

Assaignment-2: Concise summary on the key differences between traditional ML algorithms and basic neural networks, outlining scenarios where Deep Learning offers significant advantages.

Machine Learning (ML) and Neural Networks (NNs) are two major branches of Artificial Intelligence (AI). Traditional ML methods rely on manually engineered features and statistical models to learn patterns in data. In contrast, neural networks, especially deep learning models, automatically learn feature representations from raw data using layered computational architectures.

This document explains the core differences between these approaches and highlights specific scenarios where deep learning outperforms traditional ML techniques.

2. Core Concepts

2.1 Traditional Machine Learning Algorithms

Traditional ML includes algorithms such as:

- **Linear Regression**
- **Logistic Regression**
- **Decision Trees**
- **Random Forests**
- **Support Vector Machines (SVM)**
- **k-Nearest Neighbors (k-NN)**
- **Naive Bayes**

These models often require domain knowledge to extract relevant features from raw data before training.

2.2 Neural Networks (Basic to Deep Learning)

A neural network is composed of:

- **Input Layer:** Receives raw data (e.g., pixels, text tokens).
- **Hidden Layers:** Process data through weights and activation functions.
- **Output Layer:** Provides the final prediction.

A **basic neural network** has only one or two hidden layers, whereas **deep learning models** (deep neural networks) have many layers and can model more complex relationships.

3. Key Differences

Feature	Traditional ML	Neural Networks (Deep Learning)
Feature Engineering	Manually designed	Automatically learned
Data Requirements	Works well with small to medium datasets	Requires large datasets to generalize effectively
Model Complexity	Simpler, easy to interpret	Complex, with millions of parameters
Training Time	Relatively fast	Computationally intensive and slower
Flexibility	Limited to input features	Highly flexible for unstructured data
Performance Unstructured Data	Poor to moderate	Excellent (e.g., images, audio, text)
Interpretability	High	Low (black-box behavior)
Overfitting Tendency	Lower for simpler models	Higher, mitigated using techniques like dropout, regularization

4. Detailed Comparison

4.1 Feature Engineering

- Traditional ML depends heavily on manual feature selection and transformation. For example, detecting edges in an image or extracting term frequencies from text must be done before training.
- Neural Networks automatically discover hierarchical representations (e.g., from pixels to shapes to objects in image recognition) using hidden layers.

4.2 Data Requirements

- Traditional models like logistic regression or decision trees perform well on datasets with fewer features and fewer samples.
- Neural networks require large datasets to generalize well. Without enough data, they tend to overfit due to their high capacity.

4.3 Model Interpretability

- ML models like decision trees and linear regression are easy to interpret and explain. This is critical for domains like healthcare and finance where transparency is important.
- Neural networks are considered "black-box" models. Techniques like SHAP, LIME, and saliency maps can offer partial explanations but full interpretability is still challenging.

4.4 Training and Computation

- ML models are computationally efficient and can often be trained on CPUs.
- Neural networks require GPUs for faster matrix computations, especially in the case of convolutional neural networks (CNNs) or recurrent neural networks (RNNs).

5. Scenarios Where Deep Learning Outperforms Traditional ML

5.1 Image Recognition and Computer Vision

Deep learning models such as CNNs dramatically outperform traditional ML in tasks such as:

- Object detection (e.g., YOLO, Faster R-CNN)

- Image classification (e.g., cats vs dogs)
- Face recognition (e.g., FaceNet, DeepFace)

In contrast, traditional ML would require handcrafted features (e.g., Histogram of Oriented Gradients) and still perform poorly in complex vision tasks.

5.2 Natural Language Processing (NLP)

Neural networks, particularly with transformer-based models (e.g., BERT, GPT), have revolutionized NLP:

- Sentiment analysis
- Machine translation
- Text summarization
- Chatbots

Traditional ML using techniques like TF-IDF + Naive Bayes can handle basic classification but fails on context-sensitive tasks.

5.3 Speech Recognition

Deep learning is the backbone of modern speech-to-text systems (e.g., Google's voice typing, Alexa). RNNs and newer architectures like transformers are key for sequence modeling in audio.

Traditional ML algorithms cannot model time-series dependencies effectively for audio data.

5.4 Autonomous Vehicles

Deep learning enables real-time decision-making using inputs from sensors and cameras:

- Lane detection
- Pedestrian recognition
- Driving behavior prediction

No traditional ML model can handle this level of perception and reaction with high accuracy.

6. When Traditional ML is Still Preferable

Despite its limitations, traditional ML is still useful when:

- **Data is tabular and small:** In business analytics, fraud detection, and healthcare diagnosis using structured datasets.
- **Interpretability matters:** Regulatory requirements demand transparent models.
- **Resources are limited:** Lacking GPUs or sufficient compute power.

Examples:

- Loan default prediction using logistic regression.
- Disease classification using decision trees and structured health records.

7. Summary Table: Choosing Between ML and Deep Learning

Condition	Recommended Approach
Small dataset	Traditional ML
High interpretability needed	Traditional ML
Structured/tabular data	Traditional ML
Large dataset	Neural Network
Image, text, or audio data	Neural Network
High accuracy and flexibility required	Neural Network

8. Conclusion

Traditional machine learning algorithms are robust, fast, and interpretable but are limited in their capacity to understand unstructured data. Basic neural networks, and more generally deep

learning, offer significant advances in performance for complex tasks such as image recognition, speech processing, and natural language understanding. As data becomes more abundant and compute power increases, deep learning continues to open new frontiers, though the use of traditional models remains relevant for simpler or resource-constrained problems.