**Latent Space Representation of CAD geometry for Surrogate Modelling**

**Research Objectives**

1. **Develop a Neural Network-Based Latent Representation of CAD Geometry**
   * Train an autoencoder or similar deep learning model to encode complex CAD geometries into a compact, low-dimensional latent space.
   * Ensure the latent space captures meaningful shape variations while maintaining valid geometric structures.
2. **Evaluate the Use of Latent Representations in Surrogate Modeling**
   * Investigate whether the latent space representation can effectively serve as input to a pre-trained surrogate model for predicting aerodynamic or mechanical performance.
   * Compare performance predictions using raw CAD parameters versus latent space embeddings.
3. **Explore the Generative Capabilities of the Latent Space for Design Exploration**
   * Assess whether interpolating within the latent space can generate new valid designs with desirable properties.
   * Demonstrate how engineers can leverage this representation to optimize or modify designs efficiently.
4. **Validate the Methodology Using Publicly Available Datasets**
   * Use an existing dataset (e.g., UIUC airfoil database, NASA Shape Parameterization Data, or OpenVSP models).
   * Evaluate how well the method generalizes across different design categories with limited data.

**Research Questions**

1. How effectively can an autoencoder-based latent space capture key geometric features of CAD models?
2. Can a latent space representation serve as a more efficient input for surrogate models compared to traditional CAD parameters?
3. What is the trade-off between compact representation and predictive accuracy in surrogate modeling?
4. Can interpolating in the latent space produce novel, valid designs that adhere to engineering constraints?
5. How transferable is the learned latent space across different design families (e.g., airfoils vs. turbine blade sections)?

**Expected Outcomes**

* A trained autoencoder (or alternative neural network) that reduces CAD geometry into a lower-dimensional latent space.
* A comparative analysis of surrogate model performance using raw CAD parameters vs. latent space representations.
* A demonstration of latent space interpolation for generating new, optimized design variants.
* A proof-of-concept framework for integrating AI-driven design parameterization into engineering workflows.

Some approaches:

1. **Variational autoencoders**
2. **Generative Adversarial Networks**
3. **Diffusion Models**
4. **Implicit Neural Representation**

**Comparison of representation of shapes: E.g., signed distance fields, point clouds vs. PCA**

**Design space optimisation -> 2D shapes.**

**Geometry:**

* Area-to-perimeter / Optimise to control heat loss or diffusion.
* Compactness = C 4pi \* A/Perimiter -> Measures how close a shape is to aa circle for minimising material usage.
* Aspect ratio – Ratio between longest and shortest dimension useful for optmising elongated or compact designs.
* Symmetry index – Measure of shaoe symmetry 0 useful for otpmising designs that require balanced geometry.
* Enclosed volume (for hollow shapes) – Optimise for the largest or smallest enclosed space while minimising external perimeter.

**Physical Performance**

**Title:** **Exploring Geometry Representation Methods in AI for Efficient Design Exploration and Optimization**

**1. Introduction** Modern engineering design involves optimizing complex geometries to achieve desired performance outcomes. Traditional methods for design exploration often struggle with high-dimensional, intricate shapes, making the optimization process computationally expensive and time-consuming. Recent advancements in AI and machine learning offer promising approaches to encode these complex geometries into lower-dimensional representations, facilitating efficient exploration and optimization.

This research aims to investigate and compare different AI-based geometry representation methods to support design exploration and optimization. By learning a compact latent space of 2D shapes, we can navigate and manipulate complex geometries to optimize performance-related quantities of interest, such as compactness, area-to-perimeter ratio, or aerodynamic efficiency.

**2. Research Objectives**

1. To evaluate and compare different AI models (e.g., Variational Autoencoders (VAEs), Generative Adversarial Networks (GANs), and Implicit Neural Representations) for encoding 2D geometries into low-dimensional latent spaces.
2. To assess how well these representations facilitate design space exploration for optimizing geometric and physical quantities of interest (e.g., compactness, drag coefficient, area-to-perimeter ratio).
3. To analyze the structure and smoothness of the learned latent spaces and their suitability for gradient-based or evolutionary design optimization techniques.
4. To identify which geometry representation method provides the most interpretable and controllable latent space for efficient design modification and optimization.

**3. Research Questions**

1. How do different AI models structure and organize the latent space for 2D shape representation?
2. What are the trade-offs between model complexity, representation fidelity, and optimization efficiency in these latent spaces?
3. How effectively can each model's latent space be used to perform design optimization tasks (e.g., maximizing compactness or minimizing drag)?
4. What role does the choice of geometric encoding (e.g., contours, signed distance functions) play in optimizing performance metrics?

**4. Methodology**

1. **Dataset Generation and Preprocessing:**
   * Generate or source a dataset of 2D geometries representing a range of shapes and design variations.
   * Preprocess these shapes into different formats (e.g., pixel grids, contour outlines, signed distance functions) suitable for input to various generative models.
2. **Model Selection and Training:**
   * Implement and train multiple AI models to encode these 2D geometries into low-dimensional latent representations:
     + Variational Autoencoders (VAEs)
     + Generative Adversarial Networks (GANs)
     + Implicit Neural Representations (INRs)
   * Evaluate the quality and smoothness of the learned latent space.
3. **Optimization Framework:**
   * Define target performance metrics (e.g., compactness, area-to-perimeter ratio).
   * Implement gradient-based and evolutionary optimization techniques to explore the latent space and identify designs that optimize these metrics.
4. **Evaluation Metrics:**
   * Latent space continuity and navigability (how smoothly designs evolve).
   * Fidelity of shape reconstruction.
   * Optimization efficiency (time and computational resources required).
   * Interpretability and control of the latent variables.

**5. Expected Outcomes**

1. A comparative analysis of how different generative models encode and represent 2D geometries.
2. Insights into the efficiency and effectiveness of latent spaces for design optimization.
3. Identification of the most promising geometry representation approach for enabling interpretable and scalable design exploration.
4. Recommendations for future applications of AI-based design optimization in engineering contexts.

**6. Significance of the Study** By understanding how to effectively represent and explore complex geometries using AI, this research could facilitate more efficient design workflows in engineering. The ability to manipulate low-dimensional latent spaces allows for faster optimization of performance-driven designs, potentially reducing development time and computational costs. This work provides foundational insights for applying generative models to real-world design problems where complex geometries are prevalent.

**7. Conclusion** This research will contribute to the field of AI-driven design optimization by exploring the potential of various generative models to encode and optimize 2D geometries. The findings will inform future methodologies for handling more complex 3D geometries, offering a pathway to improved design exploration, optimization, and efficiency in engineering applications.