A Blueprint for Precision: Achieving 95% Accuracy by 27 January

Our Strategic Recommendation for AI Implementation

TARGET: 95% ACCURACY

DEADLINE: 27 JANUARY

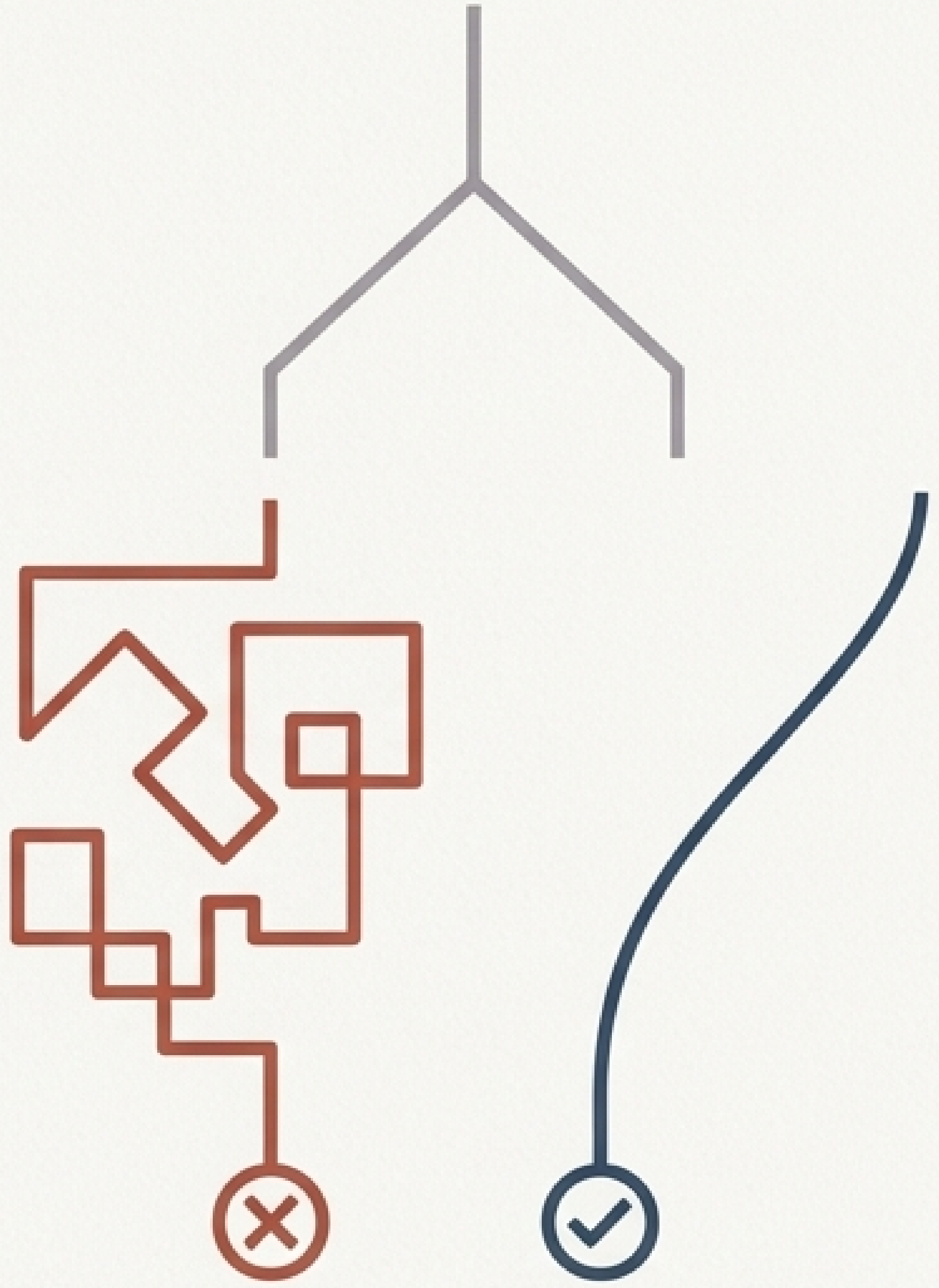
Our Strategy is Decisive: We Will Use Transfer Learning

To meet our goals, we will **not build a neural network from scratch**. We will **adapt elite, pre-trained models**. This is the definitidustry standard for production-grade AI, used by organisations like Google and Tesla.

We Must Choose the Right Path, Not the Hardest One

Build “From Scratch”

- High Risk
- Massive Data Needs
- Unpredictable Timeline
- PhD-level R&D



Use Transfer Learning

- Proven
- Data-Efficient
- Rapid Convergence
- State-of-the-Art Performance

We Stand on the Shoulders of Giants

Methodology: Transfer Learning

We will utilise models pre-trained on large-scale datasets (e.g., ImageNet, COCO) and fine-tune them for our specific domain tasks.

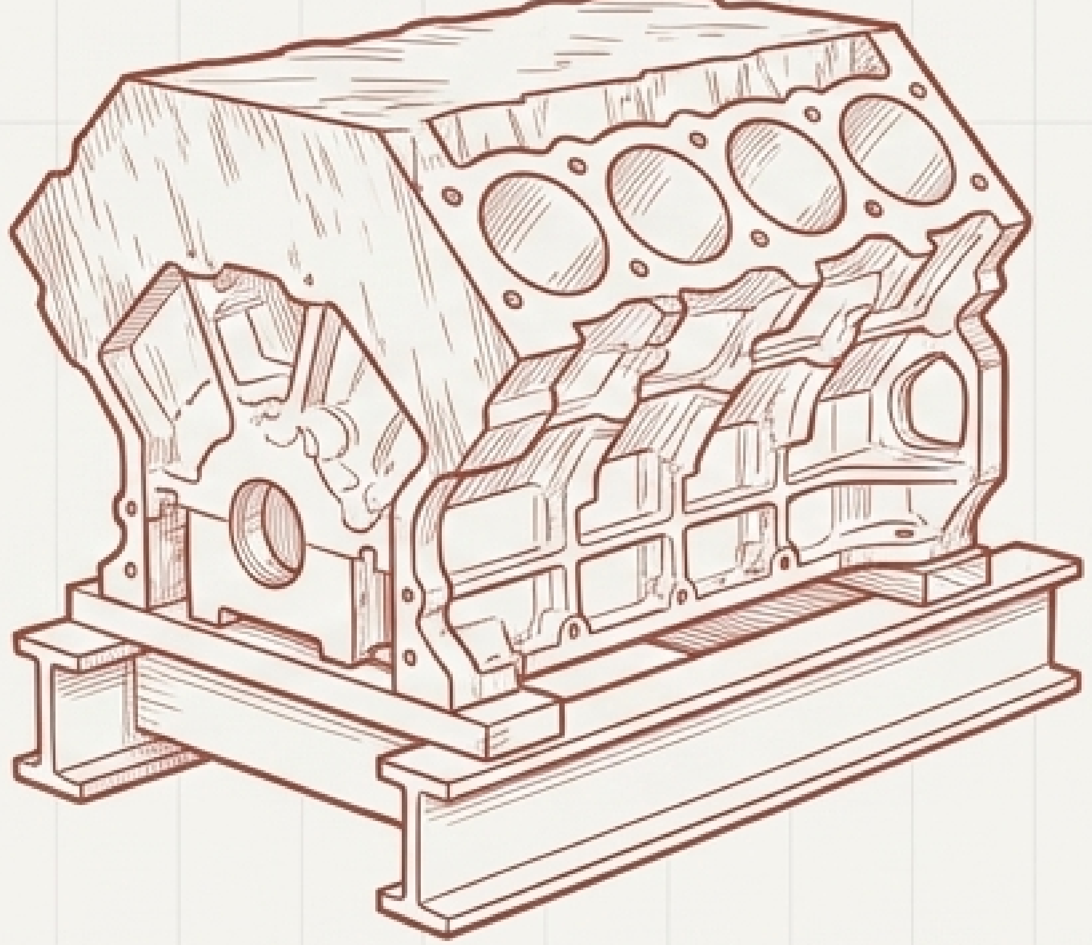
Foundation: SOTA Architectures

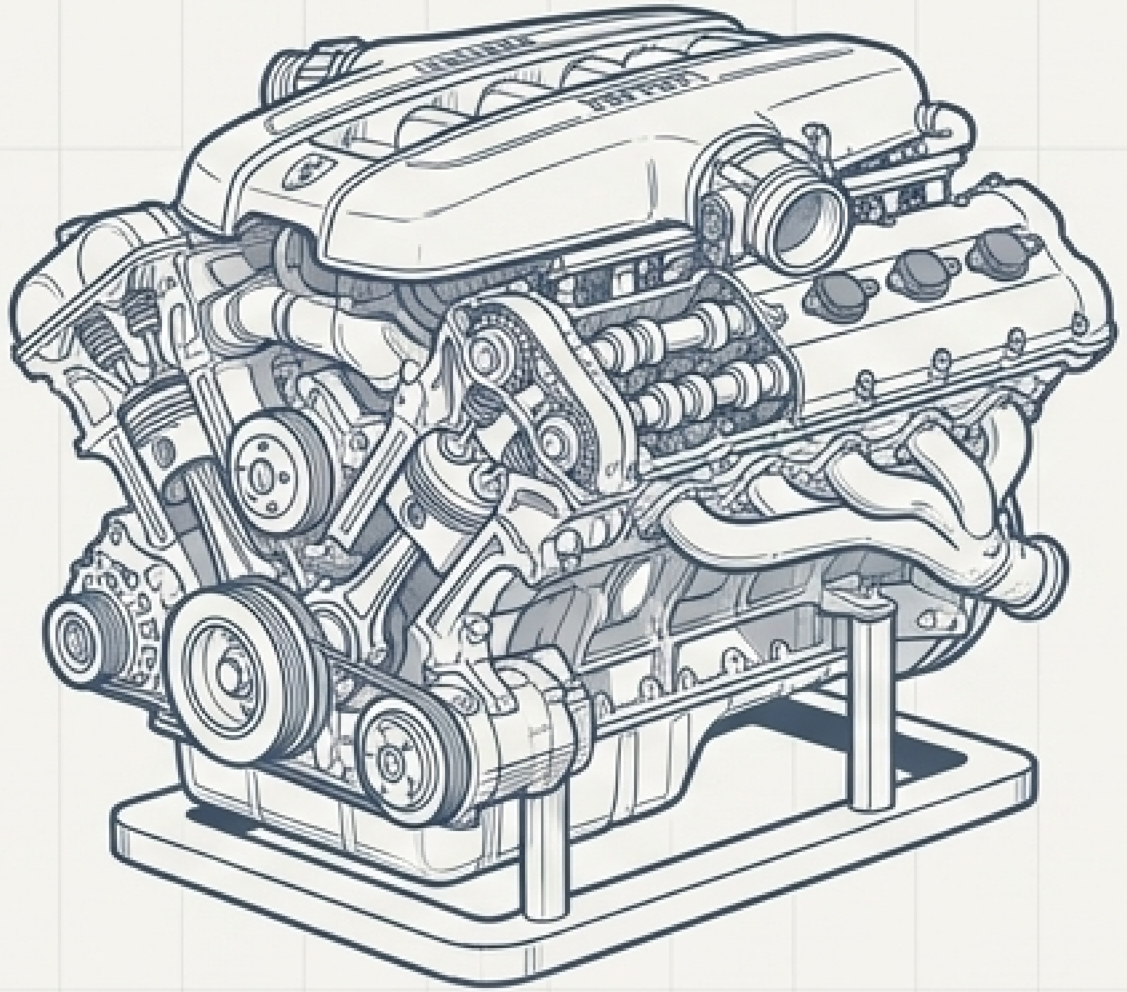
Leverage State-of-the-Art (SOTA) backbones like ResNet and EfficientNet. This is the standard operating procedure for production-grade AI.

Principle: Risk Aversion

Avoid high-risk, resource-intensive ‘from-scratch’ R&D, which involves designing novel architectures—a task incompatible with our project constraints.

You Don’t Build a Ferrari Engine in Your Garage





Building from scratch is... like trying to build a world-class engine from a raw block of metal. It requires years of expertise, immense resources, and will likely fail to start.

Transfer Learning is... taking that proven Ferrari engine and simply tuning the suspension for our specific needs (the village roads). We are not ‘cheating’; we are starting with a brain that already knows how to see, and teaching it what to look for.

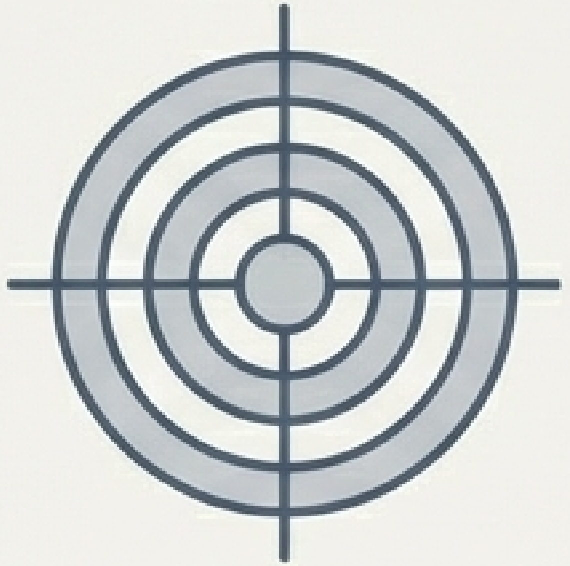
Our Strategy Directly Mitigates the Three Core Project Risks

Data Scarcity

Deep learning models require millions of parameters to learn low-level features (edges, textures). Our dataset is insufficient for *ab initio* training but is sufficient for **fine-tuning**.

Time Pressure

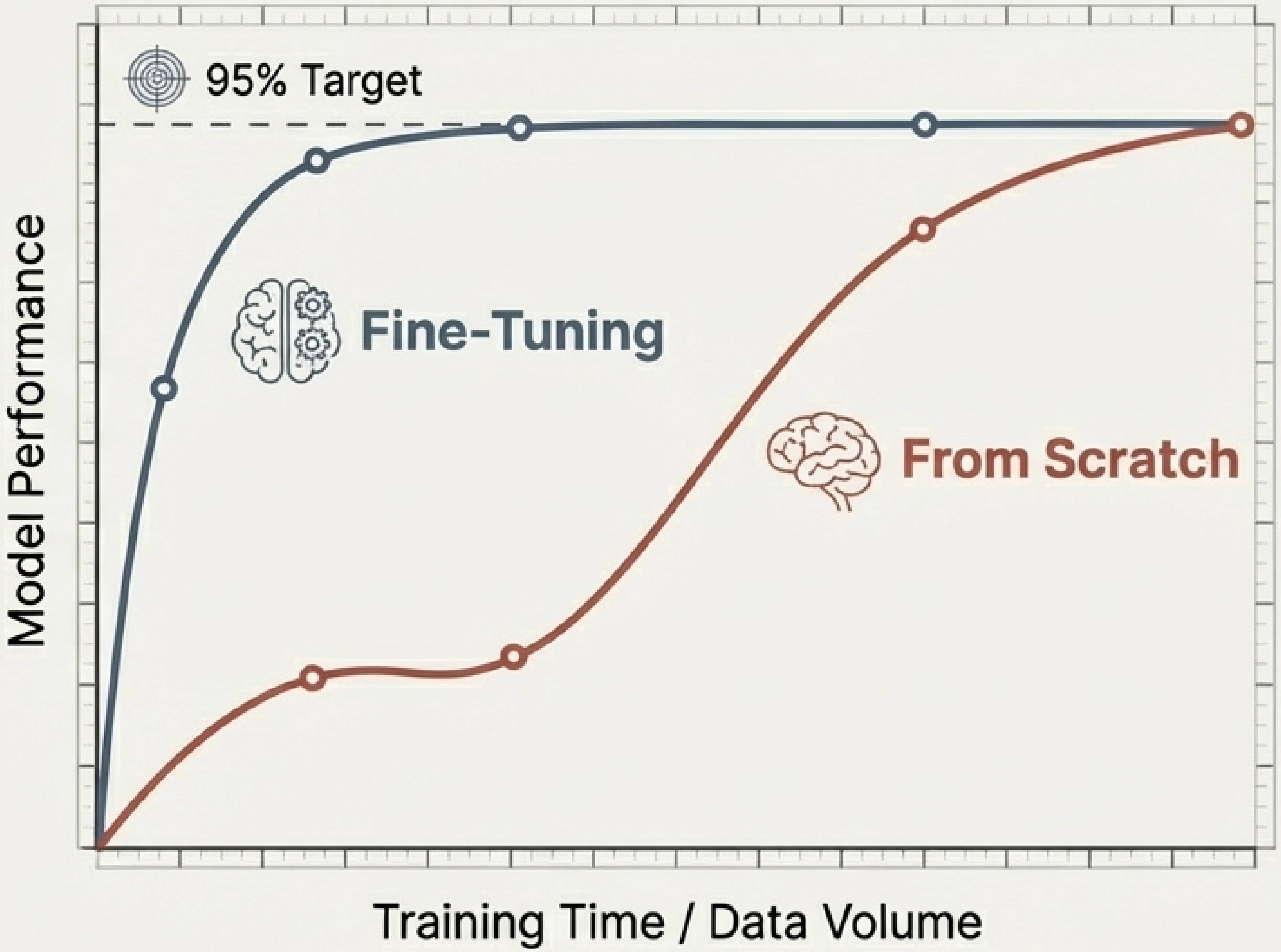
Pre-trained weights ensure rapid convergence of the model during training. This reduces training time from potential weeks to mere hours.



Performance Target

Architectures like ResNet have been optimised by thousands of researchers over a decade. Custom models rarely outperform these benchmarks without extensive, multi-year R&D.

A Smart Brain Learns Faster



Not Enough Data

A newborn needs to see millions of things to understand the world.

Our models are like PhDs; they have already seen millions of images on ImageNet and already know what a 'line' or a 'circle' is.

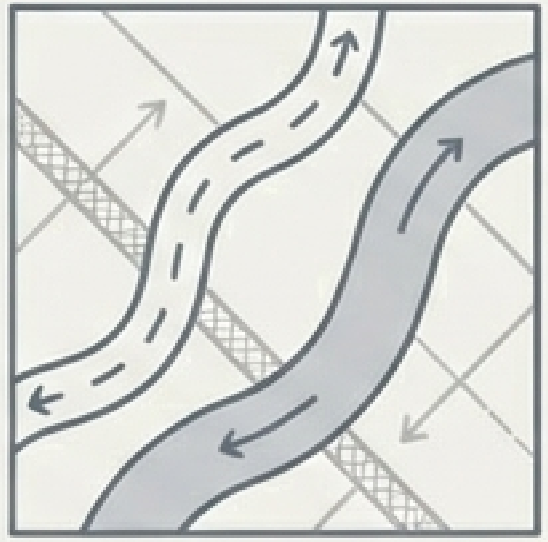
Not Enough Time

Teaching a newborn takes years. Teaching a PhD a new specialism takes weeks, or in our case, hours.

A Specialist Toolkit for a Complex Landscape

Task 1: Building Footprints (2D Imagery)

- **Model:** Mask R-CNN (Backbone: ResNet-50/101)
- **Job:** Instance Segmentation (Crucial for separating touching buildings)

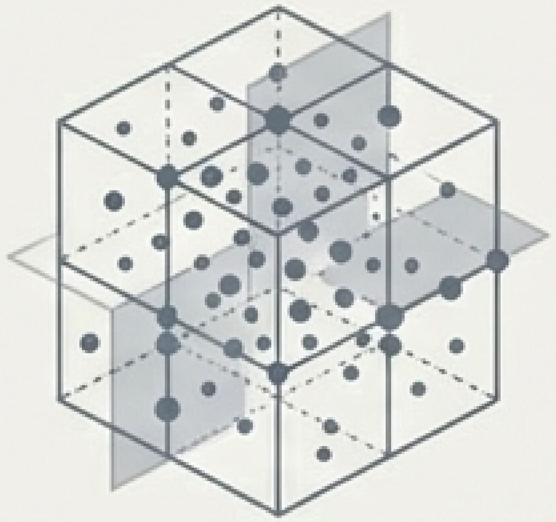


Task 2: Roads & Water (2D Imagery)

- **Model:** U-Net or DeepLabV3+ (Backbone: EfficientNet-B3)
- **Job:** Semantic Segmentation (Ideal for continuous features)

Task 3: Wells & Tanks (2D Imagery)

- **Model:** YOLOv8
- **Job:** Object Detection (Optimised for speed and small, discrete objects)



Task 4: Drainage Network (3D Point Clouds)

- **Model:** PointNet++ or RandLA-Net
- **Job:** 3D Segmentation (Handles 3D point clouds, which standard CNNs cannot)

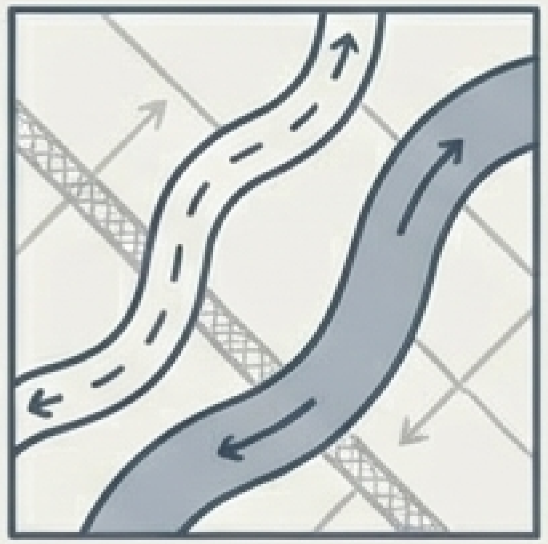
We’ve Hired a Team of Proven Specialists

The House Hunter (Mask R-CNN):

An expert at drawing precise boundaries. It knows ‘House A’ is different from ‘House B’ even if their walls are touching.

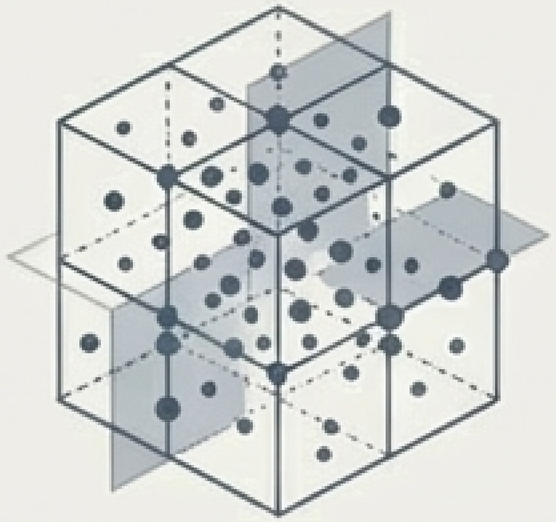
The Road Mapper (U-Net):

Stands for ‘You Only Look Once’. It is incredibly fast and sharp-eyed, perfect for spotting small objects like wells at a glance.



The Road Mapper (U-Net):

Originally famous in medical imaging for finding veins. To an AI, a road network looks just like a vein network, making this model a perfect fit.

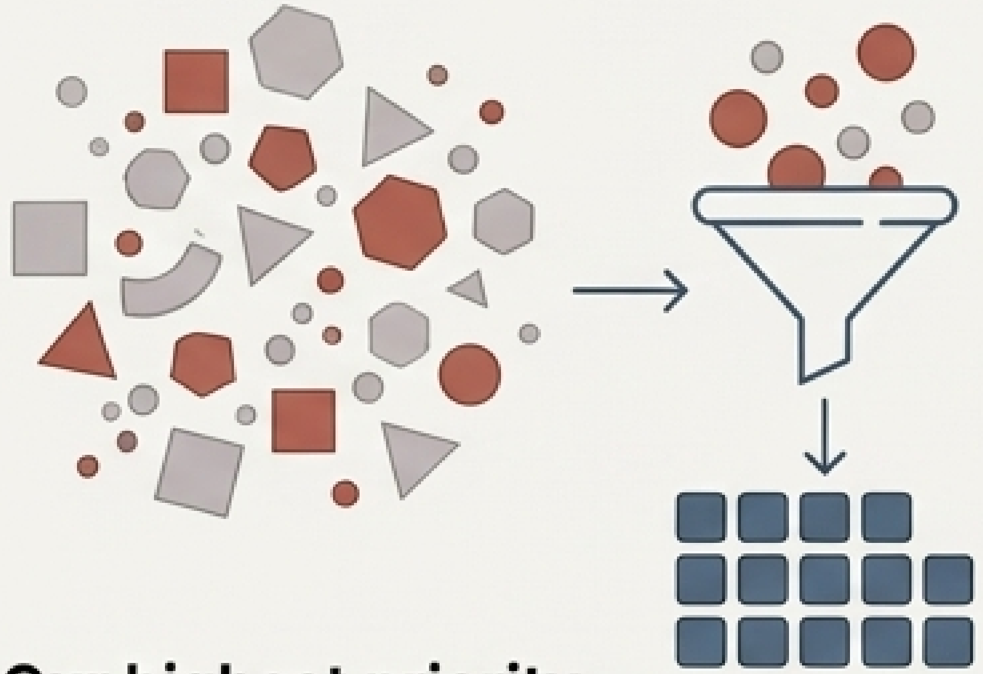


The 3D Expert (PointNet++):

Normal AI understands flat pictures (pixels). This specialist understands 3D ‘clouds of dots’, the exact language of our drone’s laser data.

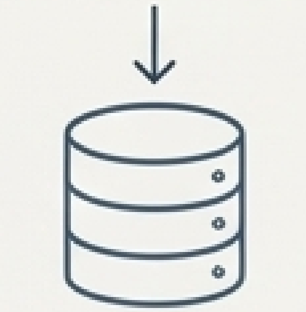
Our Work Isn’t Building the Engine, It’s Training the Driver

1. Data Curation & Annotation

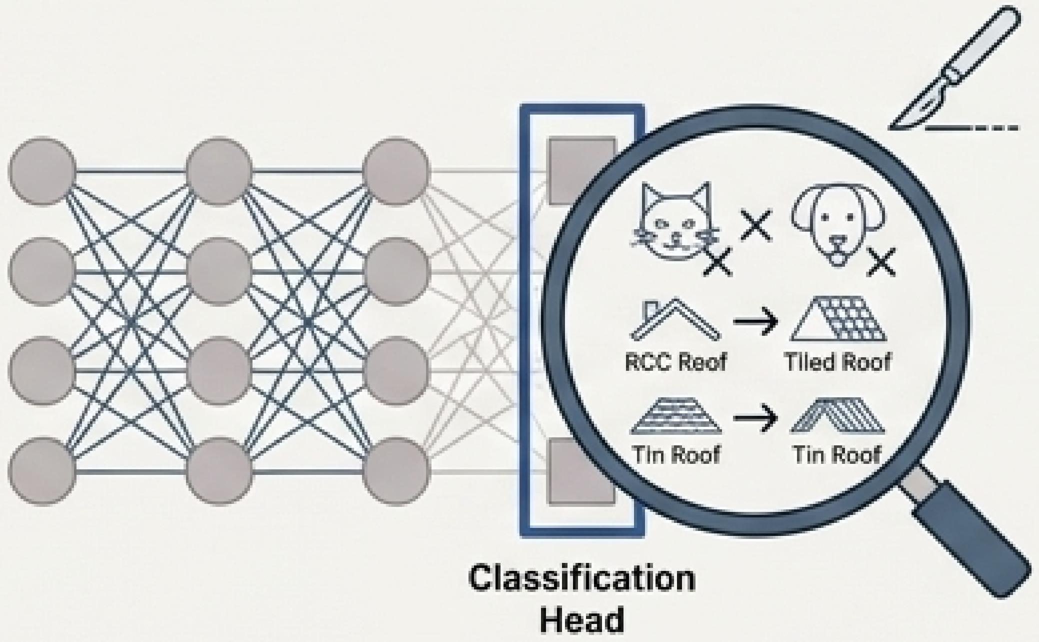


Our highest priority.

Ensuring pristine quality input to prevent ‘Garbage In, Garbage Out’.



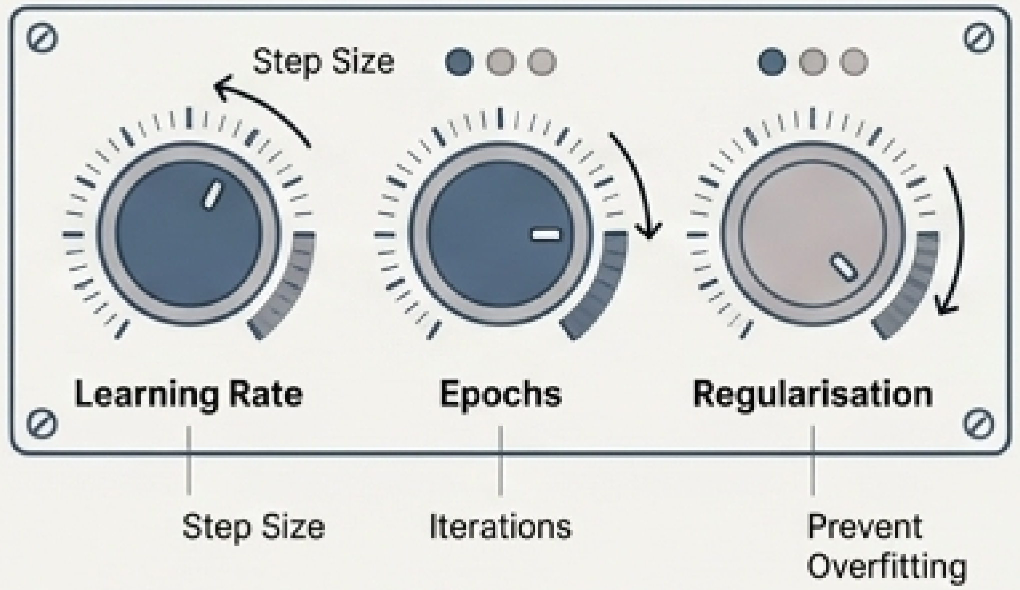
2. Architecture Modification



2. Architecture Modification

Performing precision surgery on the Classification Head (the final layer) to map generic classes (e.g., ‘Cat,’ ‘Dog’) to our specific project classes (e.g., 'RCC Roof,' ‘Tiled Roof,’ ‘Tin Roof’).

3. Hyperparameter Optimisation



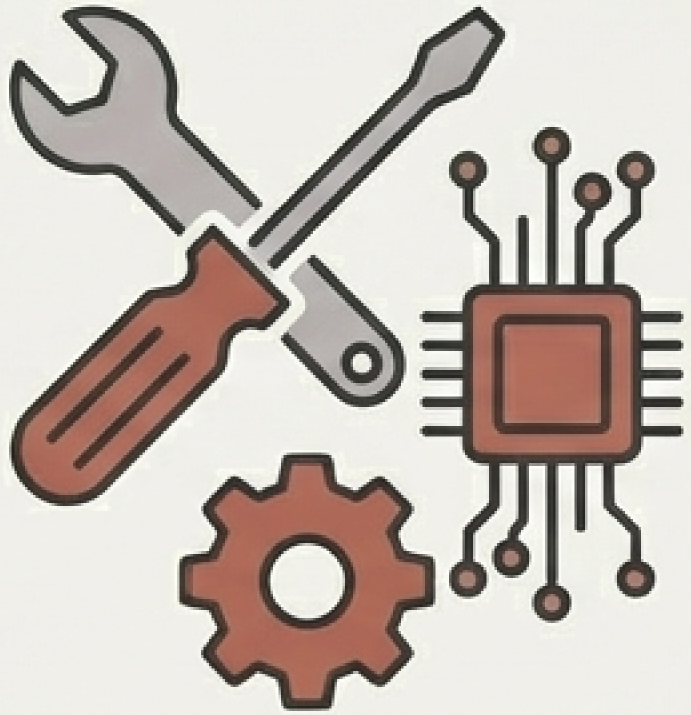
3. Hyperparameter Optimisation

Fine-tuning the controls of the learning process, such as the learning rate (gradient descent step size) and epochs (training iterations), to maximise performance and prevent overfitting.

Our Role Shifts from Raw Builder to Expert Trainer

We are the Teacher:

The AI model is brilliant but ignorant about our specific domain. Our primary job is to be the perfect teacher, providing it with flawless lesson materials (our curated data).



We are the Mechanic:

We perform delicate surgery on the model's brain to teach it new concepts (head modification). We also fine-tune the engine's controls (learning rate): if we teach it too fast, it gets confused; too slow, and it never learns.

This is Our Unwavering Plan for Success

ACTION: Do **NOT** build a neural network from scratch.

TECHNOLOGY: Utilise proven, industry-standard libraries such as `segmentation_models_pytorch` and `Ultralytics`.

MODEL: Select a State-of-the-Art architecture (e.g., Unet with a `resnet34` encoder) as a starting point.

FOCUS: Allocate 100% of engineering effort to **Data Excellence** and **Model Fine-Tuning**.

This is the only professional path to achieving 95% accuracy by the 27 January deadline.