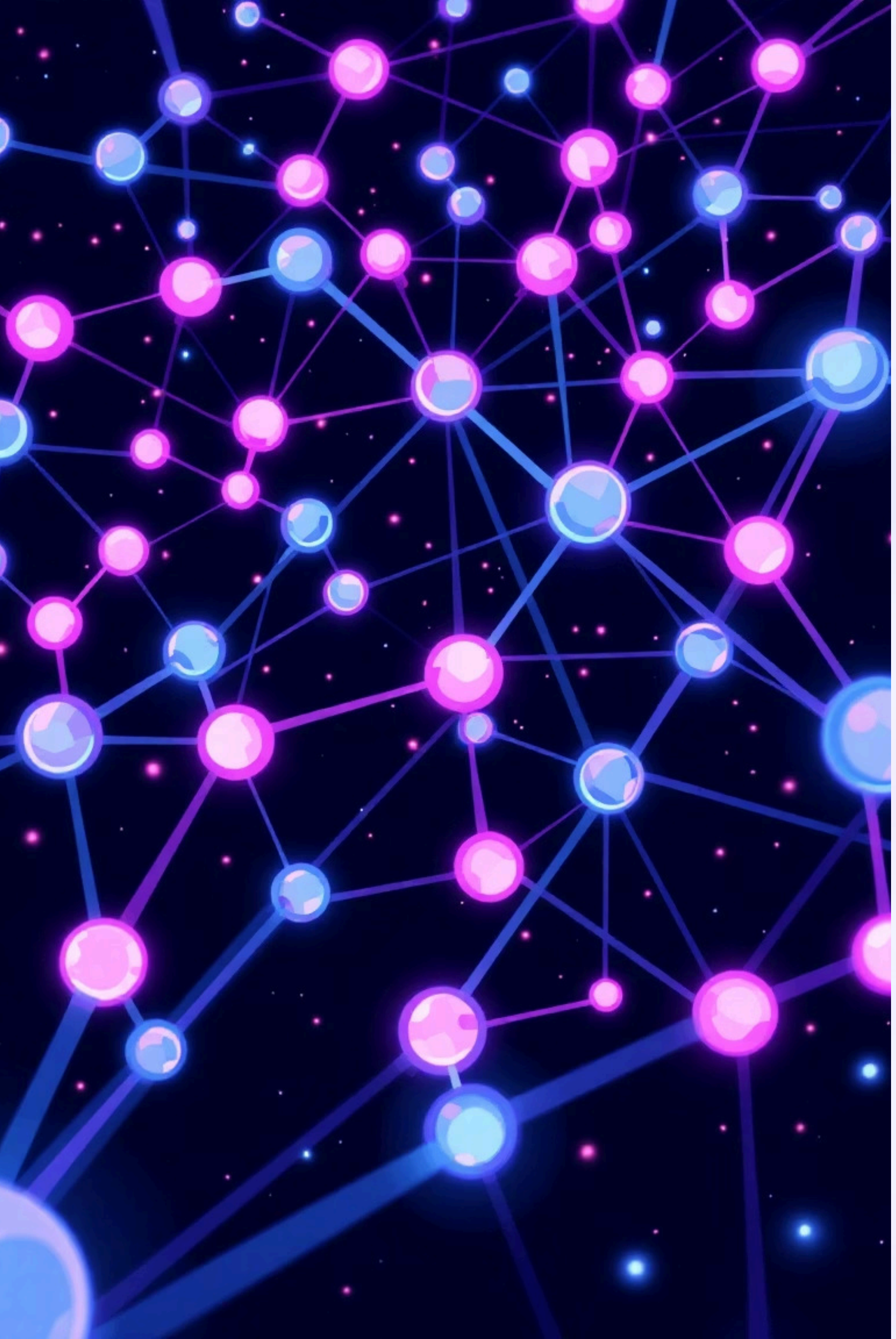


Few-Shot Learning (FSL)

How Machines Learn From Just a Few Examples

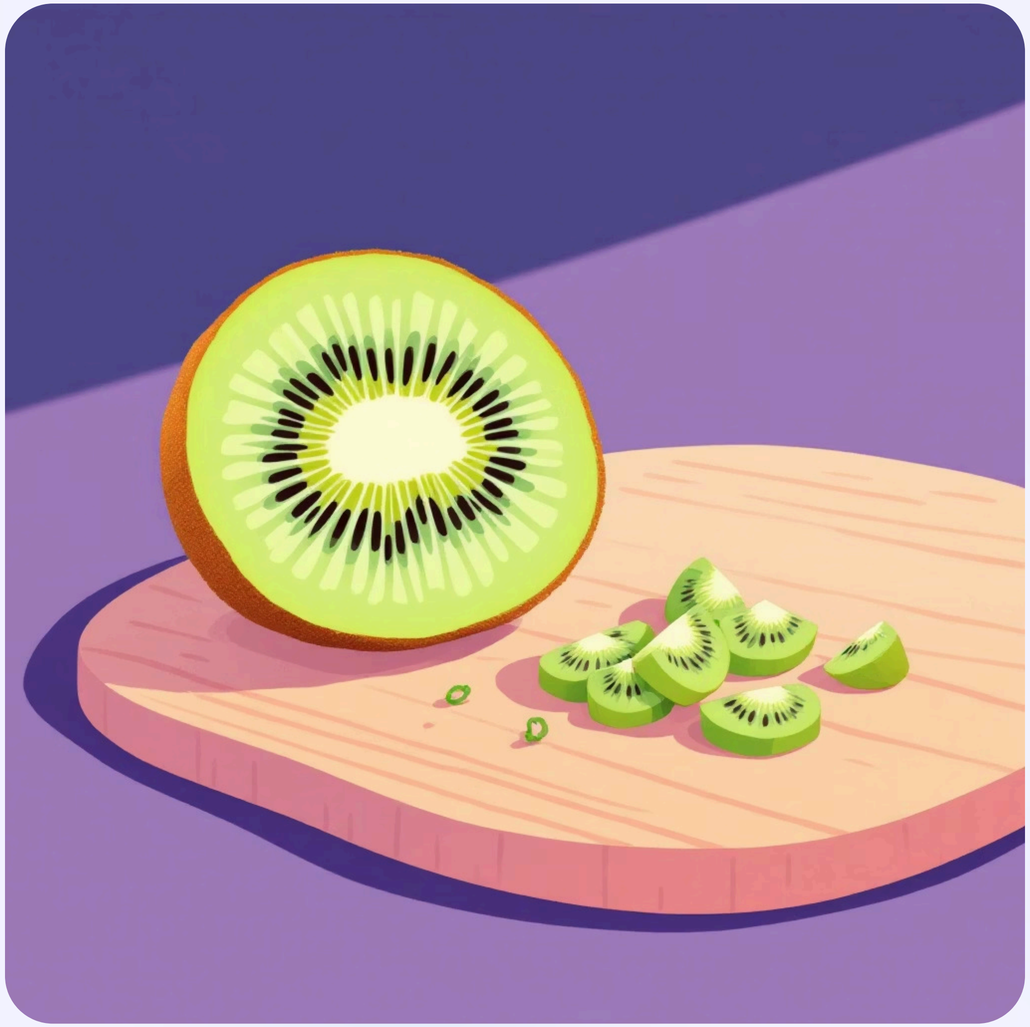
In this presentation, you'll discover what few-shot learning is, why it matters in modern AI, and how it differs from zero-shot and traditional learning approaches.

The Big Idea

"Learning a new concept with just a few examples — like humans do."

🧠 **Think about this:** You see just two photographs of a kiwi fruit and someone tells you what it is. The next time you spot a kiwi—whether in a market, on a menu, or in someone's kitchen—you recognise it instantly. That's precisely how few-shot learning works.

This mirrors human cognition, where we don't need hundreds of exposures to learn something new. A few well-chosen examples are often enough.



Why Few-Shot Learning Matters

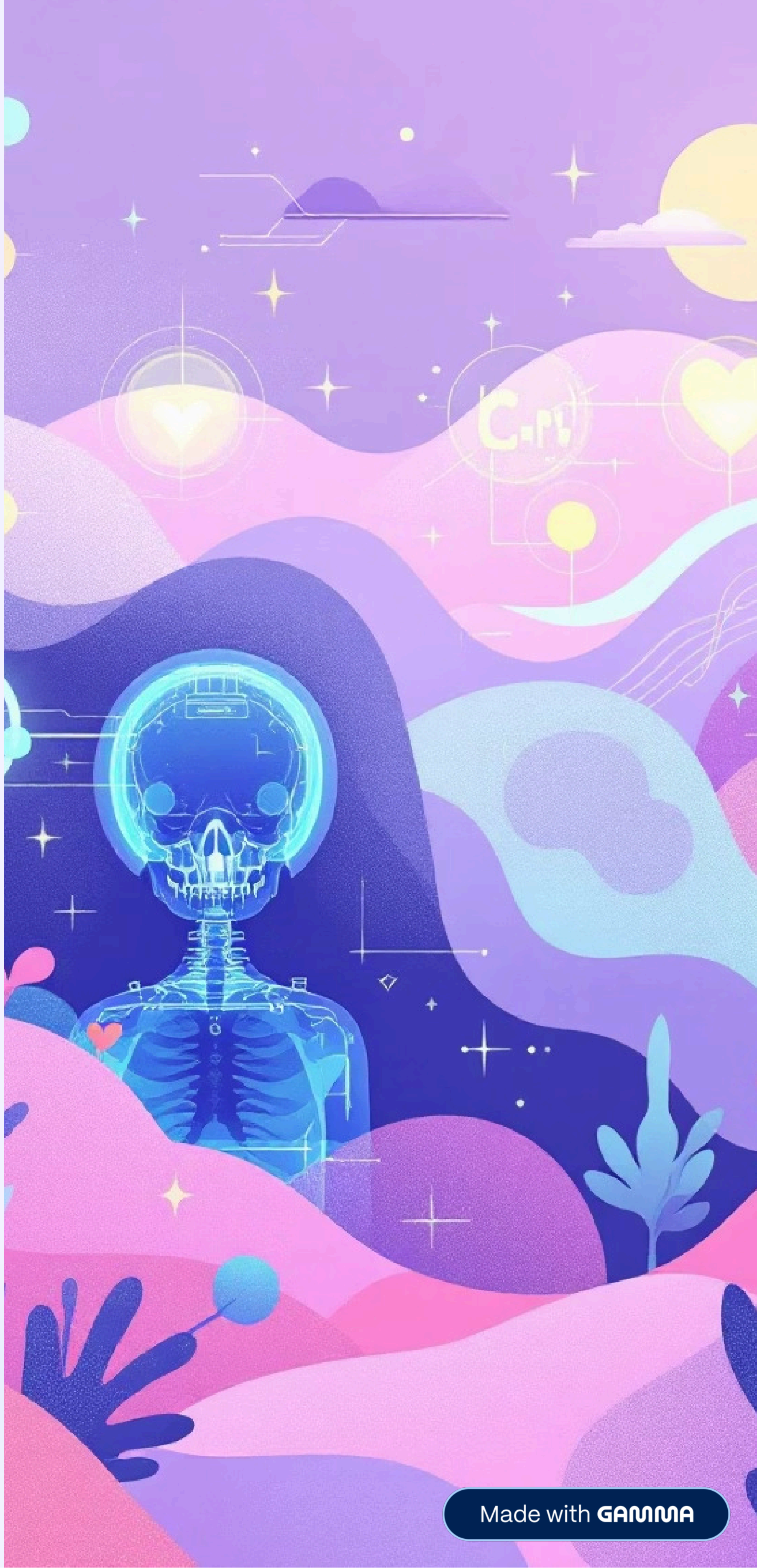
Traditional ML Challenge

- Requires thousands of labelled examples
- Expensive data collection
- Struggles with rare classes

Few-Shot Advantage

- Learns from just 1–10 examples per class
- Cost-effective and efficient
- Handles scarce data scenarios

💡 Few-shot learning is now being applied across **medicine** (detecting rare diseases), **robotics** (learning new object manipulation), **natural language processing** (understanding new languages), and **computer vision** (identifying rare species).



Breaking Down the Terminology

Understanding the "shot" terminology helps clarify the spectrum of learning approaches:

Term	Meaning	Examples Needed
Shot	Number of labelled examples per class	Varies
Zero-Shot	No examples; uses semantic descriptions	0 examples
One-Shot	Learning from a single example	1 example
Few-Shot	Learning from a handful of examples	2–10 examples per class
Many-Shot	Traditional supervised learning	Hundreds to thousands

📊 **Few-shot** represents a practical middle ground—enough data to learn meaningful patterns, but not so much that data collection becomes prohibitively expensive.

An Everyday Analogy

👩‍🍳 Think Like a Chef

1

Traditional ML Approach

Like a novice who needs to cook a dish hundreds of times, making mistakes and iterating constantly before mastering it.

2

Few-Shot Learning Approach

Like an experienced chef who knows cooking fundamentals and can master a new dish after just 1–2 attempts with a recipe.

🧩 The key insight: The model leverages *prior knowledge* from related tasks to generalise quickly to new situations.

Real-World Applications

Few-shot learning shines in domains where data scarcity is the norm, not the exception:

Healthcare

Detecting rare diseases: Limited patient scans make traditional ML impractical. FSL can learn from just a handful of cases.

Computer Vision

Identifying rare animals: When only a few photographs of endangered species exist, FSL enables accurate recognition.

Robotics

Learning new object grasps: Physical demonstrations are expensive; robots can learn from just a few examples.

Natural Language Processing

New language tasks: When minimal annotated text exists in low-resource languages, FSL bridges the gap.

Comparing Learning Paradigms

Understanding where few-shot learning fits in the broader landscape of machine learning approaches:

Aspect	Zero-Shot	Few-Shot	Supervised
Examples Needed	0	1–10 per class	Hundreds or more
Knowledge Source	Semantic descriptions	Few labelled examples	Large labelled dataset
Best Use Case	Completely new unseen categories	Limited available data	Common, well-defined tasks
Example	"Zebra" learnt from text description only	"Kiwi" learnt from 3 images	"Cat" learnt from 1,000 images
Complexity	High	Medium	Low

The Core Challenge

"How do we train a model that can learn to learn?"

Generalise From Prior Experiences

The model must extract transferable knowledge from tasks it has seen before and apply that understanding to entirely new scenarios.

Adapt to New Tasks Quickly

When presented with just a handful of examples, the model needs to rapidly adjust its internal representations without extensive retraining.

Avoid Overfitting With Few Samples

With minimal data, there's a high risk of memorising specific examples rather than learning underlying patterns. The model must stay balanced.

The Meta-Learning Paradigm

Meta-Learning

"Learning to Learn"

Instead of training a model to excel at one specific task, meta-learning trains a model to become good at *learning itself.* The model practises learning across many diverse small tasks, developing a generalised ability to adapt quickly.

Think of it as training someone not just to solve maths problems, but to become good at **learning new types of maths** efficiently.

Key Takeaways

FSL learns with very few labelled samples

Typically requiring just 1–10 examples per class, few-shot learning makes AI practical in data-scarce environments.

Inspired by human-like adaptability

Just as humans can generalise from minimal exposure, FSL mimics our natural ability to recognise patterns quickly.

Bridges the gap between zero-shot and supervised learning

FSL occupies the sweet spot—more practical than zero-shot, more efficient than traditional supervised approaches.

Foundation for modern adaptive AI

From medical diagnosis to robotics, FSL is enabling the next generation of intelligent, flexible systems.

➡️ **Coming up next:** How Few-Shot Learning Works – Techniques & Architectures