Deep Learning (DL) Methods in Construction

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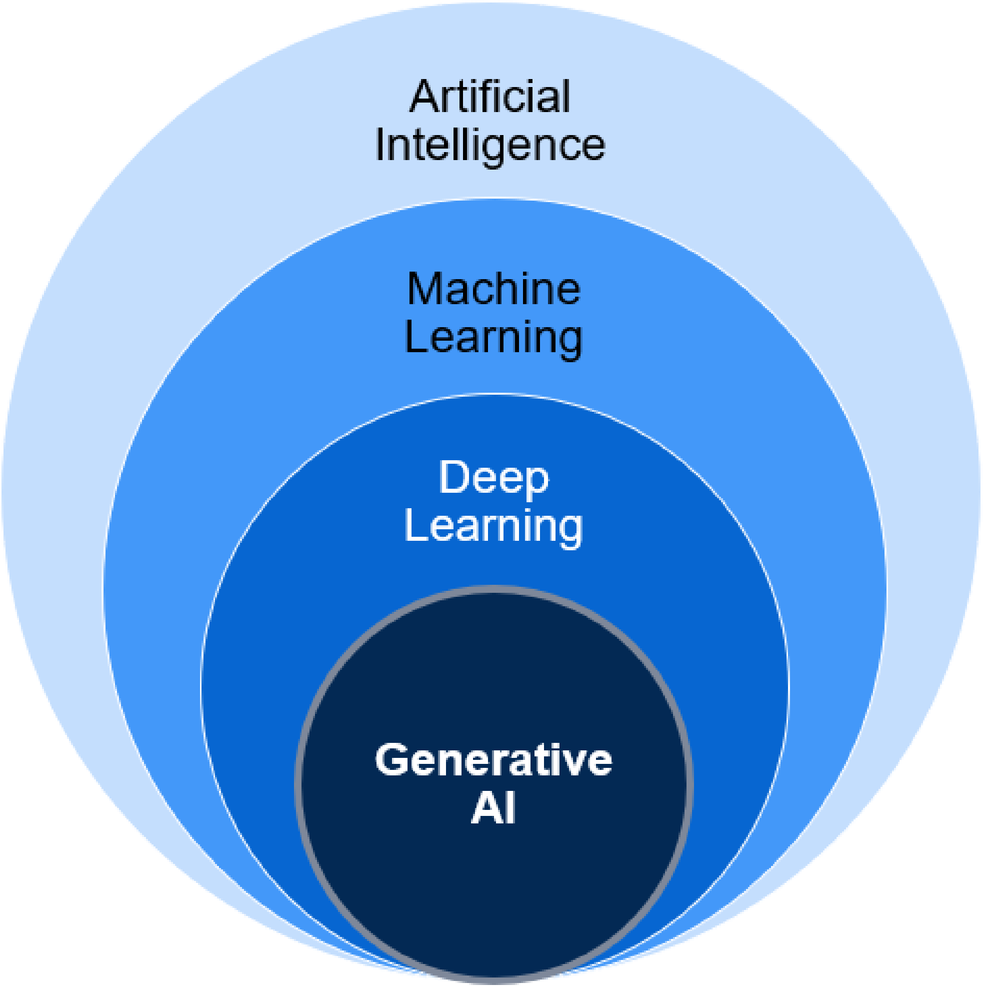
Learning Objectives

- Conceptual Understanding: Understand how deep learning differs from traditional ML.
- Core Architectures: Overview of CNNs, RNNs, and Transformers.
- Construction Applications: Quality inspection via computer vision, project schedule forecasting, document analysis, sensor data insights.
- Implementation & Challenges: Data preparation, model training, resource requirements, interpretability.

The AI Landscape



- AI is the broad field of computer science focused on creating **machines capable of performing tasks that typically require human intelligence**

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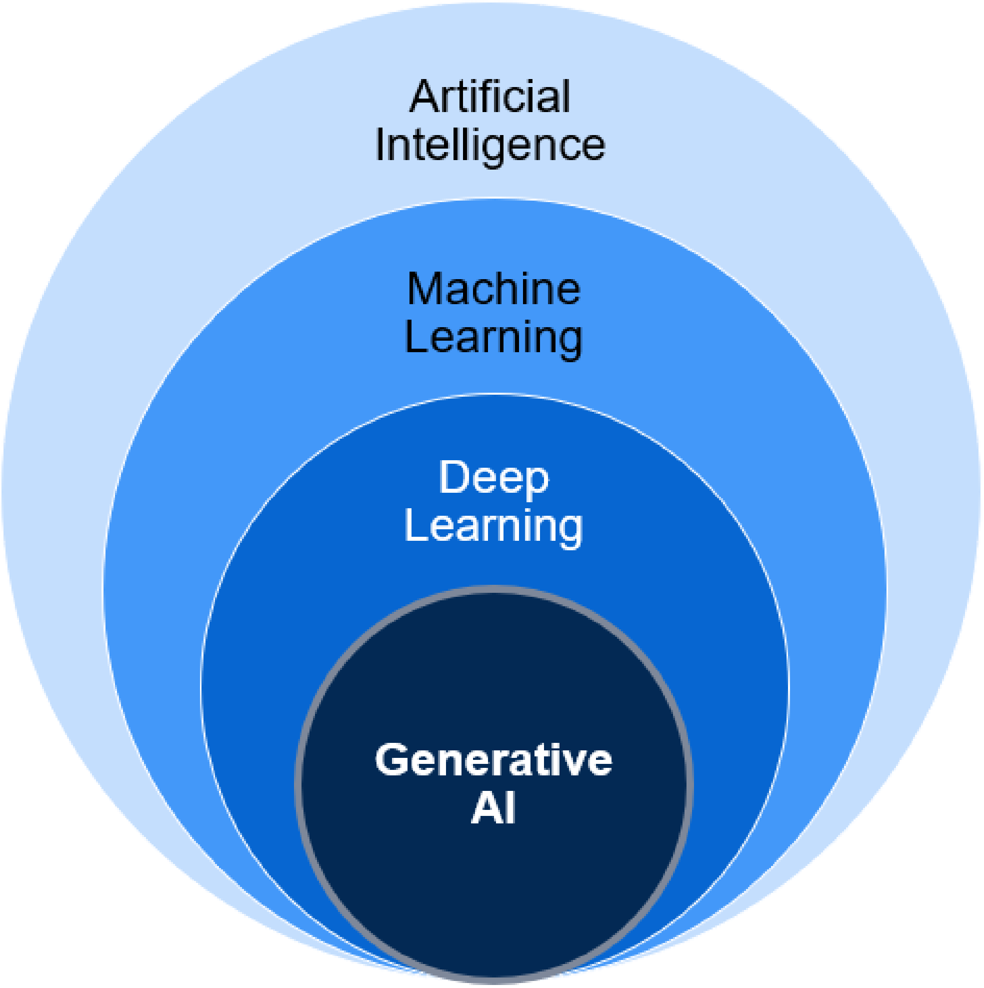

- ML is a subset of AI involving algorithms and statistical models that enable computers to **improve their performance on a task through examples**

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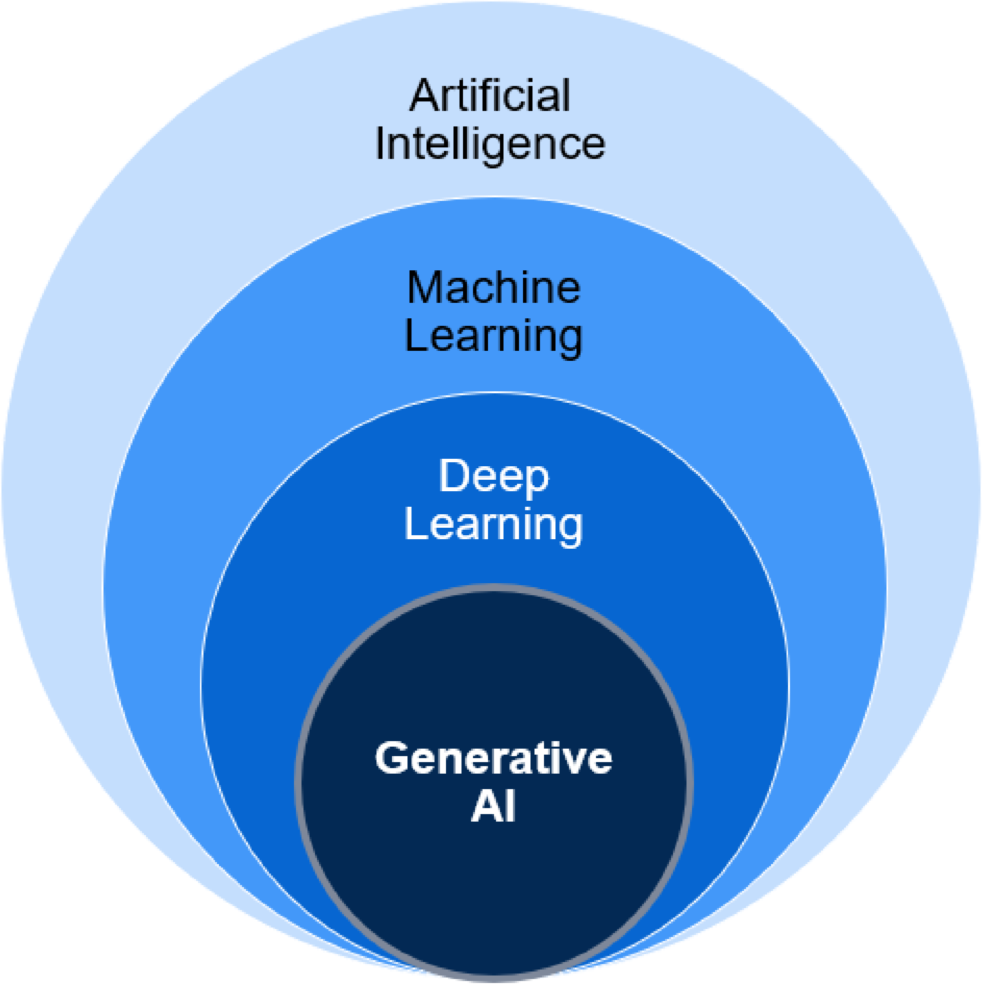

- DL is a subset of ML based on **artificial neural networks**, where algorithms learn from **large amounts of data** to identify patterns and make decisions

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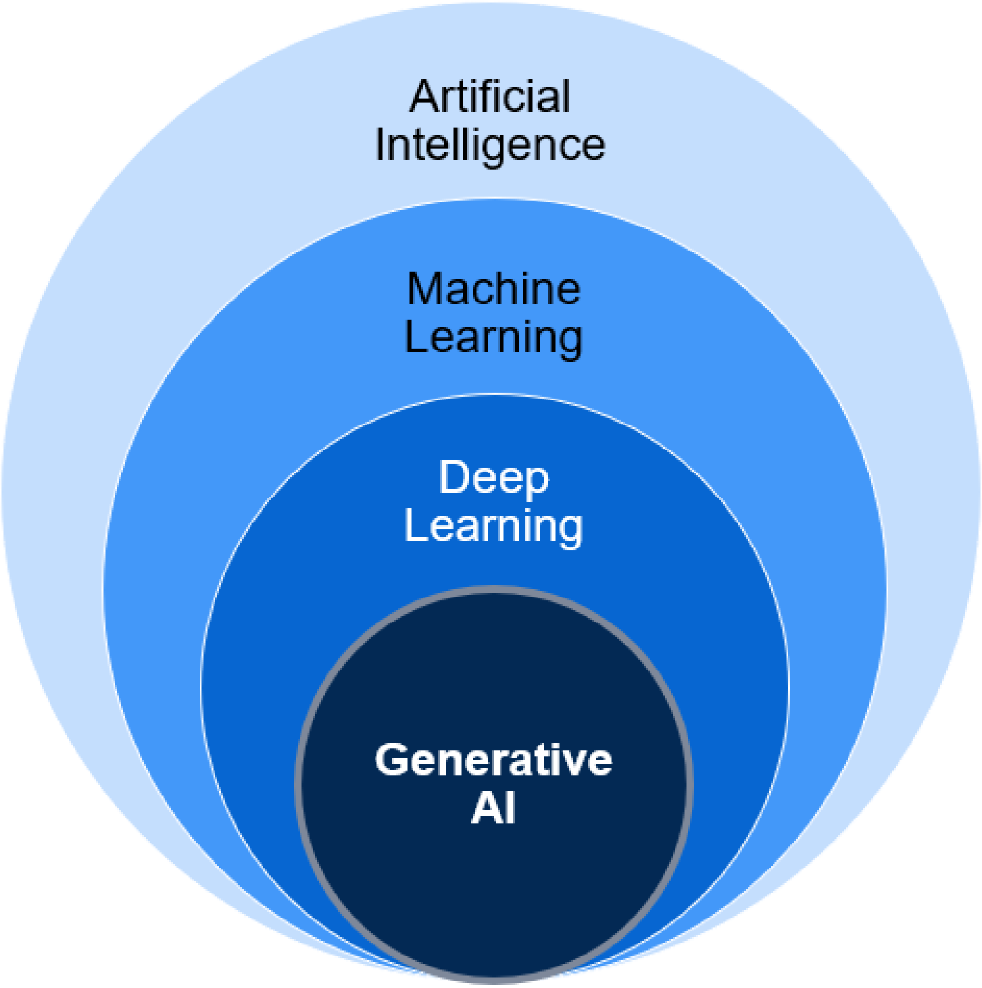


- GAI refers to AI technologies that can **generate new content, ideas, or data** that are coherent and plausible, often resembling human-generated outputs

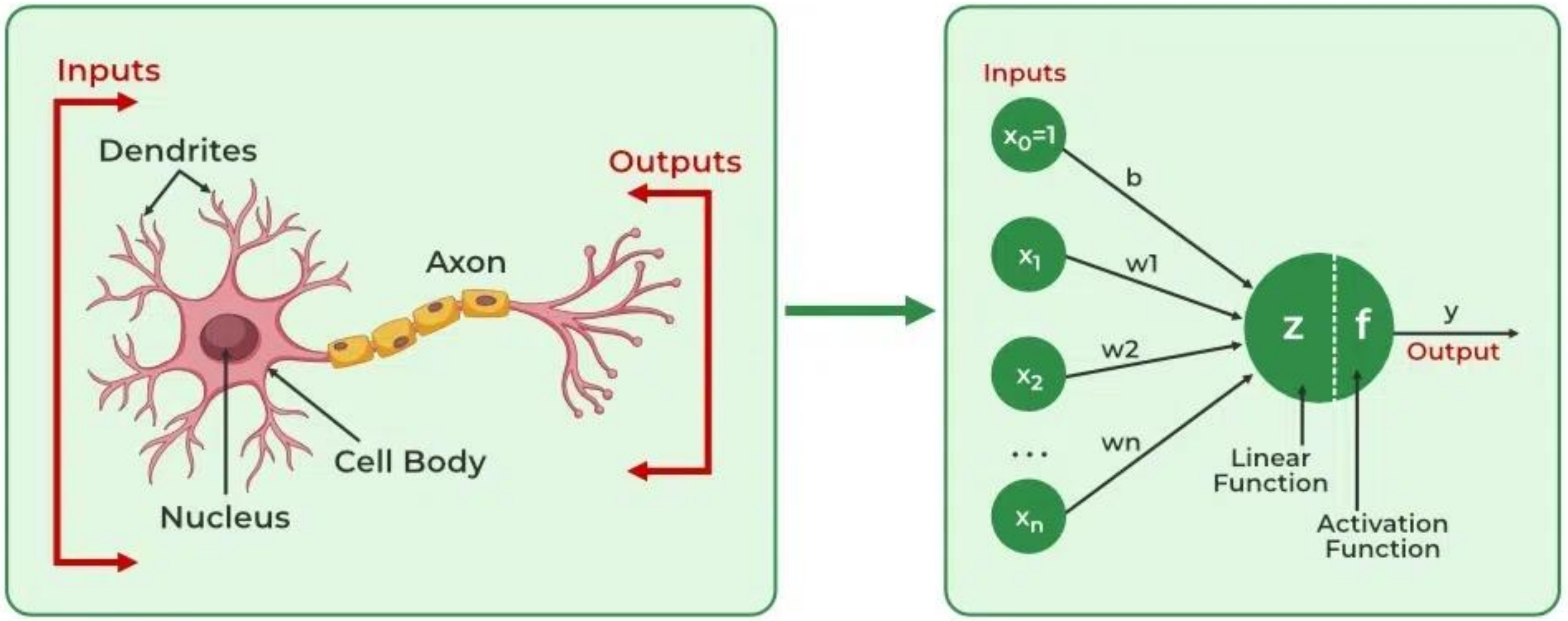
The ML Pipeline

The ML Pipeline in Construction

- **Data Collection** – from sensors, historical records, BIM.
- **Data Cleaning & Preprocessing** – handle missing values, outliers, ensure consistent naming.
- **Feature Engineering** – domain expertise to create useful features (e.g., weather delays, labor hours).
- **Model Selection** – choose algorithms (linear models, tree-based, neural networks).
- **Training & Validation** – split data, tune hyperparameters.
- **Testing & Evaluation** – measure performance on a held-out set.
- **Deployment & Monitoring** – real-time dashboards, iterative improvements.

The Basics of Neural Networks

- An artificial mathematical model used to approximate nonlinear functions



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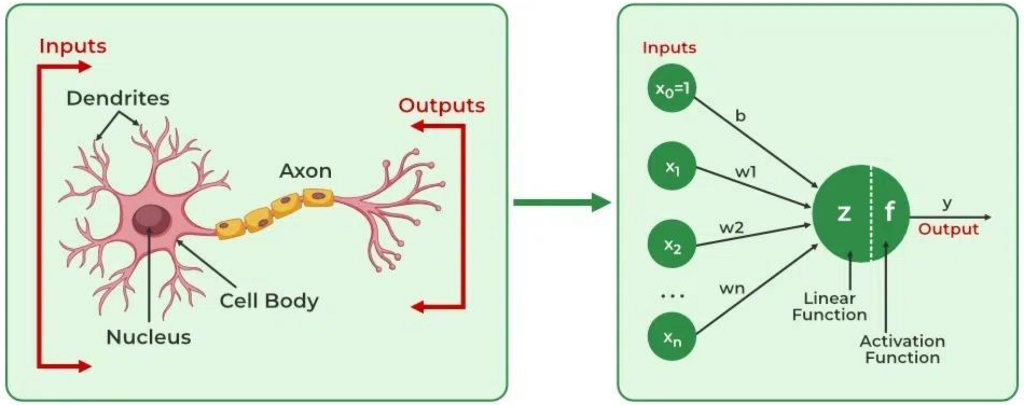

- **Structure:** Composed of interconnected neurons (nodes) arranged in layers (input, hidden, output)

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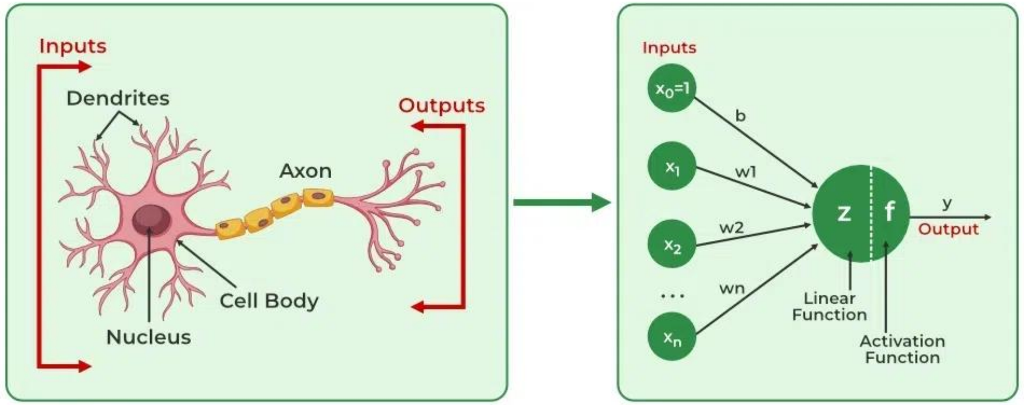

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- **Learning Mechanism:** Uses weighted connections, activation functions, and backpropagation to adjust weights

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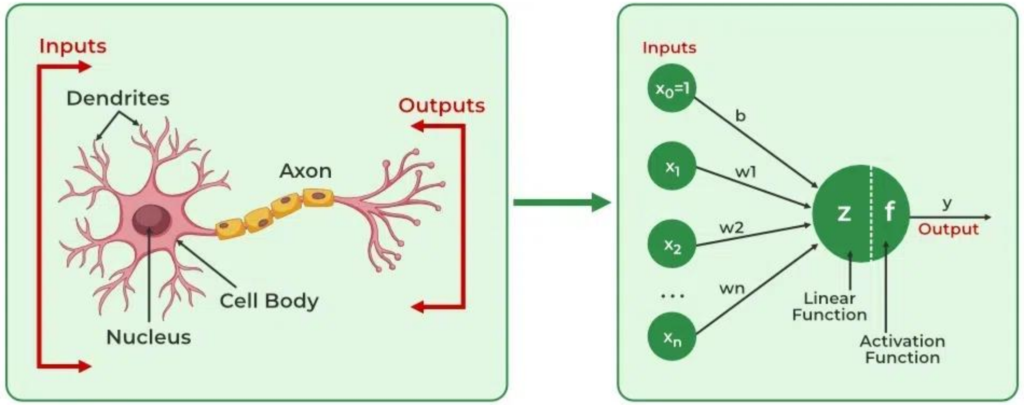

- **Structure:** Composed of interconnected neurons (nodes) arranged in layers (input, hidden, output)
- **Learning Mechanism:** Uses weighted connections, activation functions, and backpropagation to adjust weights
- **Key Advantage:** Ability to model complex, non-linear relationships automatically

Why NNs can model complex, non-linear relationships automatically?

Linear function

Non-linear function

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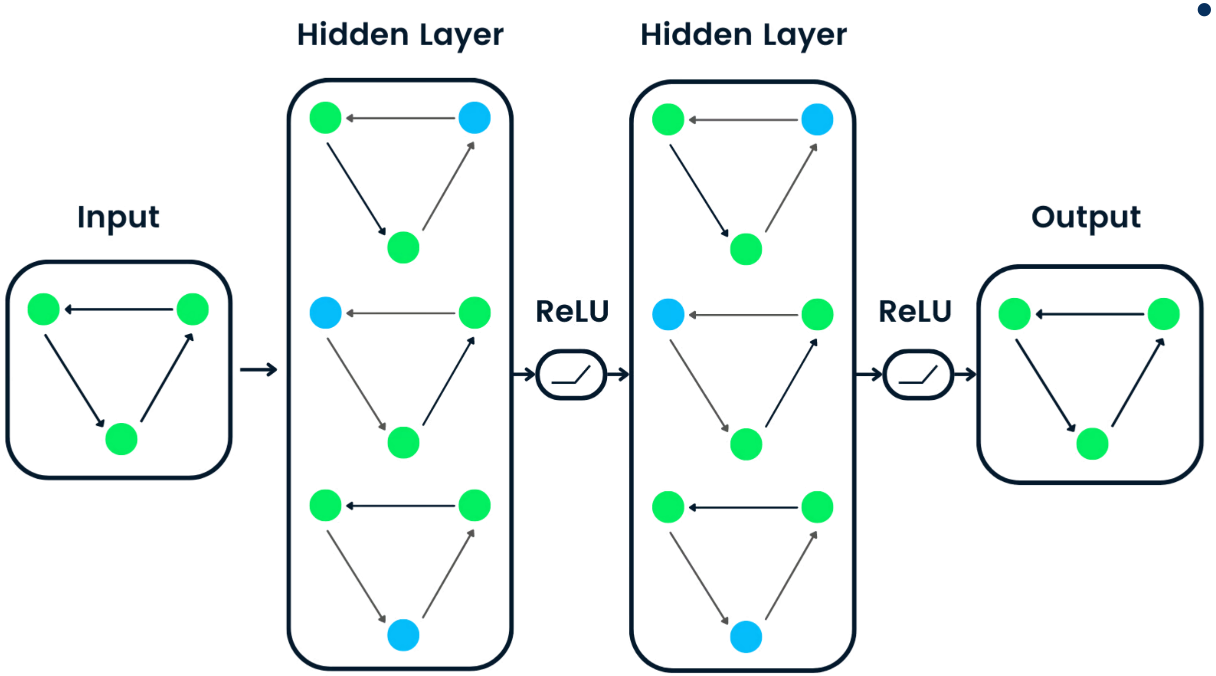
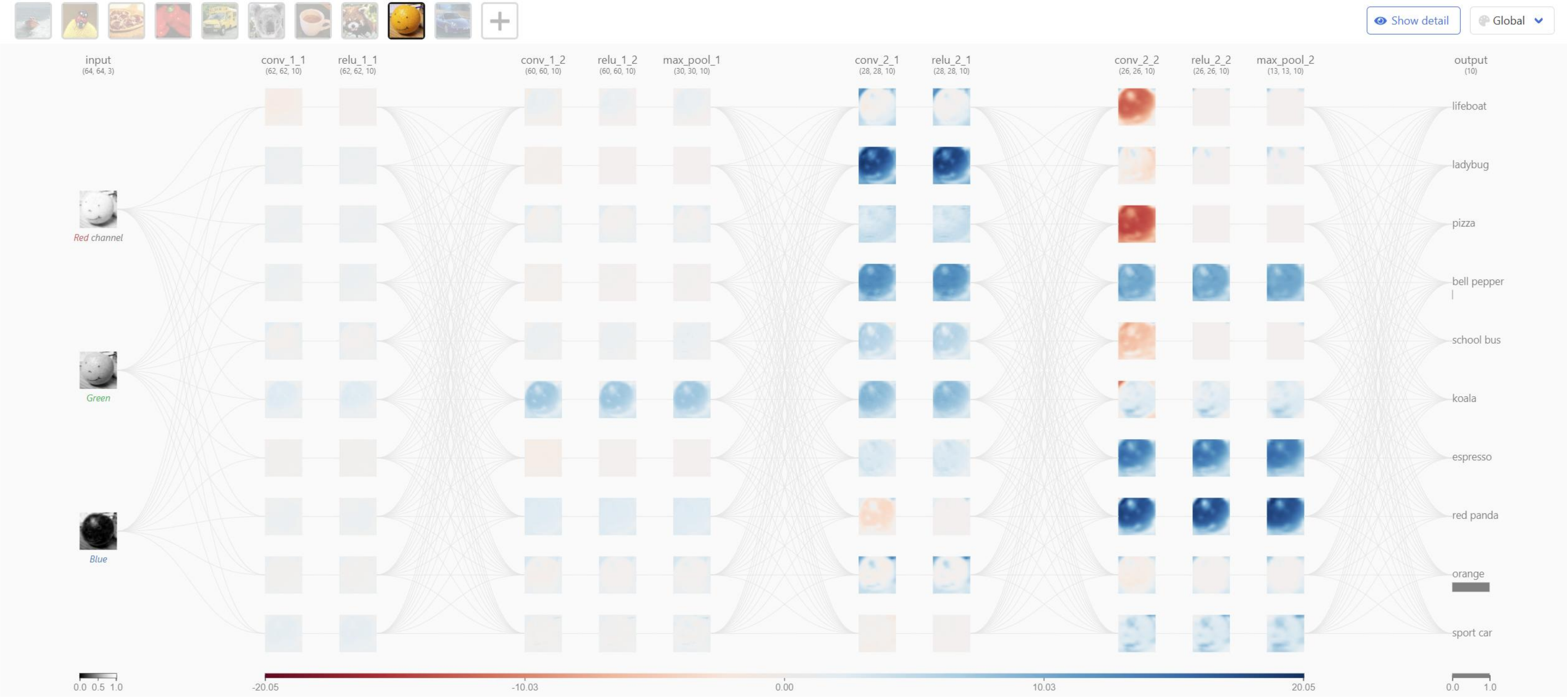


- **Layered Architecture:**
  - Structured in layers
  - Each layer transforms its input into increasingly abstract representations
  - **Early layers** might capture simple patterns (like edges in an image), while **deeper layers** capture more complex structures (like shapes or even entire objects)

Demo: NN Explainer

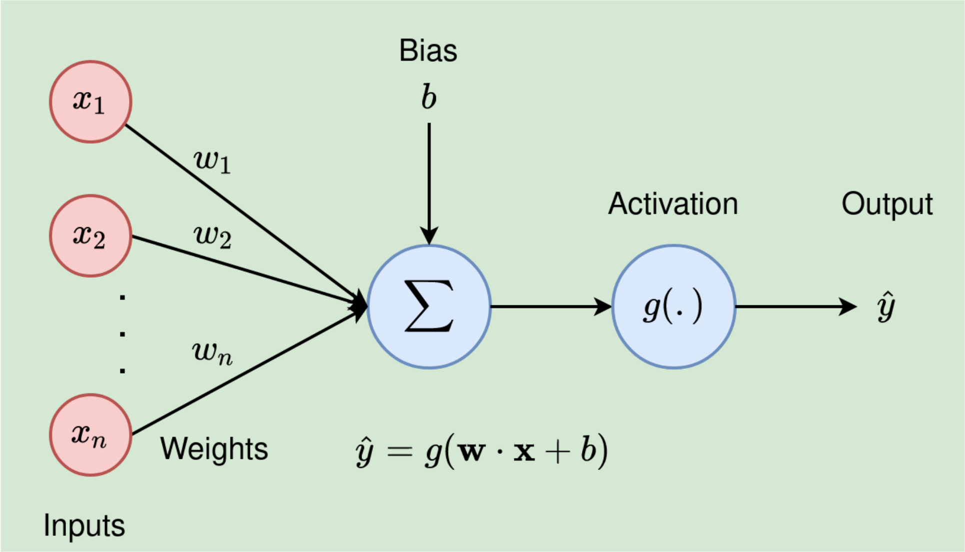


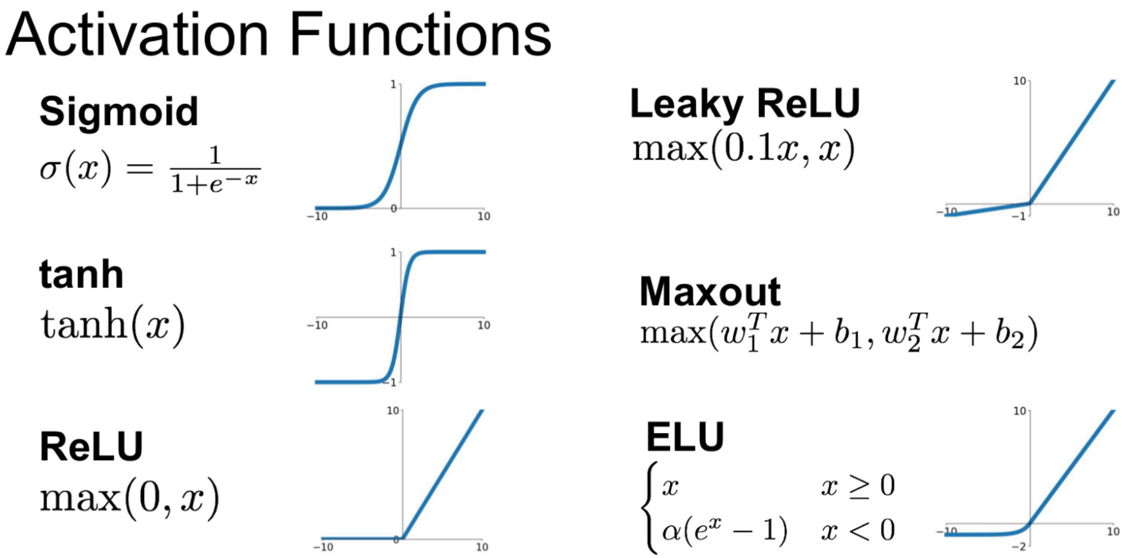
Why NNs can model complex, non-linear relationships automatically?

Non-Linear Activation Functions:

- Every neuron computes a weighted sum of its inputs and then applies a non-linear activation function (e.g., ReLU, sigmoid, tanh)

- The non-linearity allows the network to model intricate, non-linear patterns in the data





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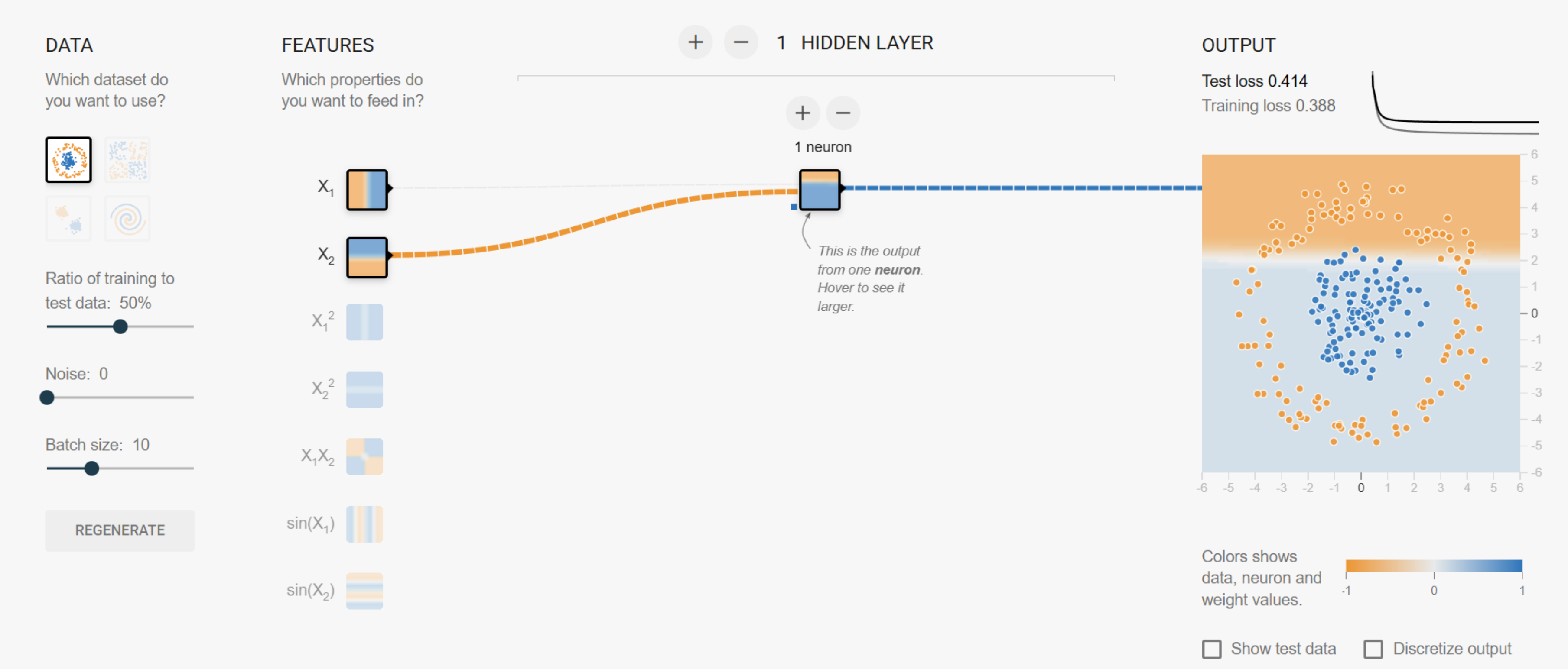
Universal Approximation Theorem:

DEMO

a feed-forward neural network with at least one hidden layer containing a finite number of neurons can approximate any continuous function on a compact domain, given appropriate parameters

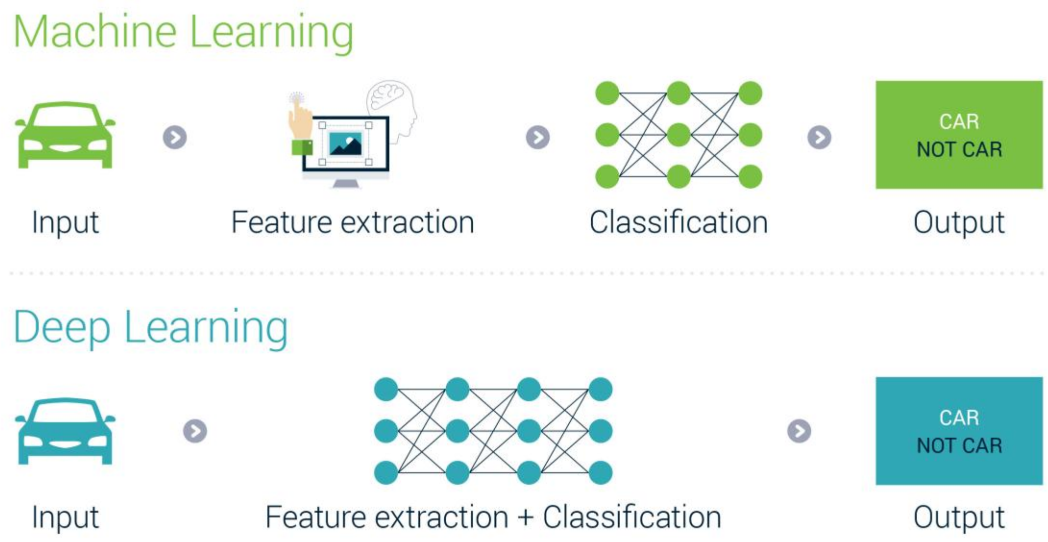


Why NNs can model complex, non-linear relationships automatically?

Automated Feature Extraction (especially beneficial for unstructured data like images, audios, texts)

- Unlike traditional machine learning methods that rely on manual feature engineering, neural networks **automatically learn the best features from raw data through training**

- The network **adjusts its weights during backpropagation to minimize error**, effectively "discovering" the non-linear relationships that exist in the data



ML vs. DL: What’s the Difference?

Machine Learning (ML):

- **Techniques**: Linear regression, decision trees, SVMs, etc
- **Strengths**: Simpler models, easier to interpret, lower data requirements
- **Limitations**: Heavy reliance on pre-engineered features, struggles with very large or unstructured data

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Deep Learning (DL):

- **Techniques**: Neural networks with many layers (**deep architectures**)
- **Strengths**: Automatic feature extraction, ability to model complex data, excels with images, audio, and text
- **Limitations**: Requires more data and computational resources, can be seen as “black boxes”

Construction Data by Format

- **Image Data:** Site Photographs, Drone Imagery
- **Video Data:** Surveillance Cameras, Drones & UAVs, Wearable Cameras
- **Point Cloud Data:** Laser Scanning (LiDAR), Photogrammetry
- **Audio Data**: On-Site Recordings, Acoustic Sensors
- **Textual / Document Data**: Project Documents, Regulatory & Legal Docs
- **Tabular / Numeric Data**: Schedules, Cost Logs, Sensor Data, Financial & Accounting Records

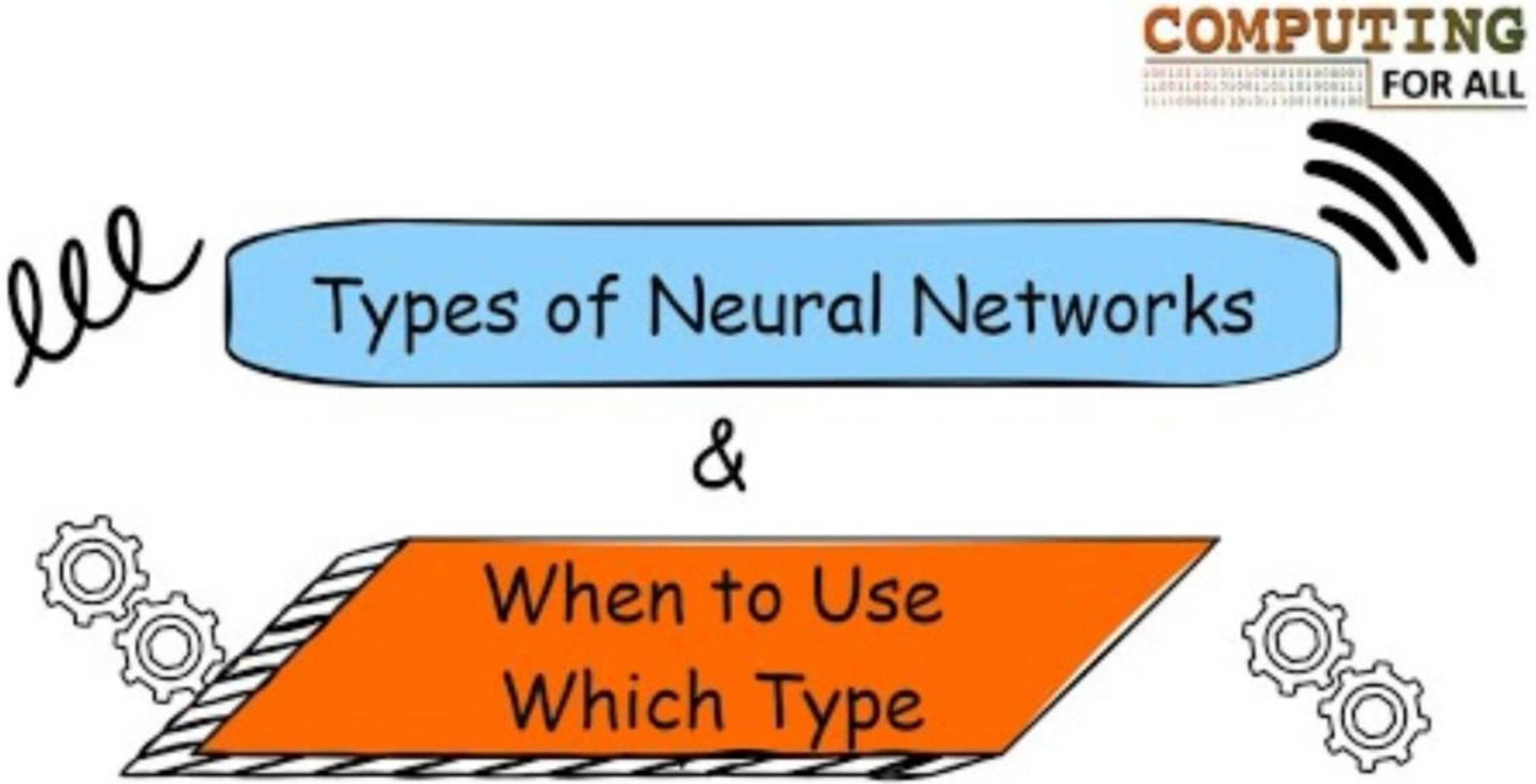
Core Deep Learning Architectures & Their Examples

- **Convolutional Neural Networks (CNNs)**
  - Best for image/video tasks: structure for 2D data, capturing spatial relationships

- **RNN (Recurrent Neural Networks) & LSTM/GRU**
  - Suited for sequential/time-series data, e.g., project schedule logs or sensor sequences

- **Emerging Architectures:**
  - **Transformers**
    - State-of-the-art for NLP and can also handle long-range sequential data
    - Possibly used for large textual data sets (contracts, safety logs) or advanced vision tasks
  - **Graph Neural Networks (GNNs)**
    - Capturing complex interdependencies, e.g., relationships between different construction elements within a BIM

Core Deep Learning Architectures & Their Examples



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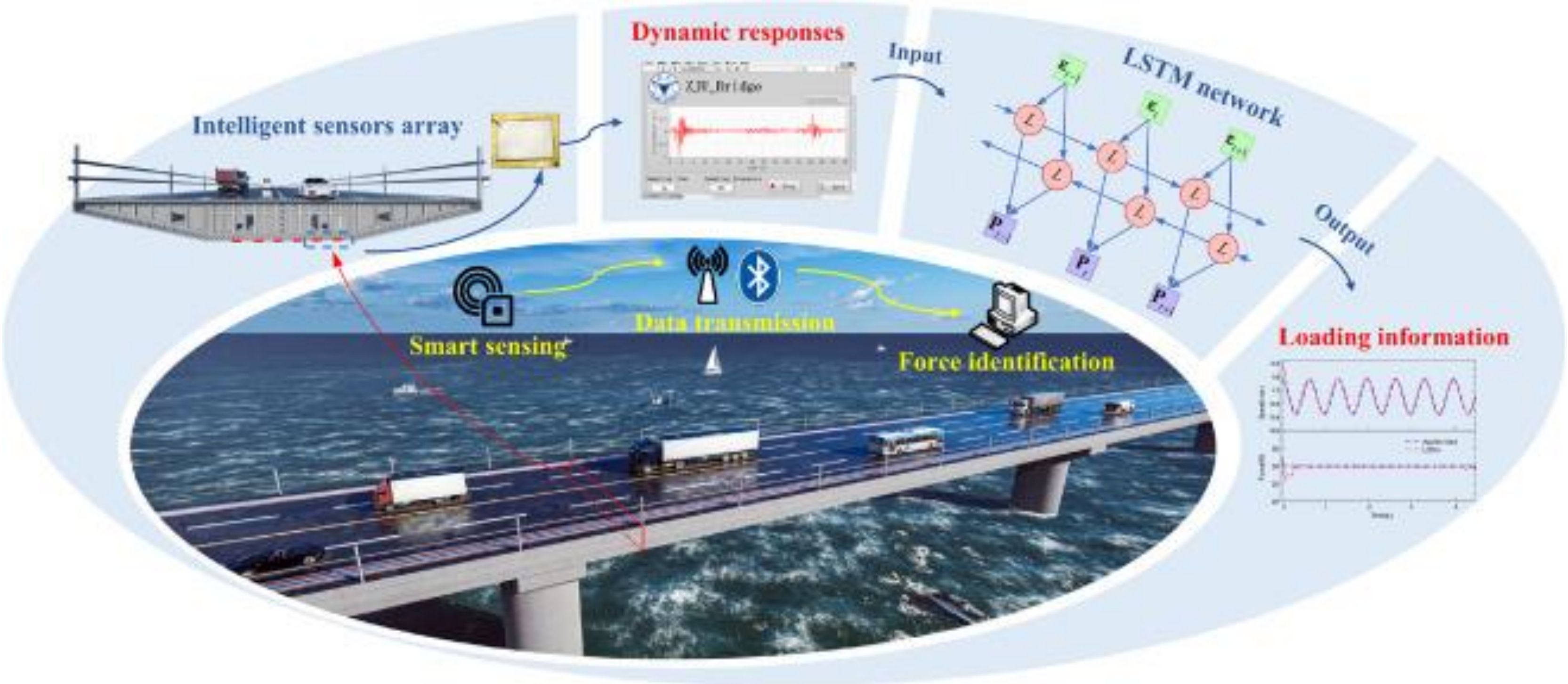
Computer Vision in Construction

- **Object Detection** (e.g., YOLO, Faster R-CNN) to detect workers, equipment, PPE compliance
- **Semantic Segmentation** (UNet, SegNet) for measuring site progress from drone images
- **Defect Detection (detection or segmentation)**: Cracks in concrete, corrosion on steel, misalignments

Time-Series & Sensor Data with RNN/LSTM

- **Construction projects often rely on temporal data**: equipment performance logs, temperature/humidity sensors, daily productivity logs
- RNN, LSTM, GRU handle sequence data, capturing patterns over time
- **Predictive Maintenance**: forecasting machine breakdown from sensor logs

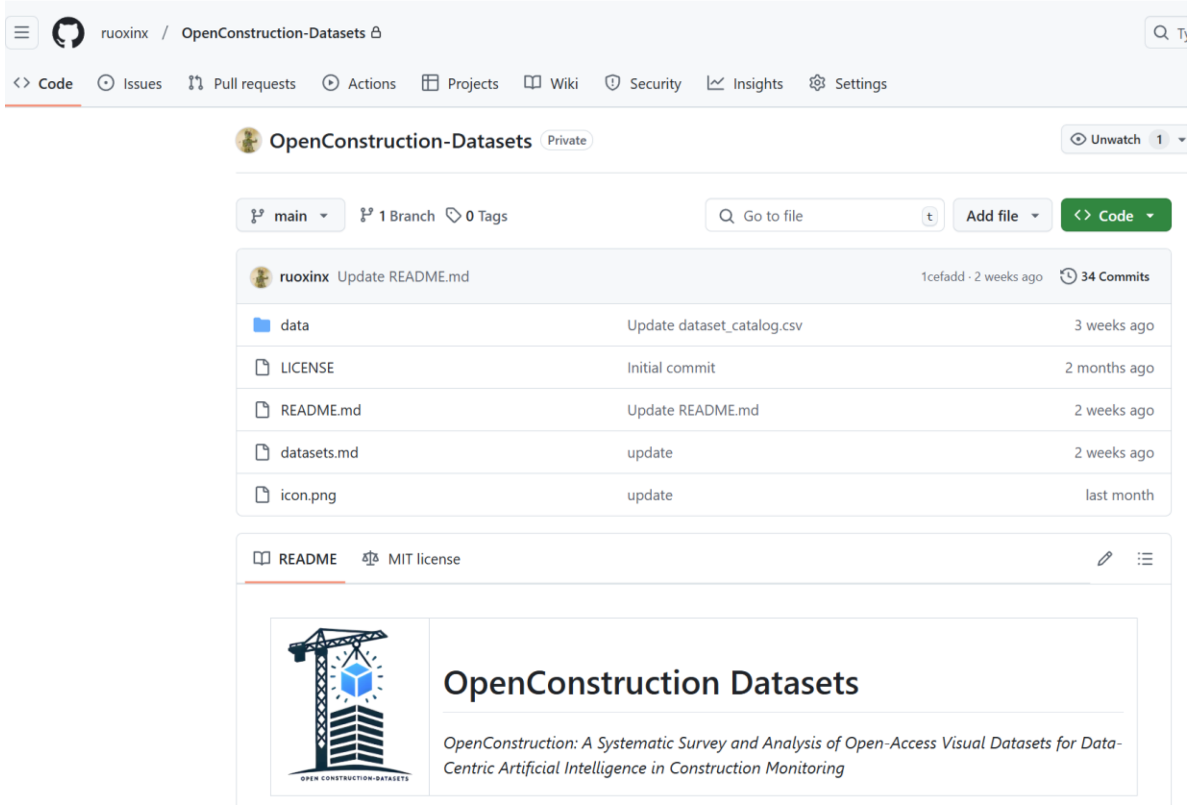


Transformers & NLP in Construction

- **Transformer Architecture (e.g., BERT, GPT)**: revolutionizing NLP with self-attention.
- **Use Cases:**
  - Contract analysis: extracting clause info, risk level.
  - Summarizing daily site reports.
  - Classifying and searching large volumes of specification documents.
- **Potential for generative tasks**: automated RFI drafting or quick summarization of multi-page building codes

Data Challenges and Strategies

- Limited labeled datasets, variability in environmental conditions
- Domain-specific data (e.g., diverse building materials, complex site layouts)



Data Challenges and Strategies

- **Strategies to Overcome:**
  - **Data Augmentation:** Enhancing dataset size by modifying existing images
  - **Synthetic Data Generation:** Using simulations to create training data
  - **Transfer Learning:** Leveraging models pre-trained on large datasets

Ethical & Practical Considerations

- Data Privacy: Worker face recognition or location tracking might violate privacy unless carefully governed.
- Bias in Models: If training data is from a small subset of projects or heavily US-based, might not generalize globally.

Summary & Next Steps

- **Deep Learning:** transforms how we handle unstructured data (images, text, sensor logs).
- **Key Architectures:** CNNs for vision, RNN/LSTM for sequences, Transformers for NLP.
- **Construction Use Cases:** defect detection, safety compliance, schedule forecasting, document analysis.
- **Challenges:** data quality, labeling, hardware costs, domain adaptation.
- **Future Trends:** advanced vision algorithms for real-time site monitoring, NLP for contract analysis, multimodal AI combining site images + textual logs + sensor data.

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Thank You!