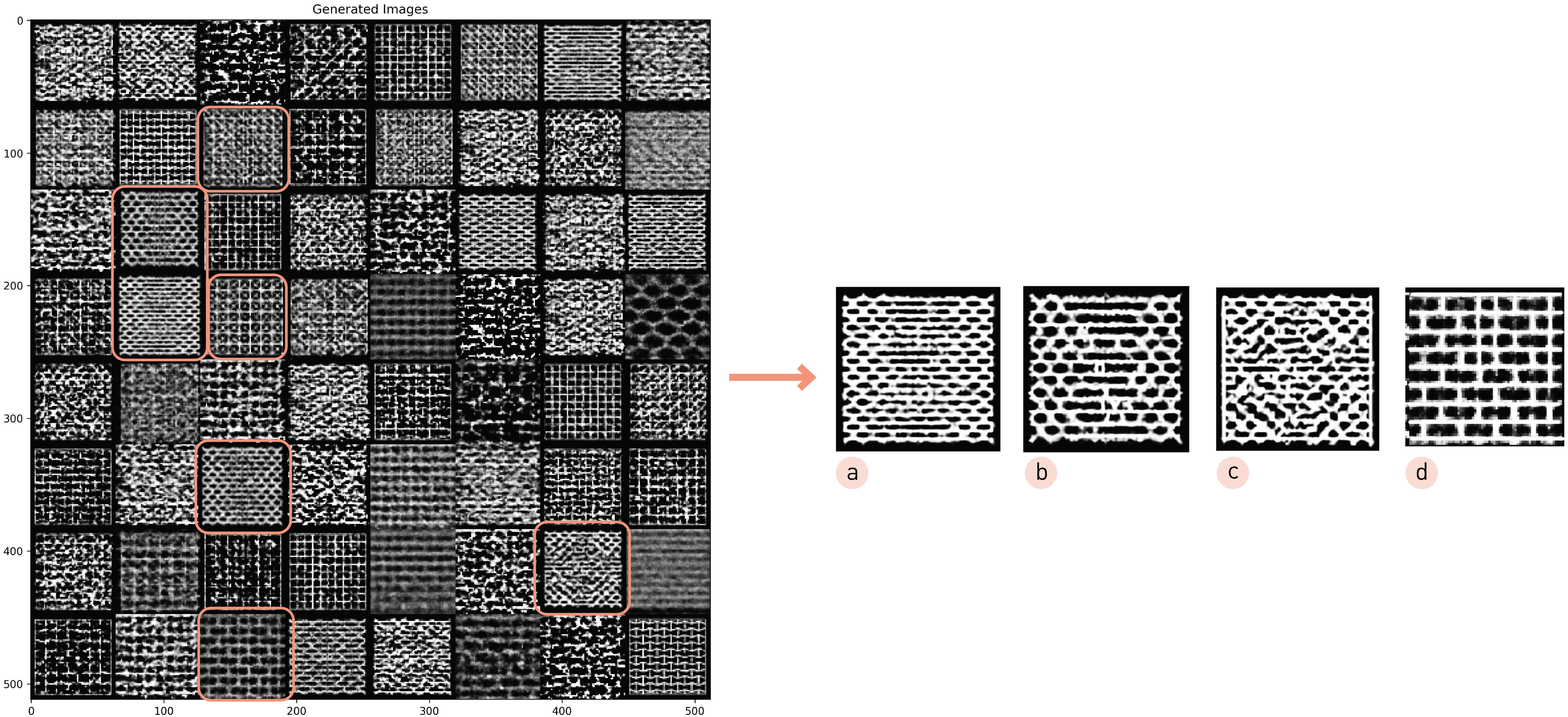


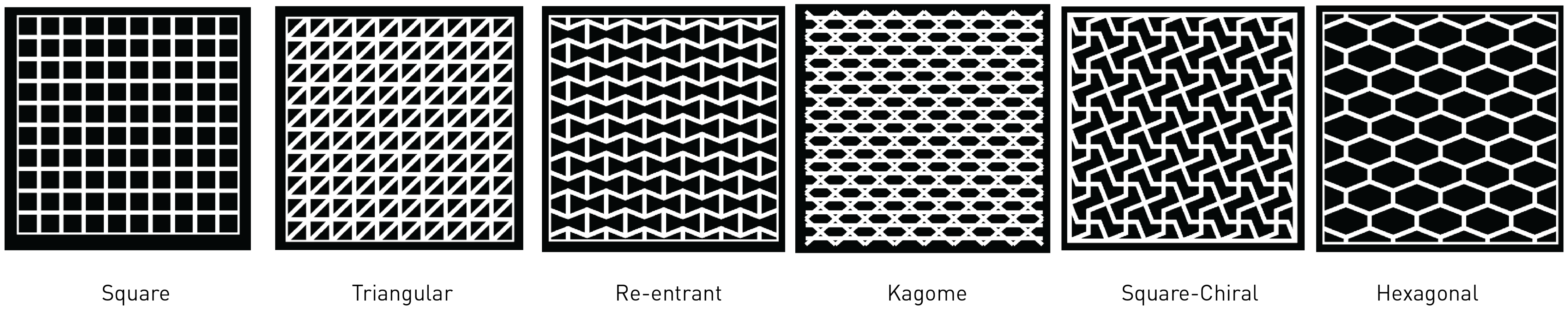
Using the VAE as a Design Tool

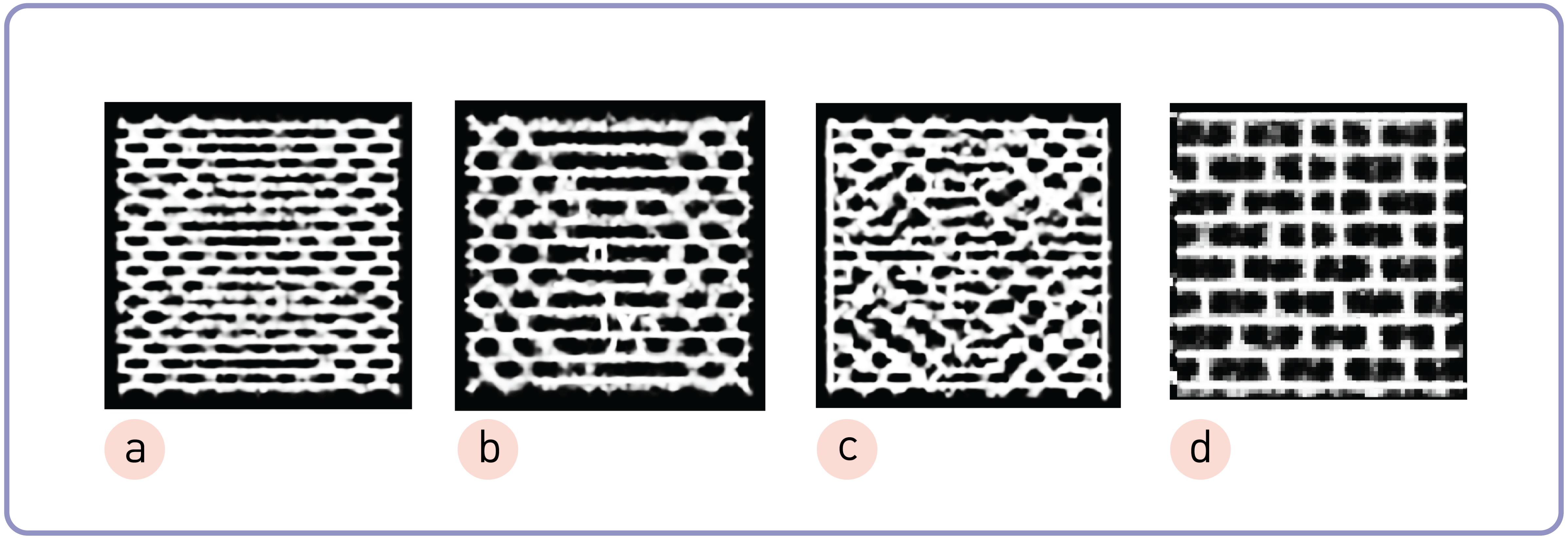
Application



From the VAE


Generated Images
0
100
200
300
400
500
0
100
200
300
400
500
a
b
c
d


Square
Triangular
Re-entrant
Kagome
Square-Chiral
Hexagonal


a
b
c
d

Application

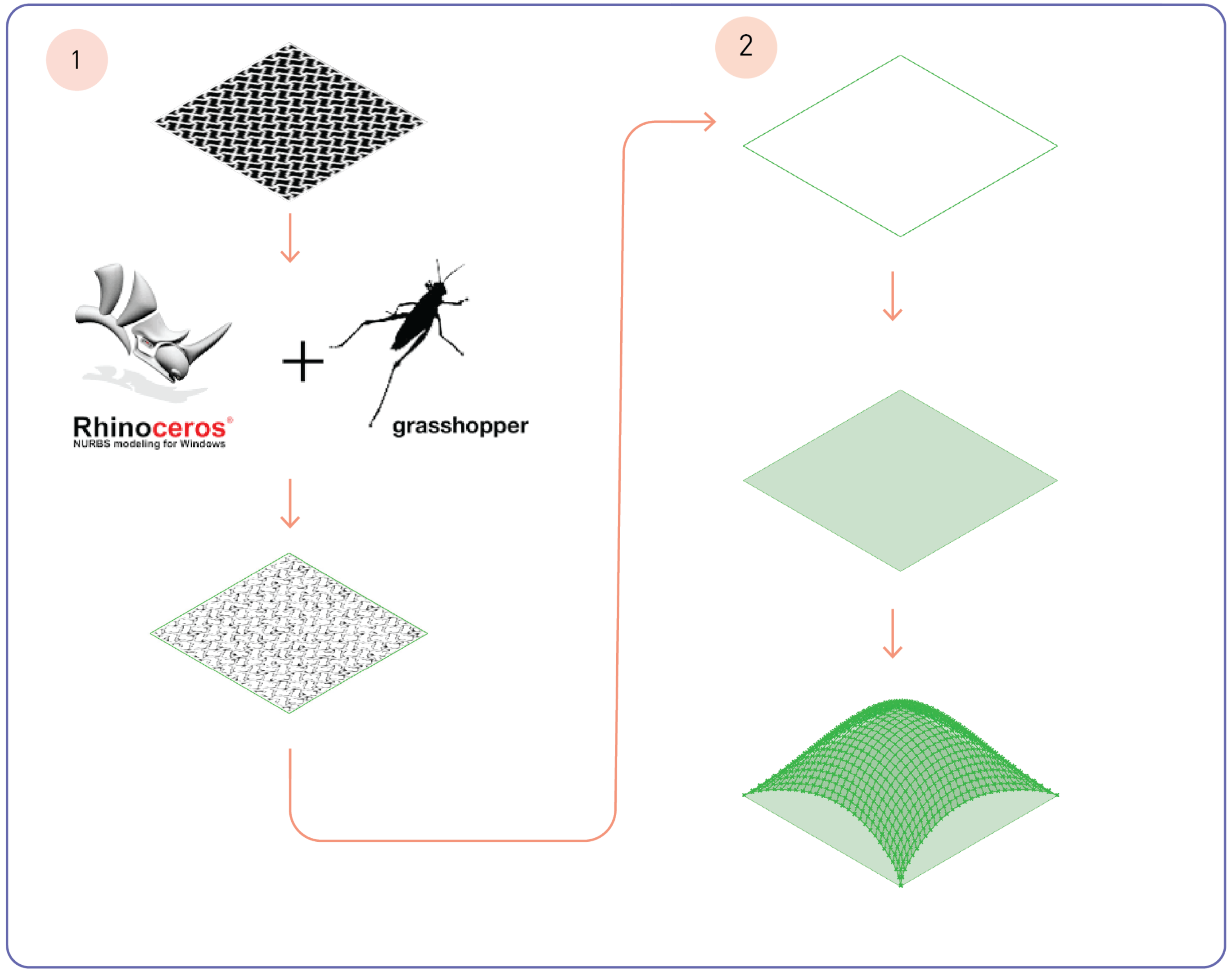
How do we use these patterns for Topology Exploration?

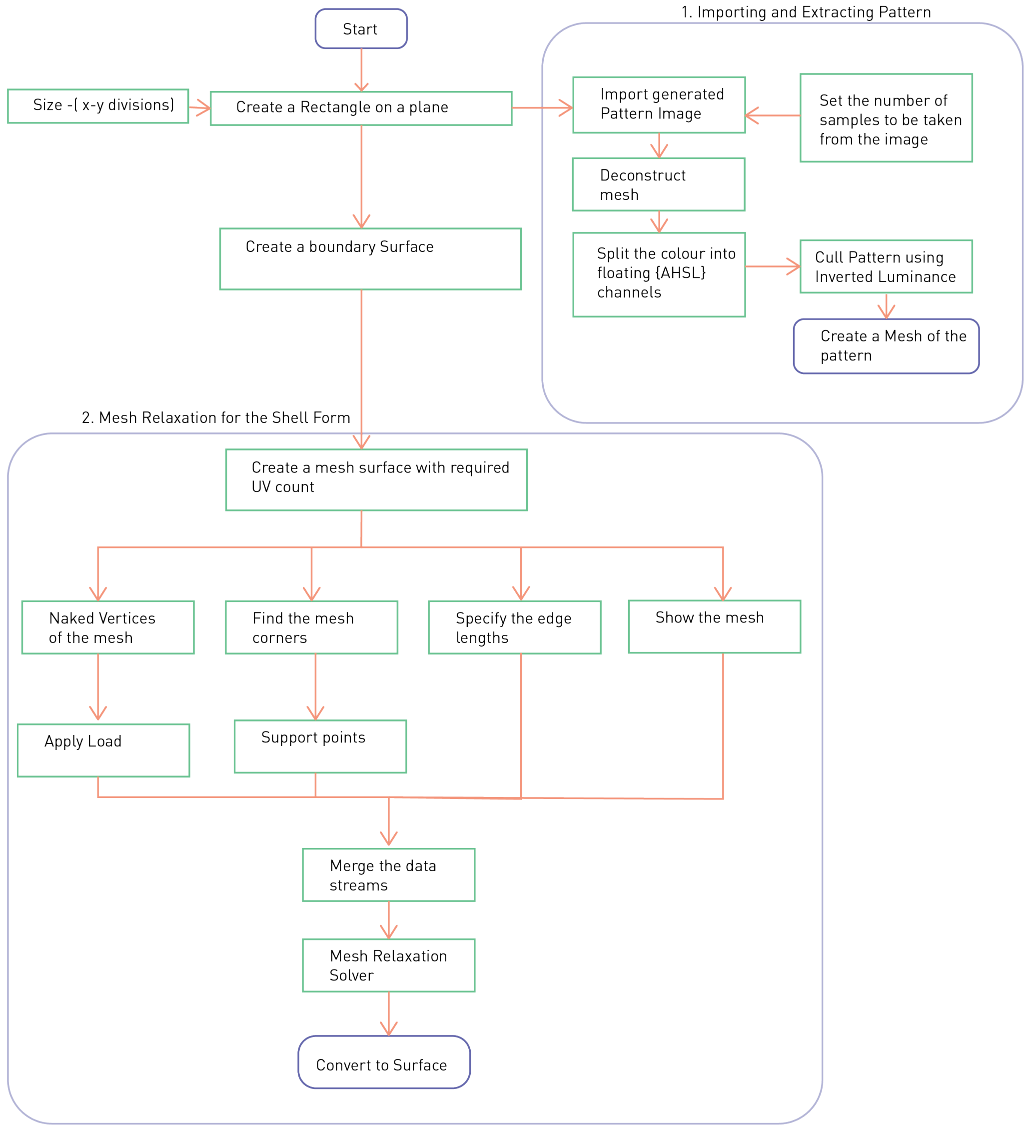
1. Extracting pattern geometry
2. Generating the form of the Shell
3. Surface Morphing
4. Preliminary structural analysis

Application

Stage 1 & 2: Extracting Pattern and Shell Form

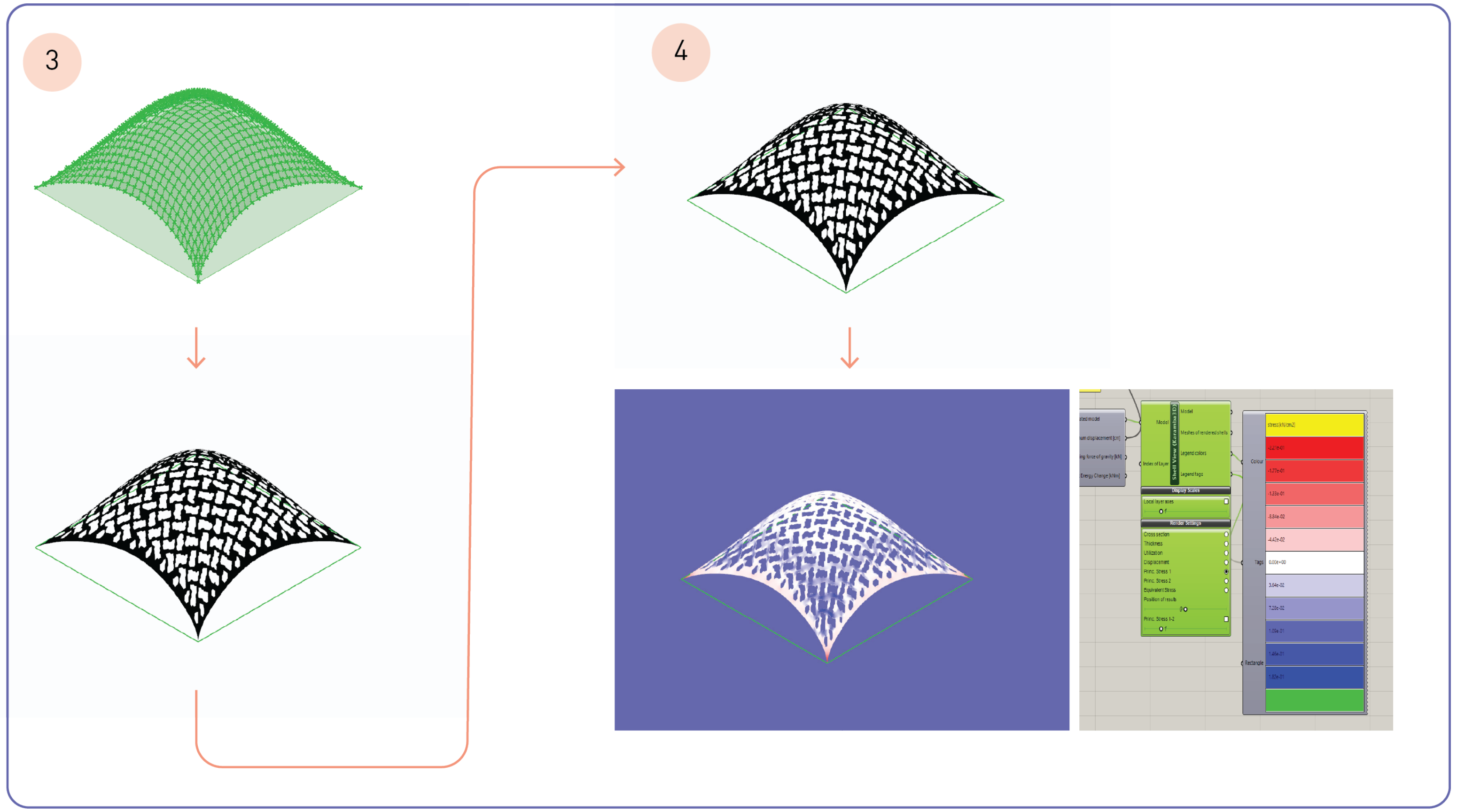
A pattern image from the dataset has been selected to show the process

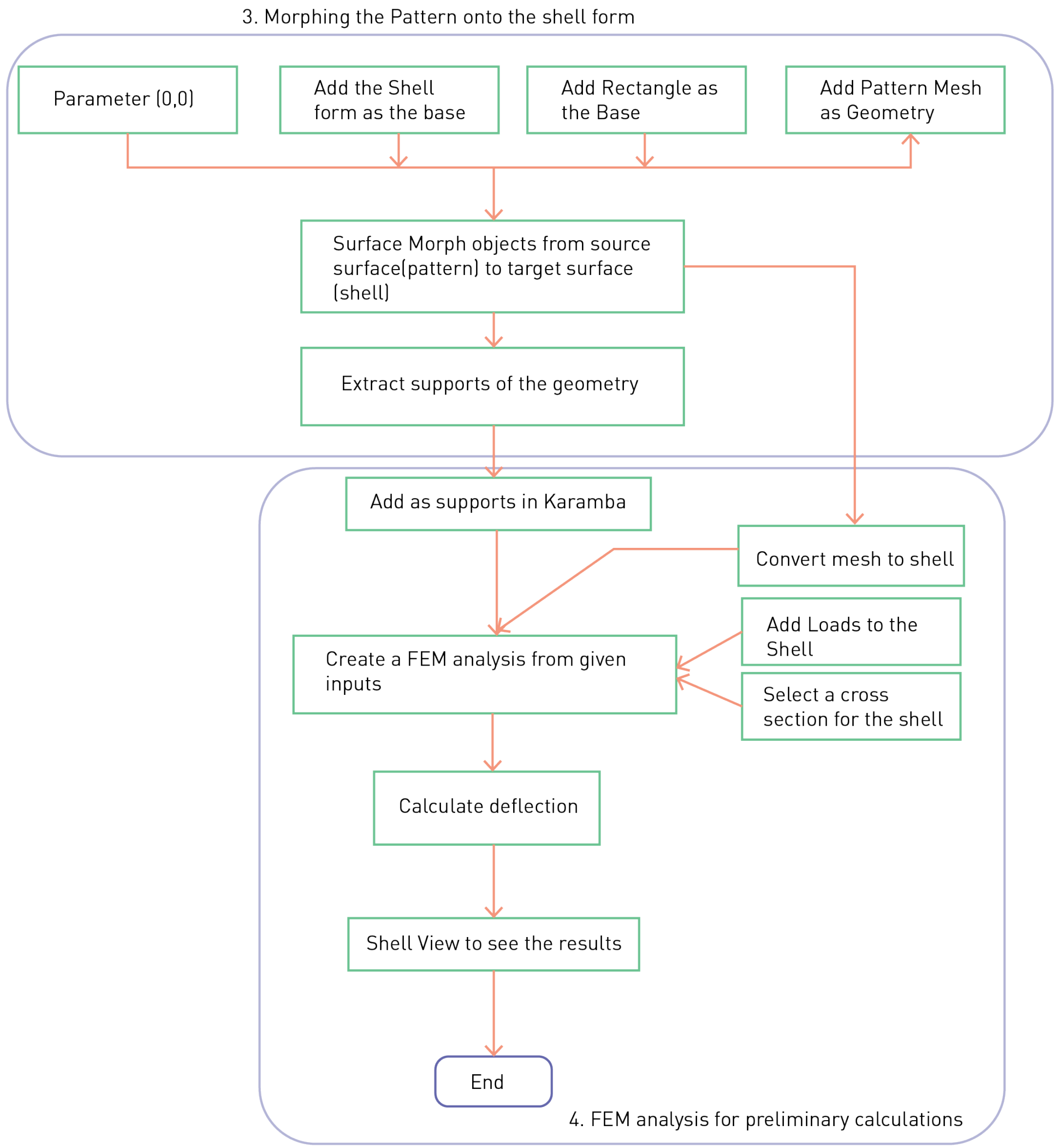




Application

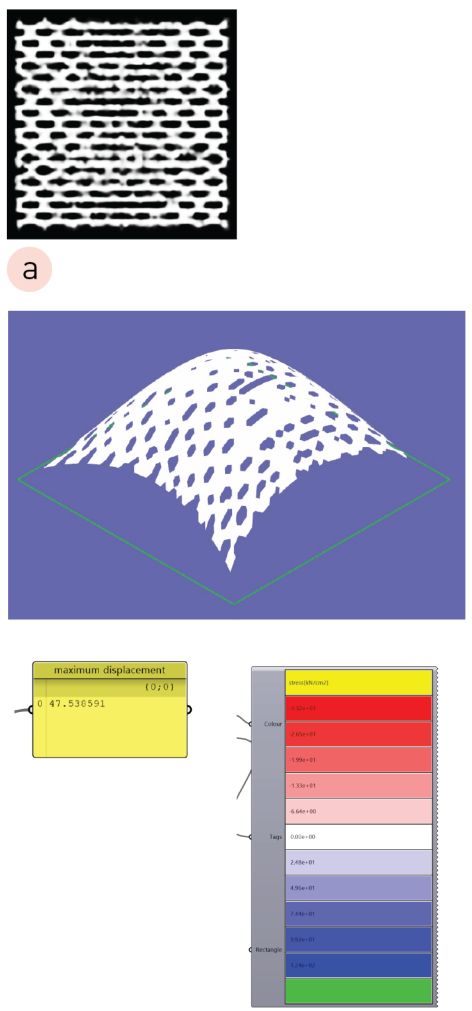
Stage 3 & 4: Surface Moph and FEM Analysis

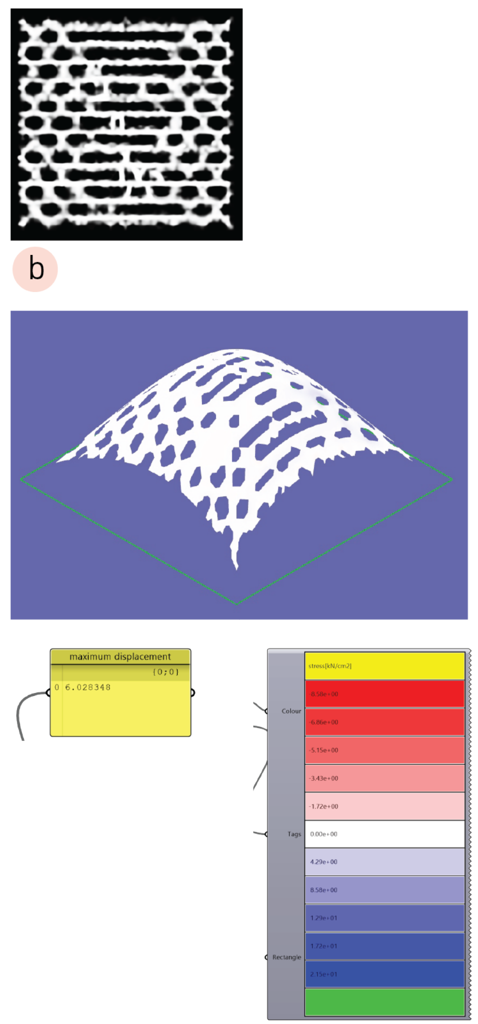


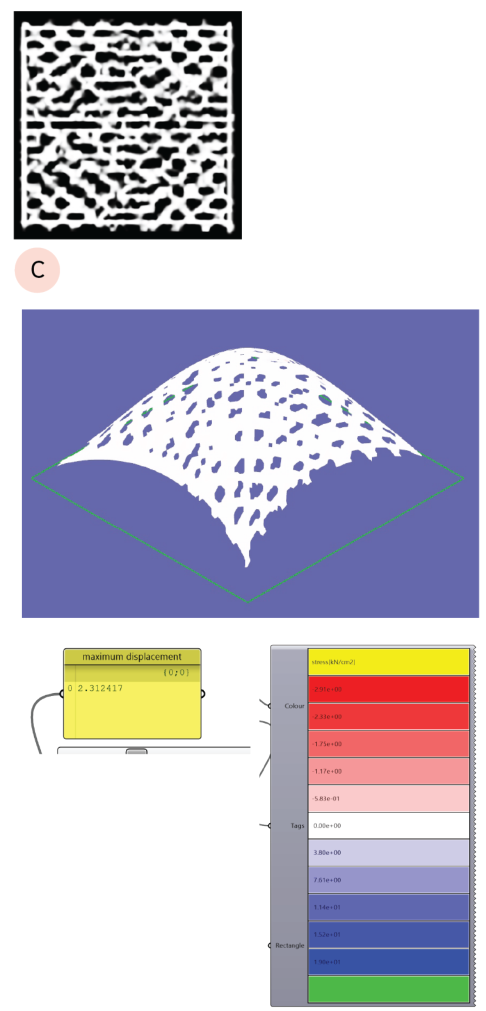


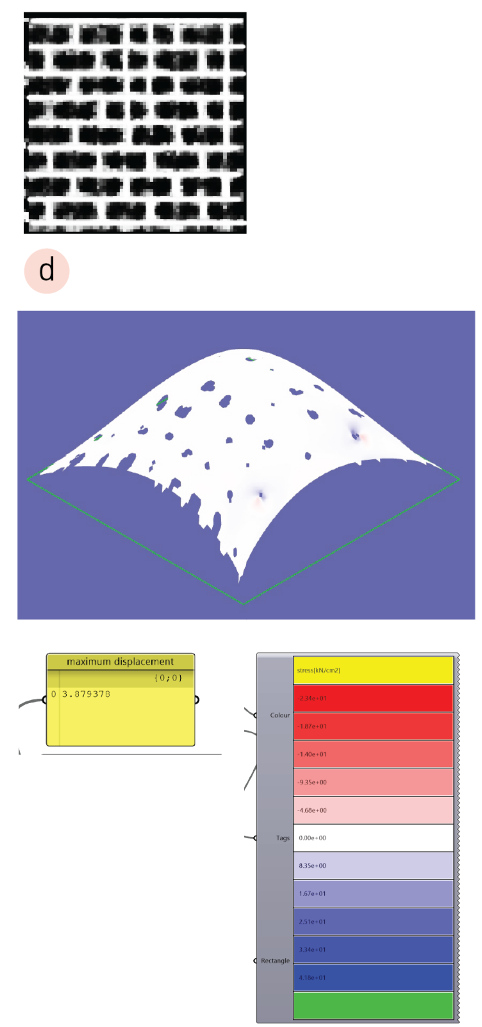
Application

Applying the Process to the genereted patterns



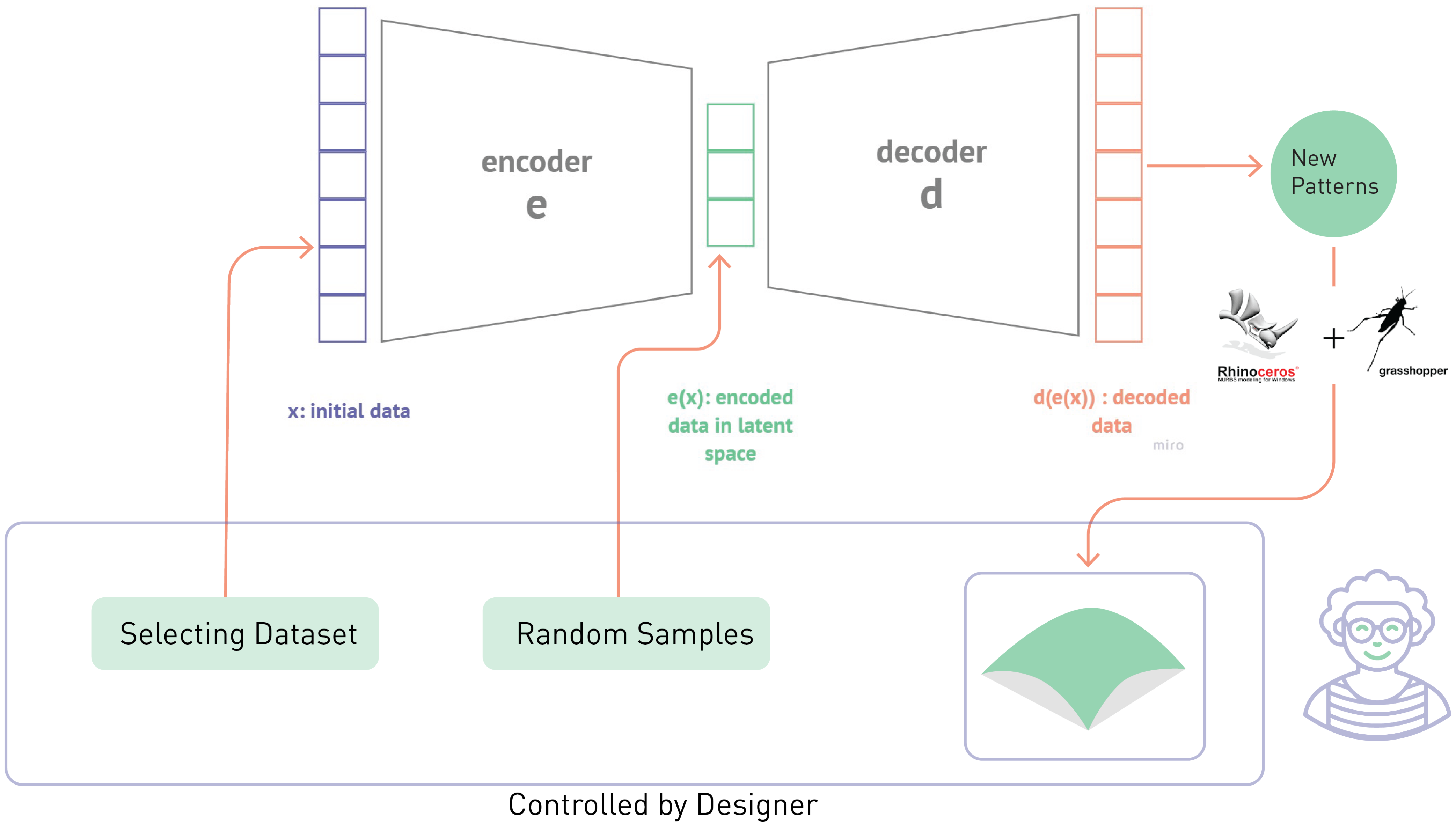






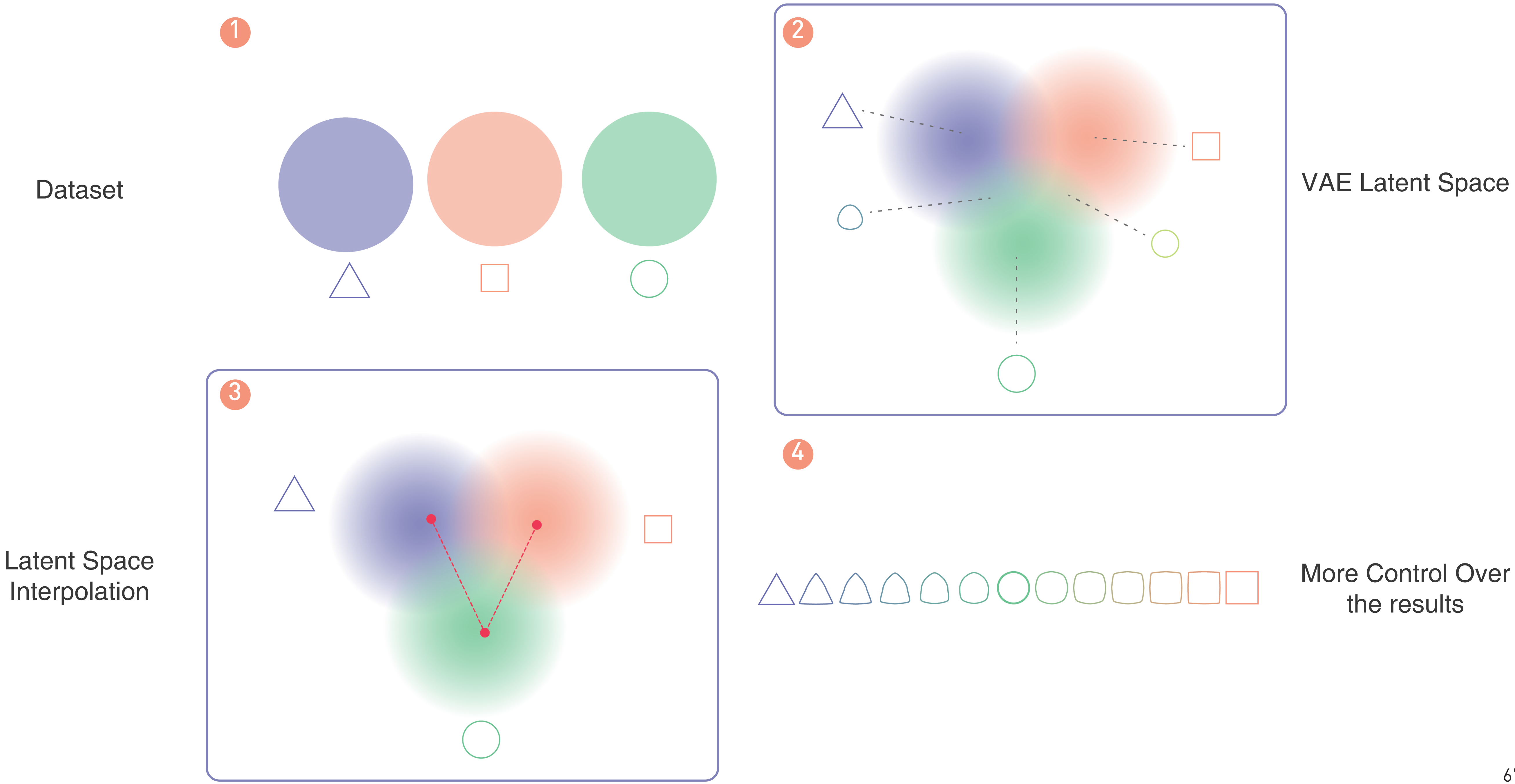
Application

Workflow



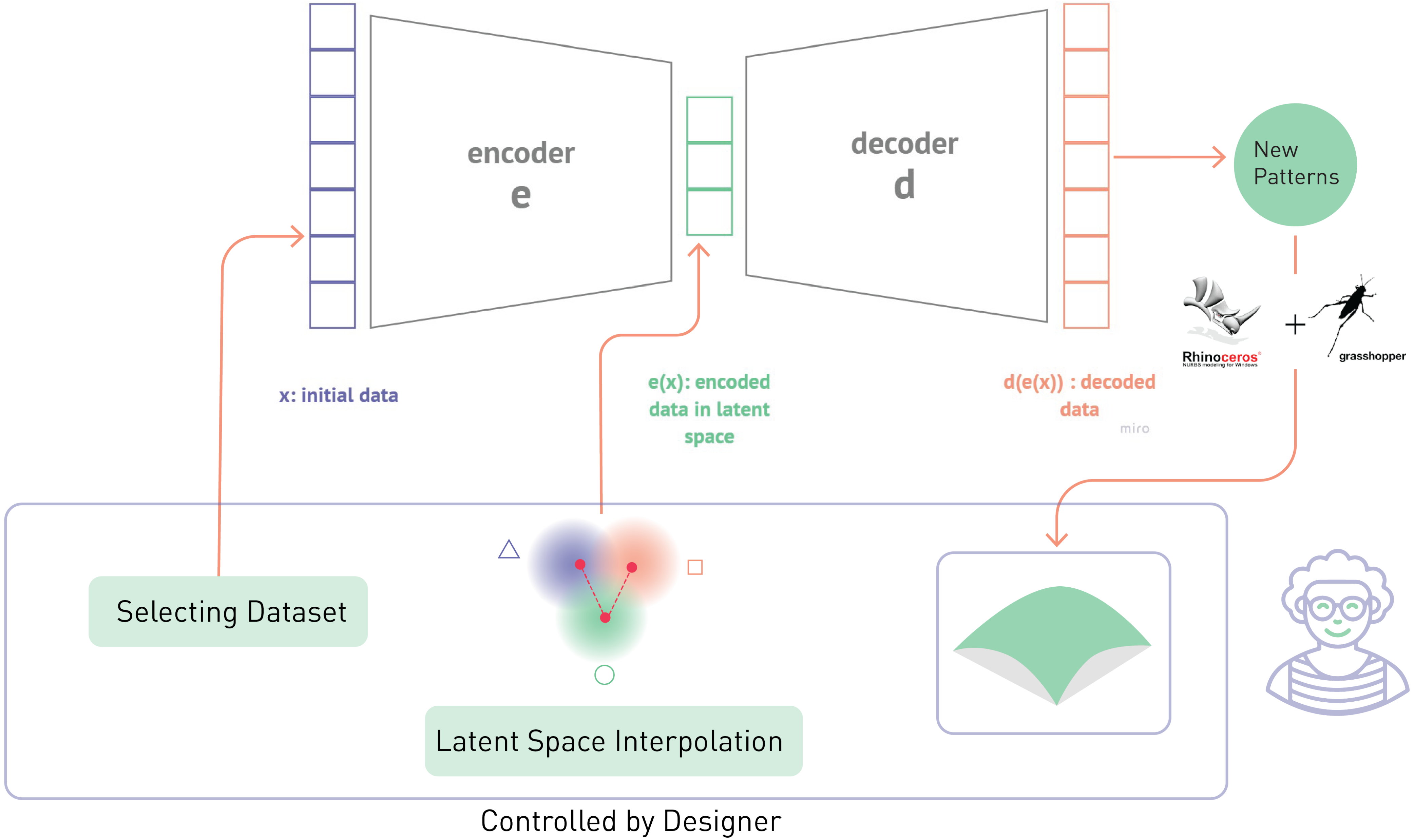
Application

Future Work : Latent Space Exploration

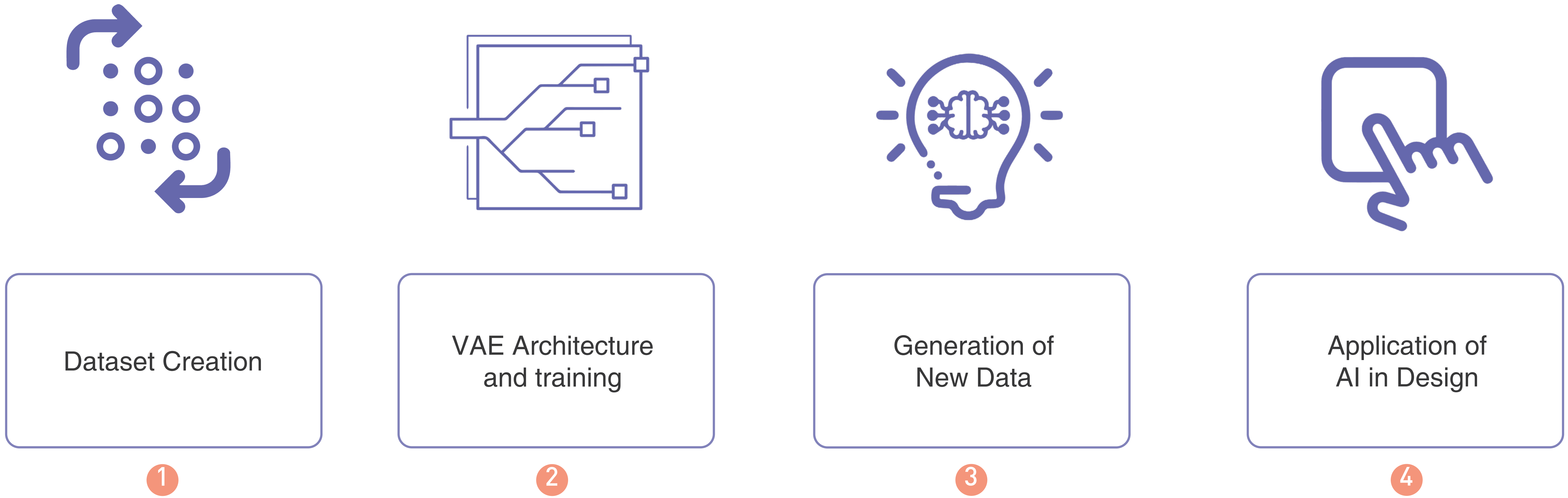


Application

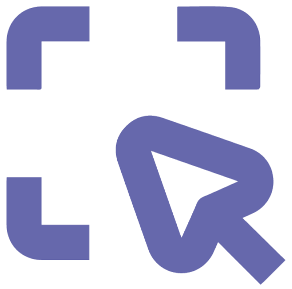
Future Work :Workflow



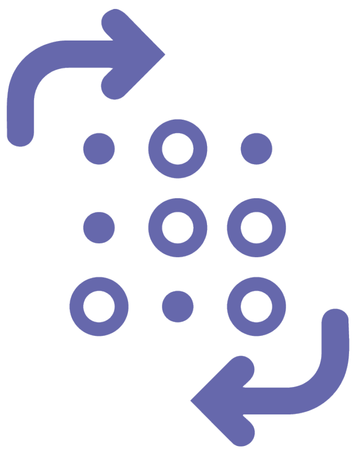
Discussion


Dataset Creation
VAE Architecture and training
Generation of New Data
Application of AI in Design
1
2
3
4

Conclusion

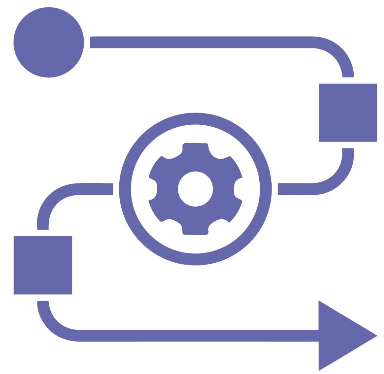


To select cellular solid patterns for creating the dataset to train the VAE model



To generate a dataset of cellular solid structure patterns.

To train an VAE model on the generated dataset



To create a workflow for application of the VAE as a design tool during conceptual design for topology optimization.

Limitations

1) The dataset was limited to only 6 lattice patterns.

2) The data augmentation is only done to crop and flip the images

3) Google collab was used to implement the code.

4) This workflow for creating the AI model is just one way of doing it.

5) The output of the VAE training can be improved further

6) The application process is only to show an example of how a VAE can fit into the design process.

7) The detailed mechanical properties of the lattice structures are not studied for this paper.

Thank you

Open for Questions!