CREATIVITY EXCELLENCE SERVICE

NIGER DELTA UNIVERSITY

Wilberforce Island, Bayelsa State, Nigeria

2nd NIGER DELTA UNIVERSITY PUBLIC LECTURE

Title:

Artificial Intelligence, Machine Learning and Deep Learning Revolution with Applications

By

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Artificial Intelligence, Machine Learning and Deep Learning Revolution with Applications

By

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November 8, 2023

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Dept. of Electrical & Computer Engineering,

School of Engineering, Santa Clara University

Santa Clara University

School of Engineering

Invited Public Lecture presented at Niger Delta University, Bayelsa, Nigeria

NIGER DELTA UNIVERSITY

Wilberforce Island, Bayelsa State, Nigeria

Motto

Creativity, Excellence, Service

Vision

To be a centre of excellence defined by well articulated programme that will produce creative and innovative minds

Mission

To strive to maintain an international reputation for high quality scholarship, research and academic excellence for the promotion of thesocio-cultural and economic well-being of mankind

NIGER DELTA UNIVERSITY ANTHEM
(THE BRIGHTEST STAR)

Like the brightest star we are, to lead the way
To good education that is all our due,
The dream of our fathers like the seed has grown;
Niger Delta University if here to stay.

Let us build on this noble foundation
And with love, let our dedication increase,
To rise and uphold this noble vision
Ev'ry passing moment let our zeal never decrease.

In all that we do, let us bring to mind
Our duty as staff and students of N.D.U
Ev'rywhere to promote peace towards mankind.
Creativity, Excellence and Service

CHORUS
Rejoice, great people old and new, rejoice
For the good fruit through us is shown;
Be glad in our worthy contribution
To the growth of humanity (x2)

Protocol

Welcome

Invited Public Lecture presented at the

Niger Delta University

Bayelsa, Nigeria

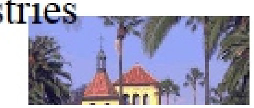
Creativity, Excellence and Service

NIGER DELTA UNIVERSITY
Creativity, Excellence and Service

Santa Clara University
School of Engineering

Santa Clara University

- Founded 1851, #1 in California
- Located in Santa Clara, California (Silicon Valley)
- About 8,000 students
  - 4,600 undergraduates
  - 3,400 graduates
  - Average class size = 26
- Schools & Colleges
  - Arts and Sciences
  - Law (founded 1911)
  - Engineering (founded 1912)
  - Business (founded 1926)
  - CP & E and Pastoral Ministries



Santa Clara University
School of Engineering

Santa Clara University

Main Entrance to SCU Campus

The Santa Clara Mission Church

New STEM Building housing the School of Engineering
(Sobrato Campus for Discovery & Innovation)

http://www.scu.edu

SCU Mission

- To develop students of
  - Competence
  - Conscience
  - Compassion

A Santa Clara education should result in students and future leaders who have had a top, second-to-none, education that also focuses on ethical and compassionate development and formation

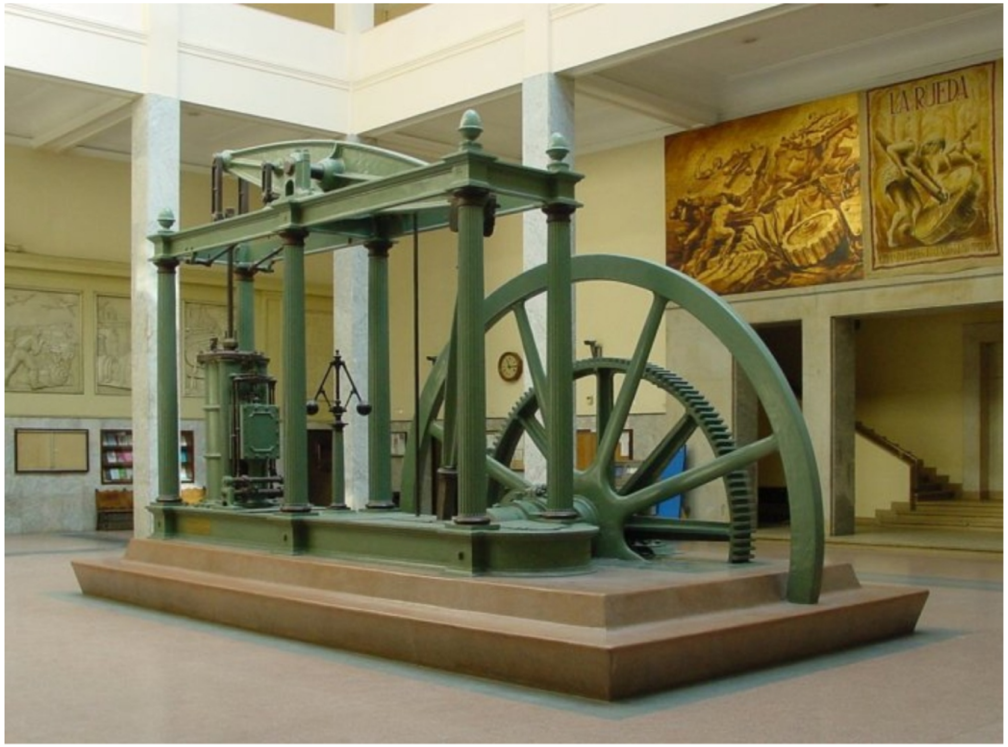
Thomas G. Plante, SCU Professor.

Outline

- □ Introduction
- □ Machine Learning(ML),
- □ Convolutional Neural Networks (CNN)
- □ Deep Learning (DL)
- □ Architectures for Hardware
- □ Generative AI
- □ Applications (Medical, Autonomous cars, etc.)
- □ Concluding Remarks

The Industrial Revolution

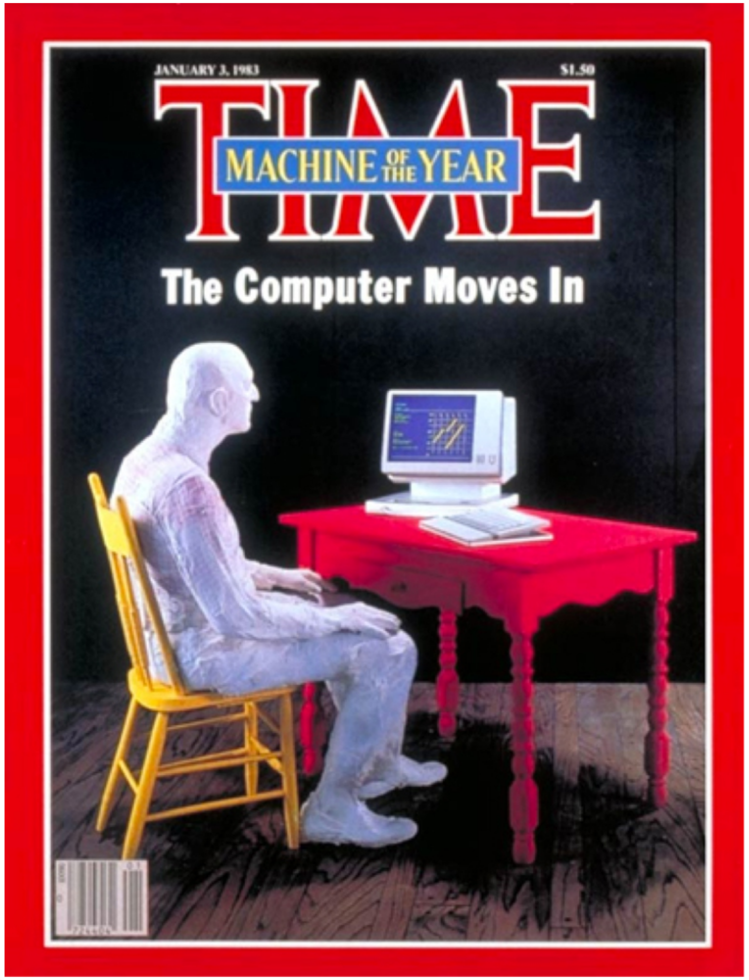
Iron and Coal Industry



A Watt steam engine made of iron, fueled primarily by coal, propelled the Industrial Revolution in Great Britain and the world

The Computer Revolution: IBM 360 Mainframe Computer

The PC Revolution: The Personal Computer

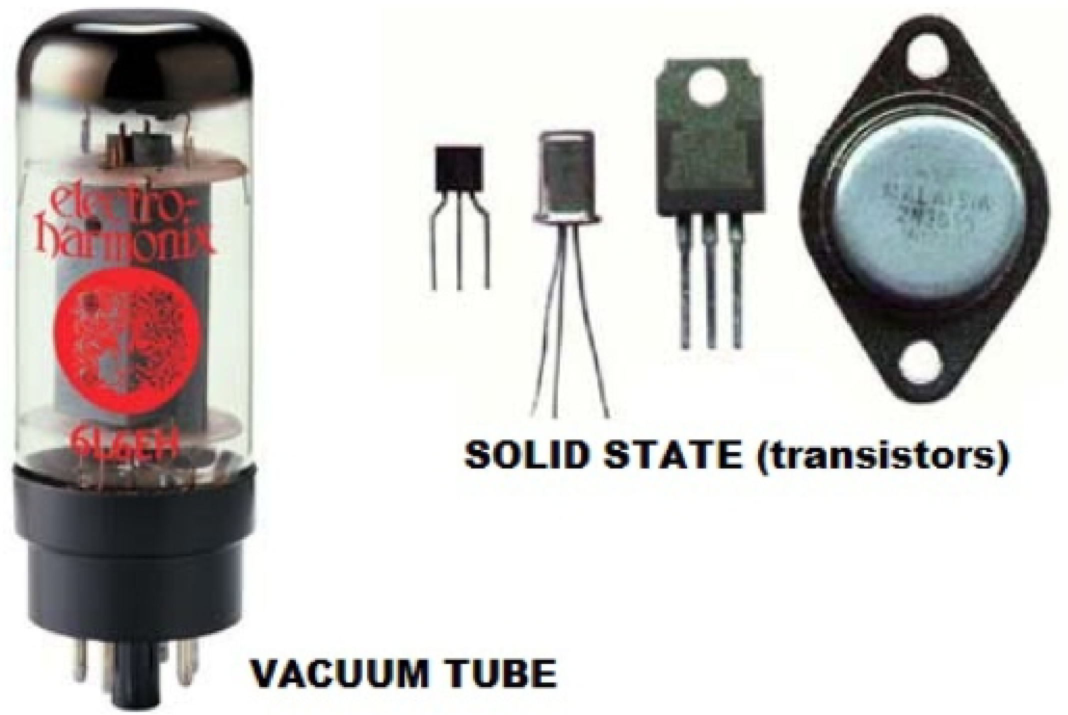


TIME magazine Man of the Year 1982 is the Personal Computer

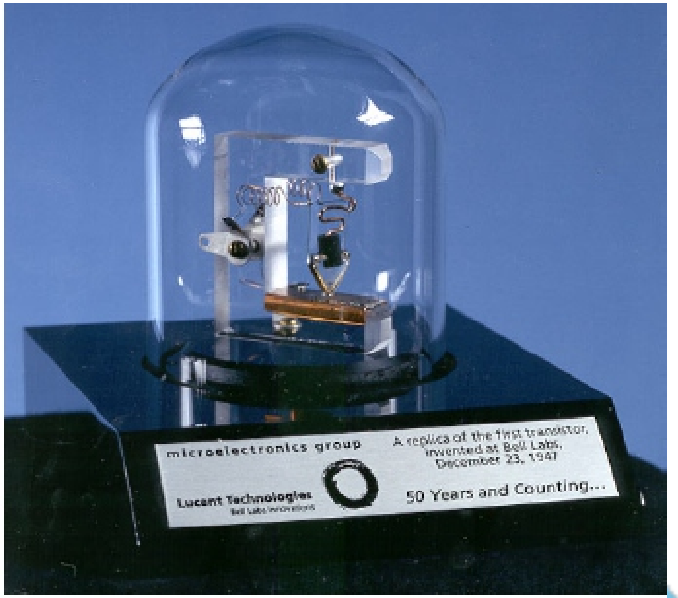
The PC Revolution has morphed into the Mobile Phone Revolution with the advent of the Internet and Wide bandwidth connectivity all over the world.

We live in the **Mobile Phone Revolution** Now

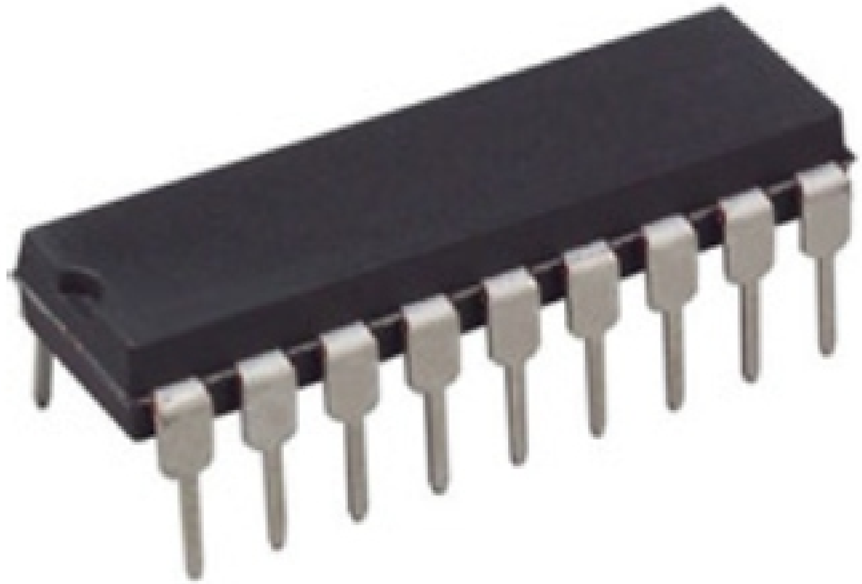
The Discrete Transistor



Replica of First Transistor



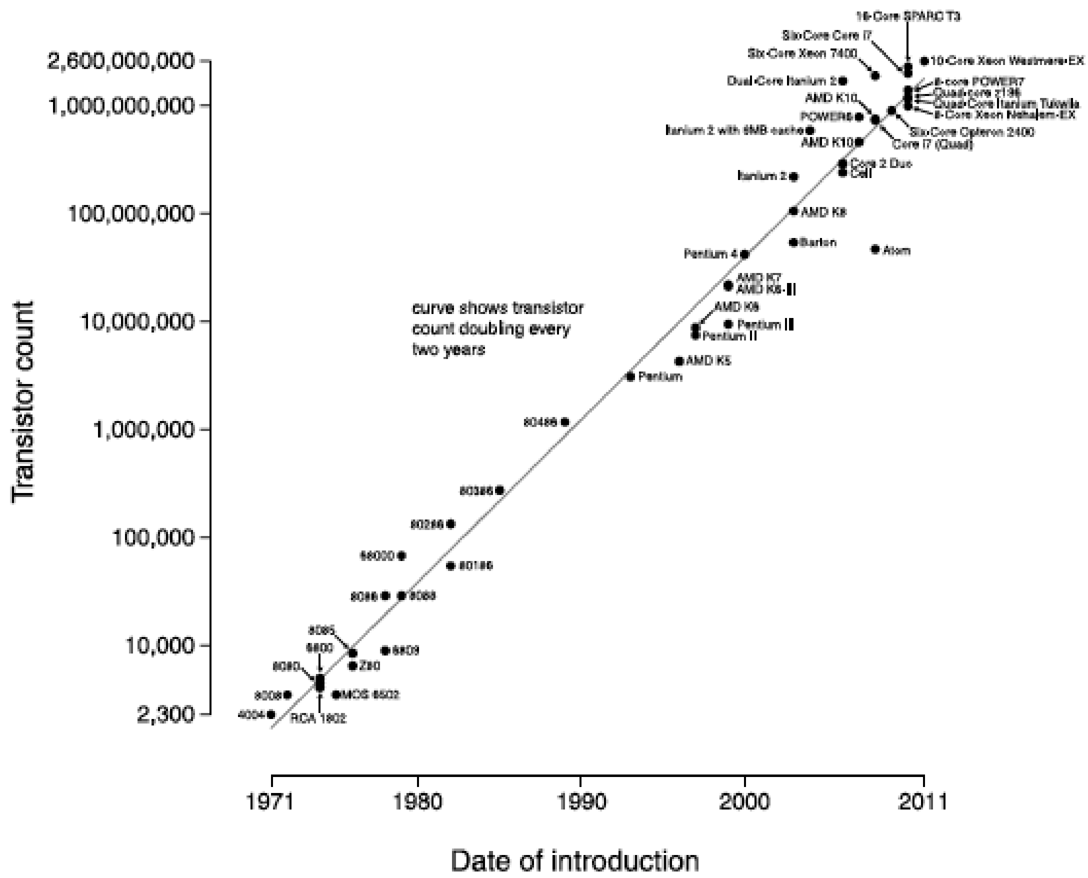
Integrated Circuits (IC)

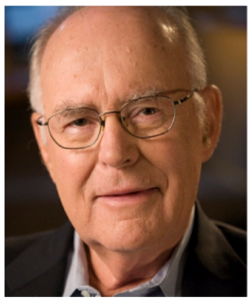


Integrated Circuits contain many transistors

Moore's Law

Microprocessor Transistor Counts 1971-2011 & Moore's Law





Gordon Moore,
Co-Founder Intel

CPU transistor counts vs. dates of introduction; note the logarithmic vertical scale; the line corresponds to exponential growth with **transistor count doubling every two years**.

Electronics

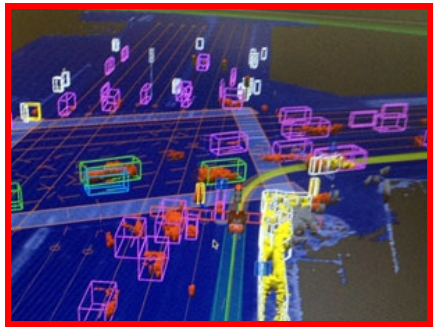
- Enables devices we rely on every day

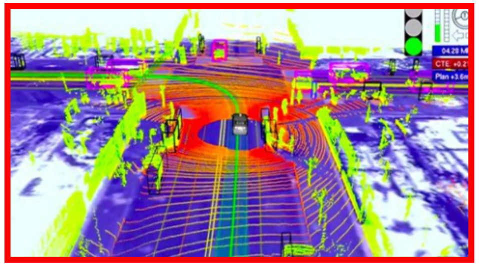
Communications

- Devices, systems, networks
  - Mobile, wireless, satellite

Future Automobiles

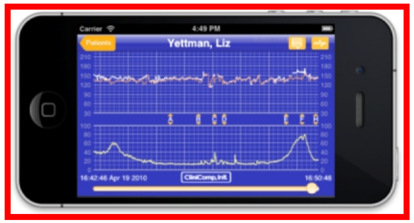
- Electric cars, safer more efficient cars, self driving cars:
  - sensors, signal processing, communications control





Medical Applications and Devices

- Prosthetics, noninvasive imaging, monitoring



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- Concluding Remarks

Biological Inspiration
=> Automobile Industry

Horse-drawn carriage

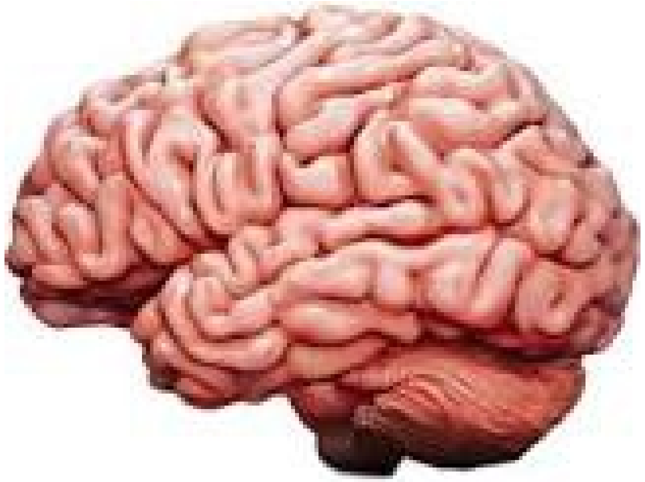
Tesla Model S Electric Car

Biological Inspiration => Airplane Industry

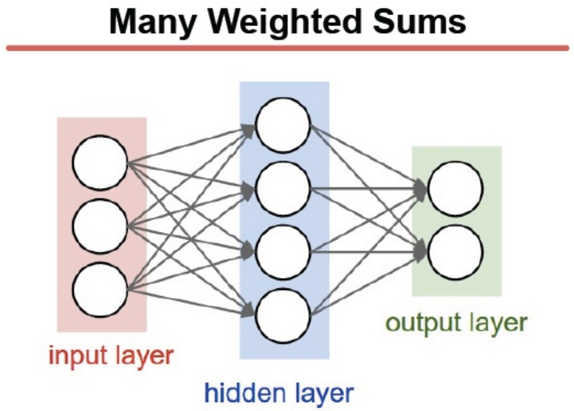
Flying eagle

Flying Airplane

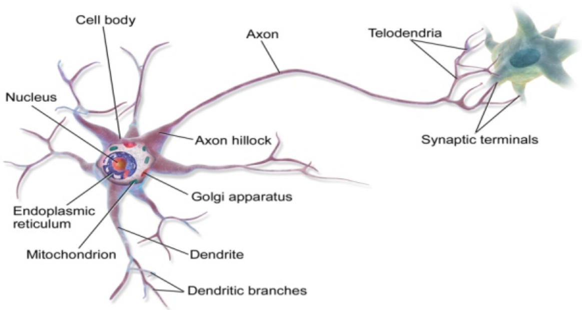
Biological Inspiration
=> Artificial Intelligence



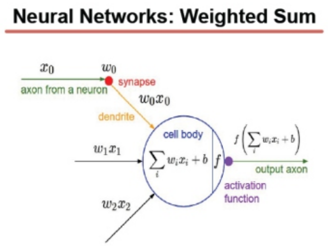
Human Brain
Billions of Neurons



Artificial Neural Network



Single Neuron



Single Artificial Neuron

What is AI ?

Artificial Intelligence

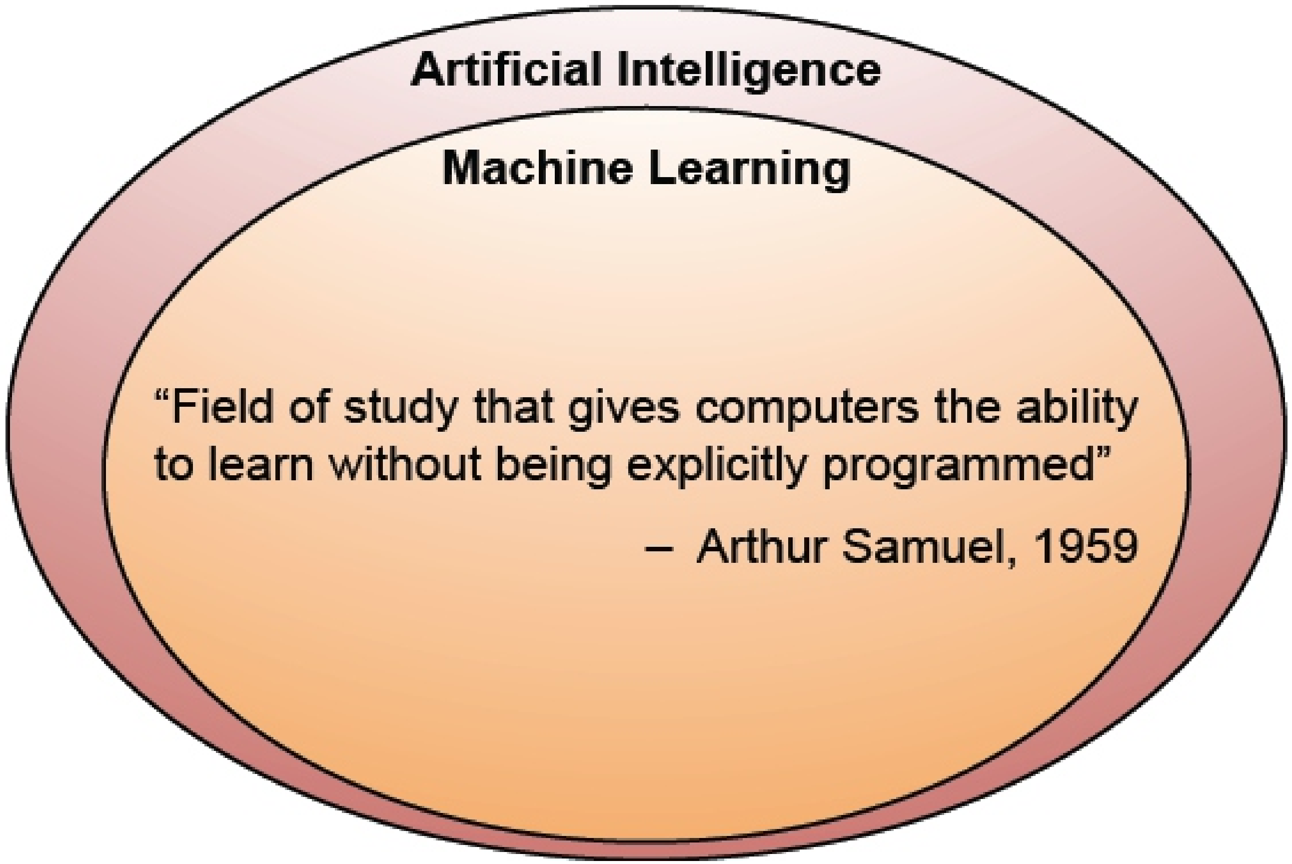
Artificial Intelligence

"The science and engineering of creating intelligent machines"

- John McCarthy, 1956

What is ML ?

AI and Machine Learning



Types of Machine Learning

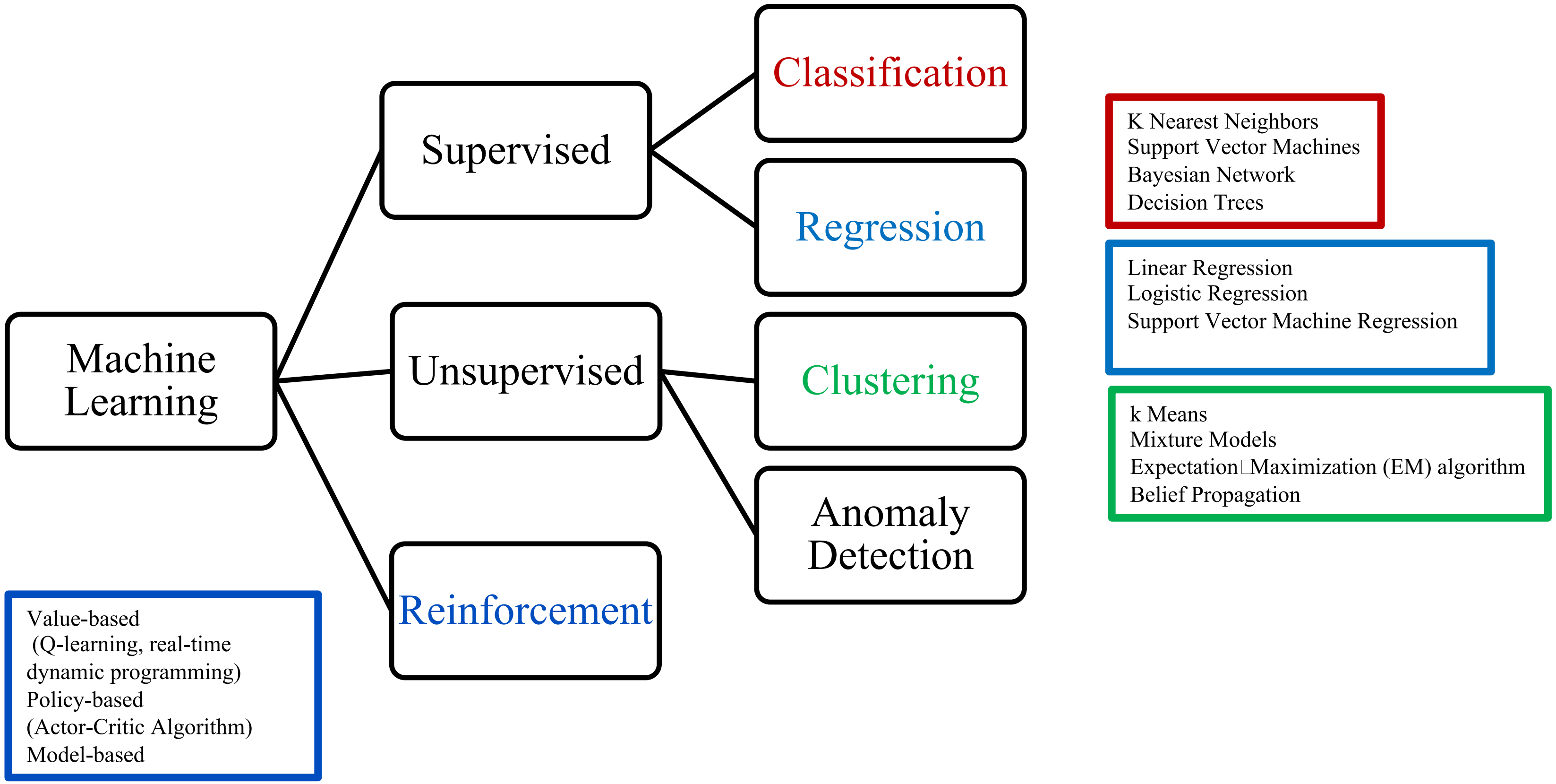
- Supervised Learning
  - Training data is labeled
  - Goal is correctly label new data
- Reinforcement Learning
  - Training data is unlabeled
  - System receives feedback for its actions
  - Goal is to perform better actions
- Unsupervised Learning
  - Training data is unlabeled
  - Goal is to categorize the observations

- **Unsupervised learning** is used in data mining to discover insights about unlabeled data
- An example of unsupervised learning is **clustering** or grouping flowers based on their characteristics without knowing the flower species

- **Supervised Learning** is the most common type of machine learning.
- An example of supervised learning is **classifying** emails as SPAM.
- The training data is emails that are labeled as SPAM or HAM.
- A model is then created that captures the relationship between email contents and the email label.
- The model can then predict the category for new emails.

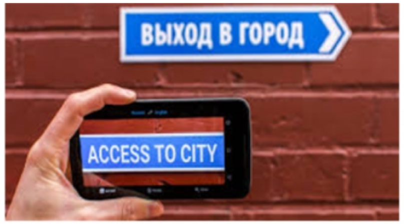
- **Reinforcement learning** is commonly used in robotics because there is usually not labeled data
- An example of reinforcement learning is **teaching** a robot to climb stairs.
- The robot is rewarded for each step that it ascends, so it learns which actions are beneficial

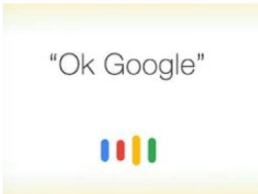
Machine learning techniques

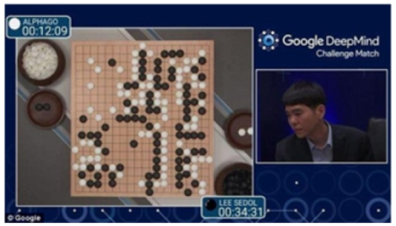


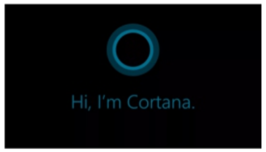
Applications of Artificial Intelligence

- Image Classification - AlexNet, GoogleNet, ResNet
- Natural Language Processing - Siri, Alexa, Cortana etc
- Medical - Prognosis tool, Genomics etc
- Financial Modelling
- Autonomous Vehicles
- Etc.









Pillars of Machine Learning

1. **Data: The Foundation of Learning**
   - The backbone of machine learning is data.
   - It serves as the basis for training the model and helps the computer learn patterns and relationships.

2. Mathematical Model: Representing the World
   - The mathematical model captures the essence of the data and the relationships between variables.
   - It provides a compact and precise representation of the phenomenon we want to study.

3. Learning Algorithm: Nurturing Intelligence
   - The learning algorithm is the "teacher" that guides the model to learn from data.
   - It automatically adjusts the model's parameters to fit the data and improve its performance.

The First Cornerstone of ML is Data

❖ **Data is the first cornerstone of machine learning, forming the foundation for training models and making predictions.**

Different Forms of Data: Data comes in various forms, and in supervised machine learning, we work with both labeled and unlabeled data.

Training Data: Consists of ECG signals (inputs) and corresponding heart condition labels (outputs) manually assigned by domain experts.

Supervised Learning: Training models with labeled data is referred to as supervised learning, where the learning is guided by domain experts to mimic their labeling process.

Generalization: The ultimate goal of the model is accurate predictions on unlabeled data during production, requiring the model to generalize beyond the training data.

Theoretical Question: How to train models capable of generalization and how to evaluate their performance is a central theoretical question.

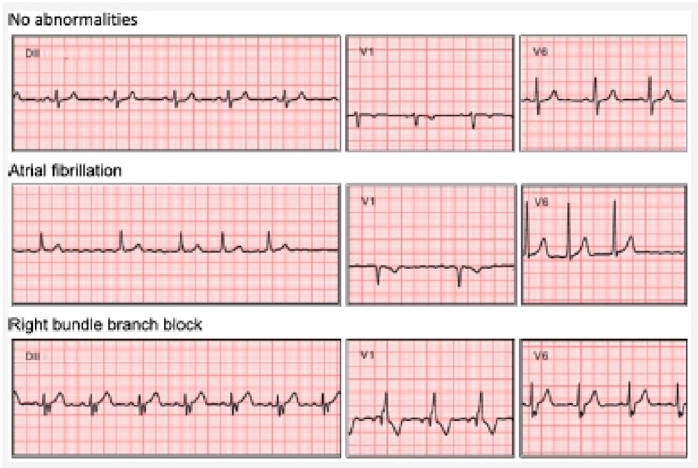
Example: ECG using ML Application

❖ **Automatically Diagnosing Heart Abnormalities:**

Objective - Automate ECG Examination for Heart Diagnosis

- **Problem**: Diagnosing heart conditions from ECG signals.

- **Data**: ECG signals from healthy hearts and hearts with various abnormalities.



ECG signals from healthy, atrial fibrillation, and right bundle branch block cases.

Example: ECG using ML Application

❖ **Automatically Diagnosing Heart Abnormalities:**

Objective - Automate ECG Examination for Heart Diagnosis

- **Problem**: Diagnosing heart conditions from ECG signals.

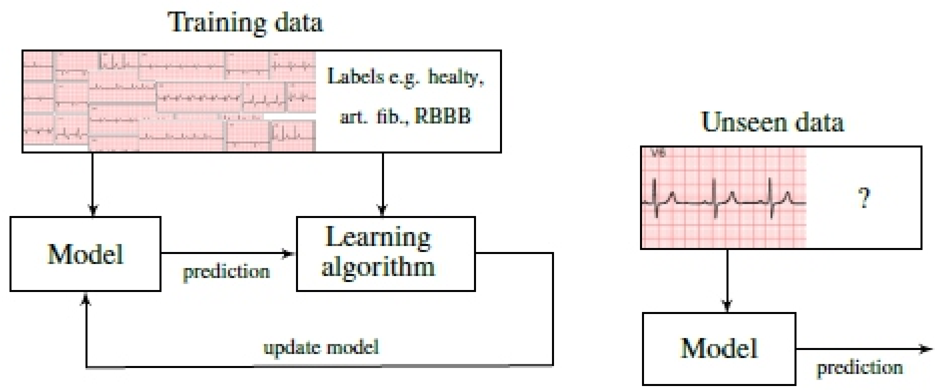
- **Data**: ECG signals from healthy hearts and hearts with various abnormalities.

- **Model**: Deep Neural Network (Residual Network) for Classification

- **Results**: The model can accurately predict heart conditions and has potential global applications, especially in regions with limited access to expert cardiologists.

Training the ECG Prediction Model

❖ **The supervised machine learning process with training to the left and then the use of the trained model to the right.**



Left: Values for the unknown parameters of the model are set by the learning algorithm such that the model best describes the available training data.

Right: The learned model is used on new, previously unseen data, where we hope to obtain a correct classification.

- It is essential that the model is able to generalize to new data, not present in the training data.

Training the ECG Prediction Model

❖ **A typical process for all supervised machine learning problems.**

Key Concepts: Supervised learning, where the model is trained on labeled data, and generalization to make accurate predictions on new, unlabeled data.

Importance: The training phase determines the model's ability to perform well in real-world scenarios and make reliable predictions.

➢ Understanding the training process is crucial for building effective machine learning solutions.

The Essence of Machine Learning

1. There is a (perhaps hidden) **pattern** in the data
2. We **cannot** describe the pattern **mathematically**
3. We have (input-output) **data** (perhaps lots of it)

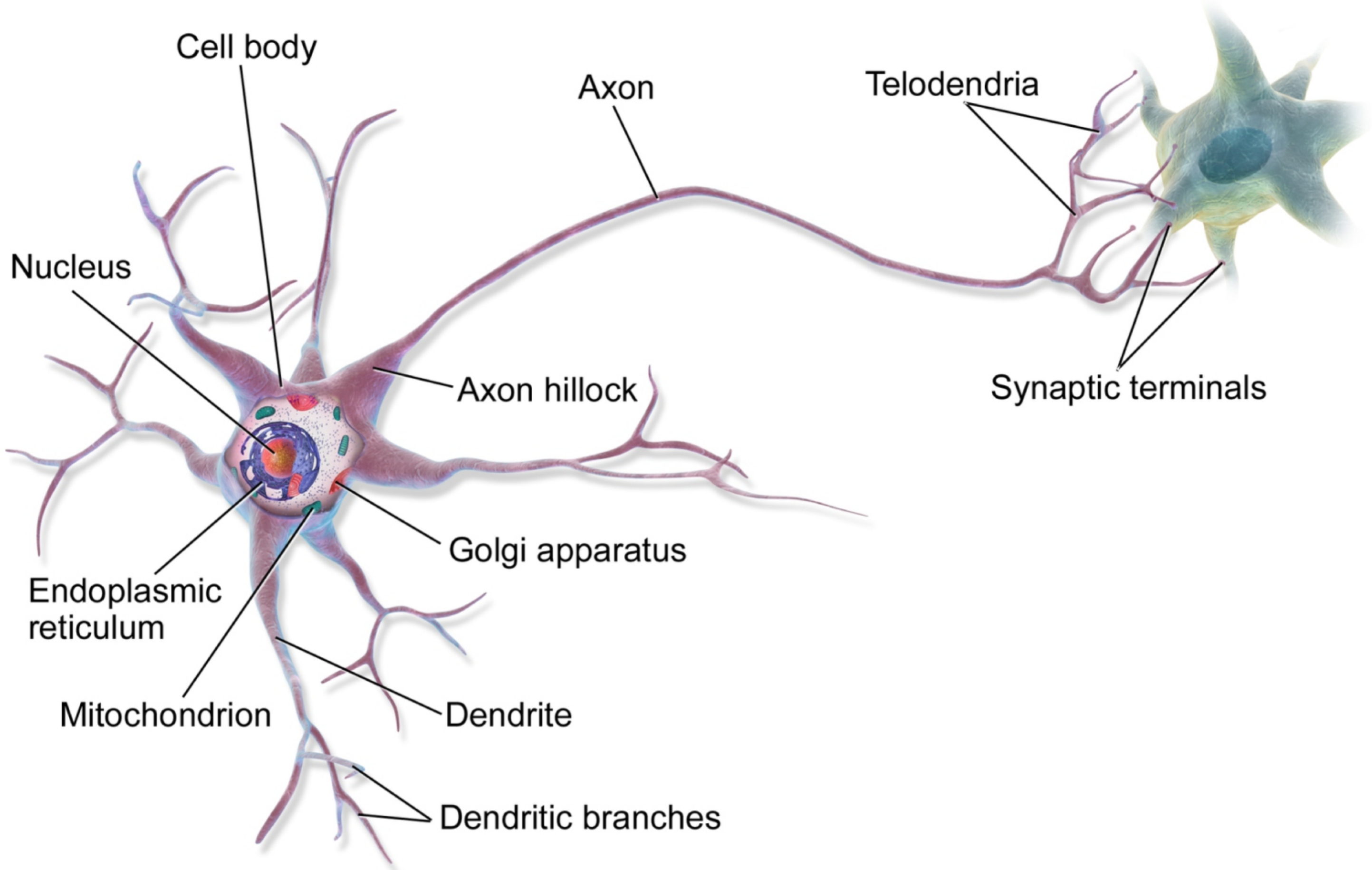
Basic Premise for Learning

Use a set of observations (data) to uncover an underlying process

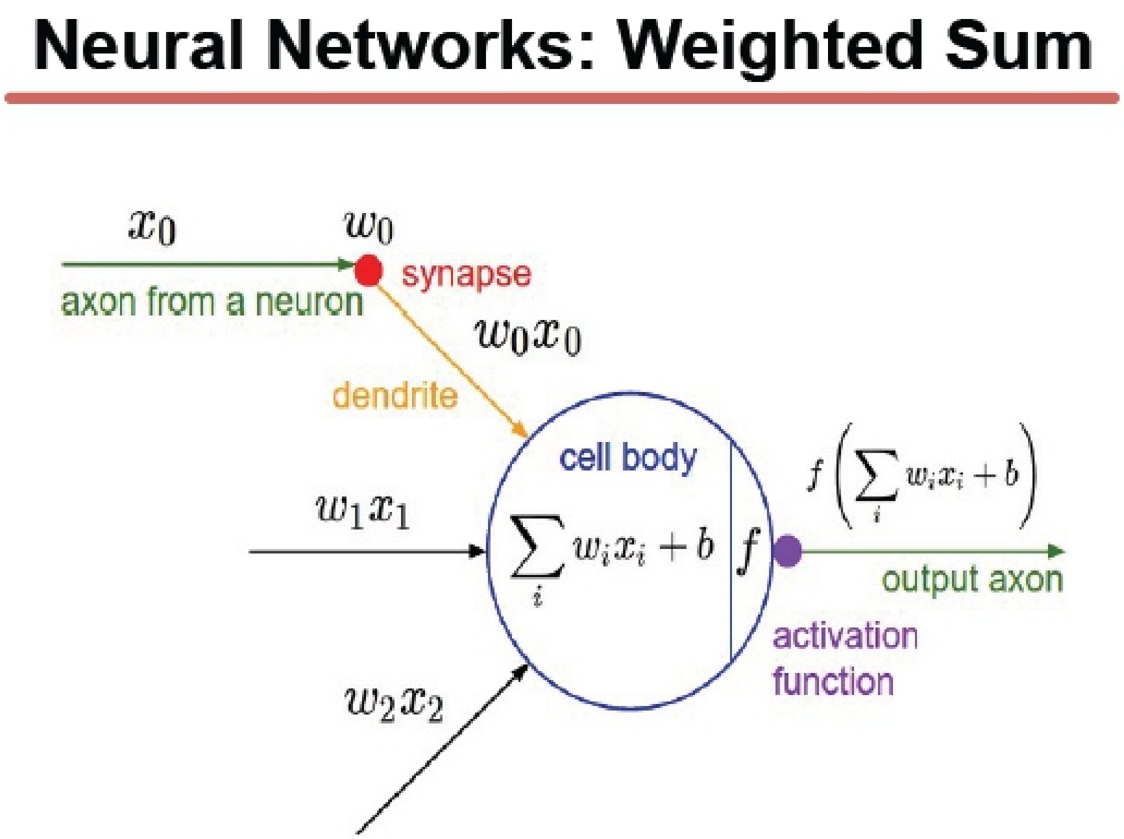
Resources for Machine Learning

- **Software Frameworks**
  - **Opensource :** TensorFlow, Pytorch, Keras, Caffe, Theano etc
  - **Licensed :** Matlab, Vivado, Quartus Prime, Visual Studio etc
- **Hardware**
  - NVIDIA Jetson TX2
  - FPGA - Xilinx, Altera
  - DSPs - TI

Biological Inspiration (Neuron)

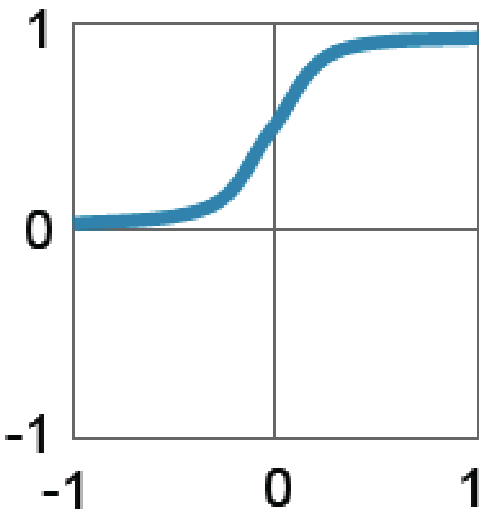


Neuron Model



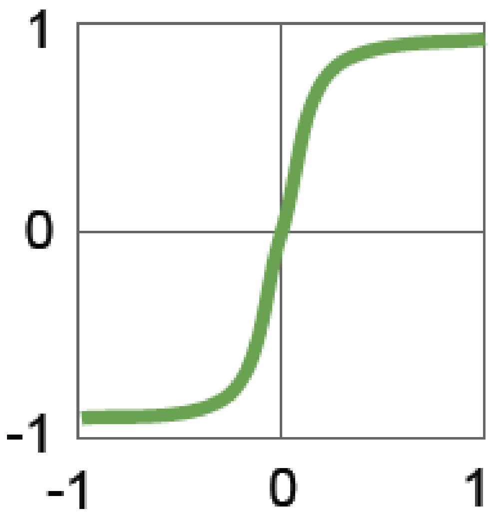
Activation Functions

Sigmoid



$y=1/(1+e^{-x})$

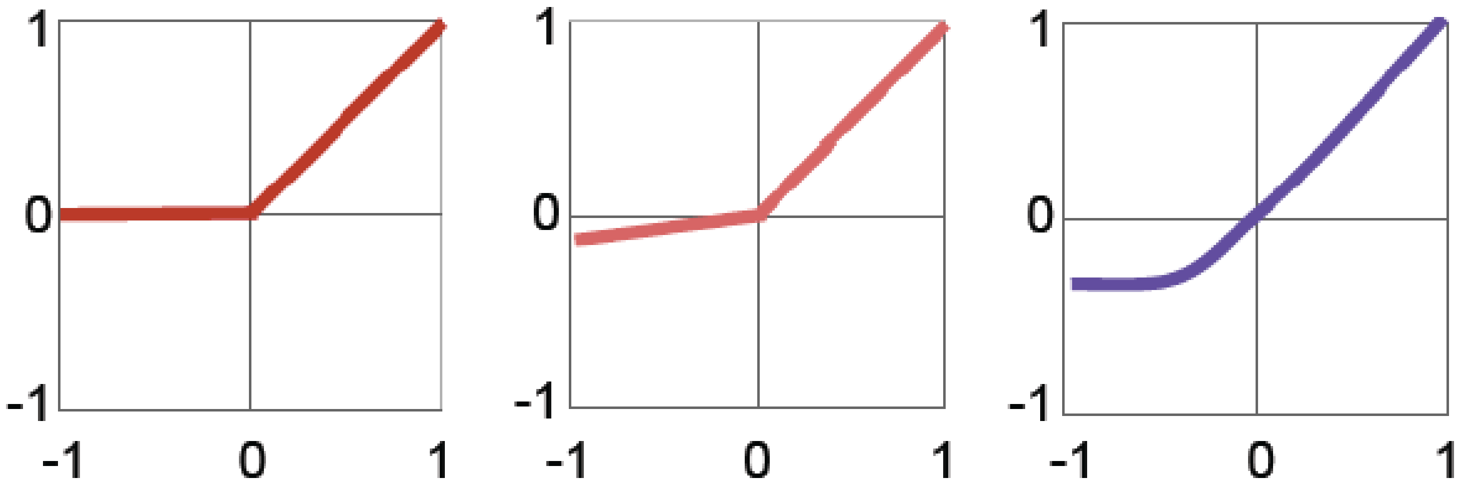
Hyperbolic Tangent



$y=(e^{x}-e^{-x})/(e^{x}+e^{-x})$

Activation Functions

Rectified Linear Unit (ReLU) | **Leaky ReLU** | **Exponential LU**



$y = \max(0, x)$

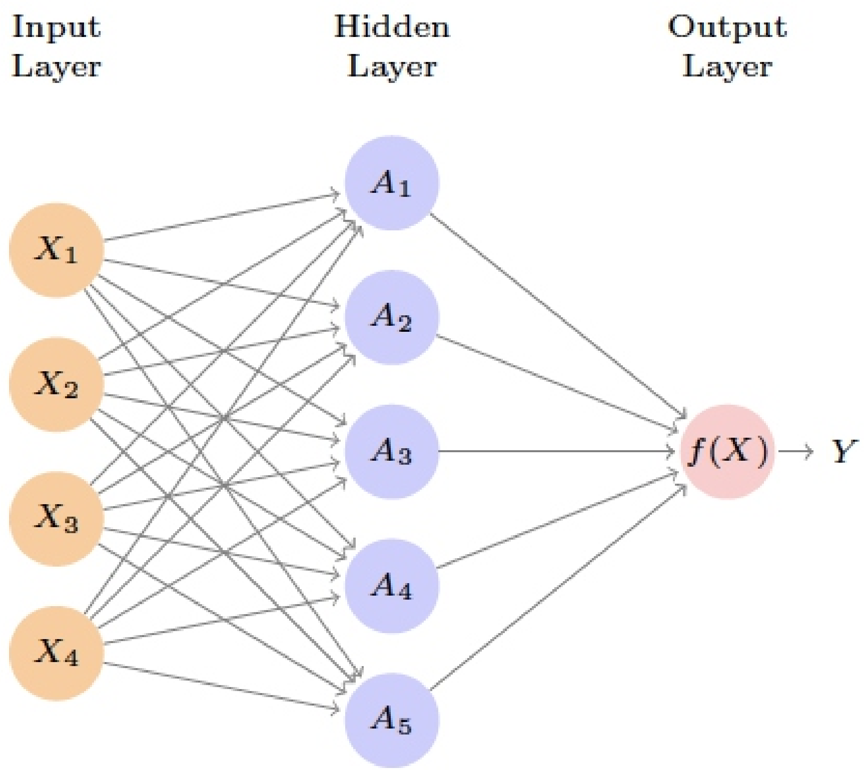
$y = \max(\alpha x, x)$

α = small const. (e.g. 0.1)

$$y = \begin{cases} x, & x \geq 0 \\ \alpha(e^x - 1), & x < 0 \end{cases}$$

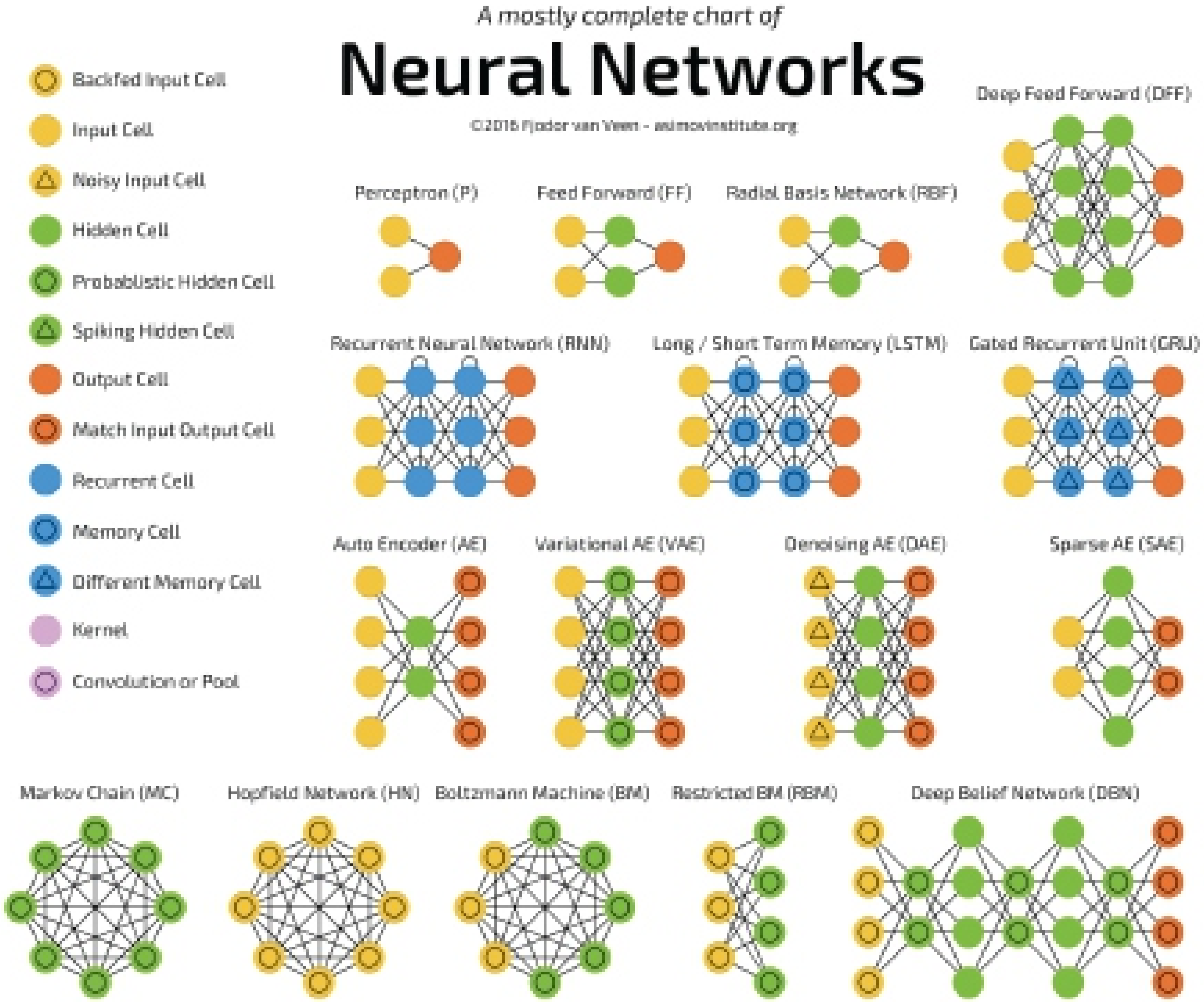
Santa Clara University
School of Engineering

A Simple Neural Network



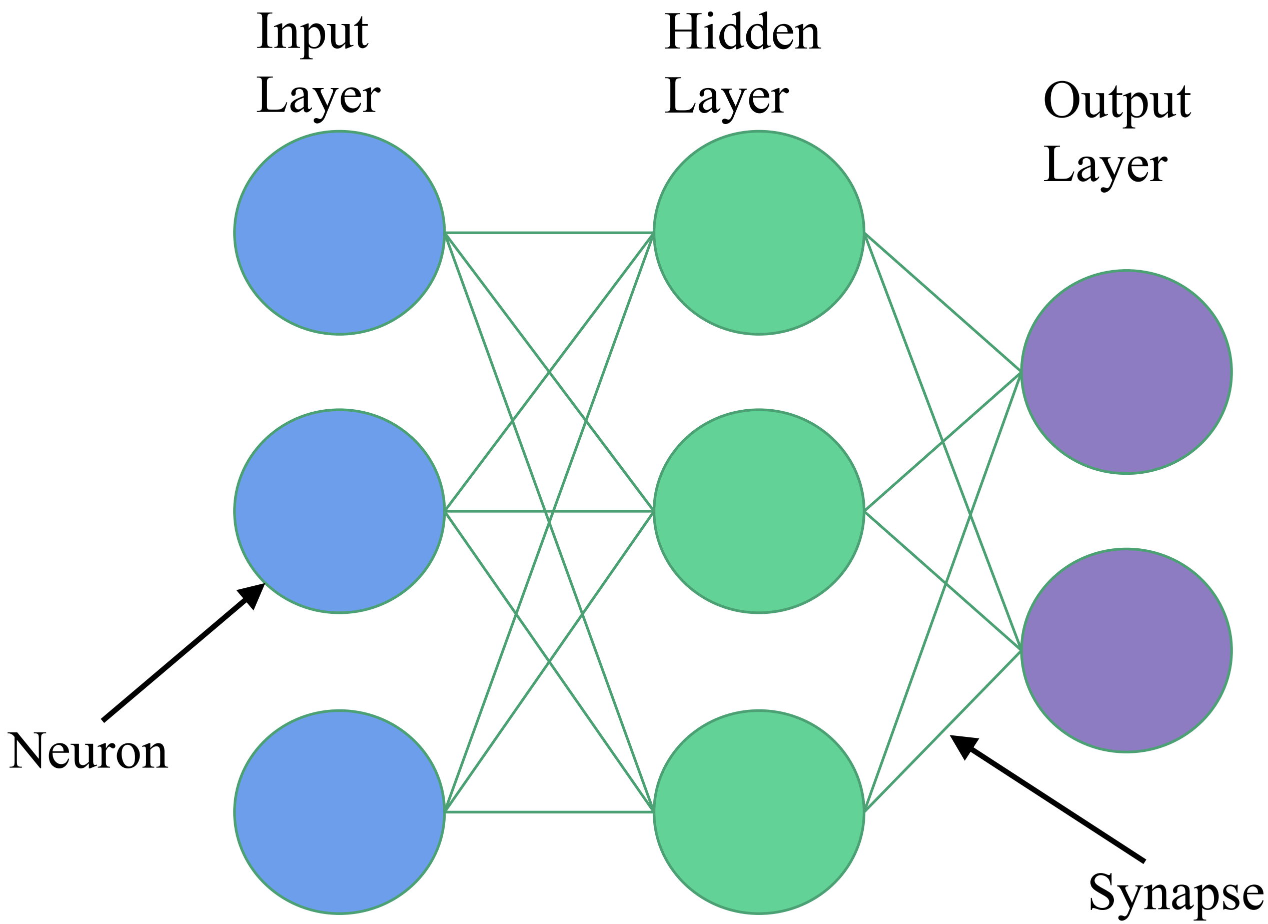
A neural network with a single hidden layer. The hidden layer computes activations Ak =hk(X) that are nonlinear transformations of linear combinations of the inputs X1, X2, □.., Xp.

Different Types of Neural Networks



http://www.asimovinstitute.org/neural-network-zoo/

Algorithms for Neural Network Learning



Gradient Descent

– Gradient Descent minimizes the neural network□s error
  – At each time step the error of the network is calculated on the training data
  – Then the weights are modified to reduce the error

– Gradient Descent terminates when
  – The error is sufficiently small
  – The max number of time steps has been exceeded

Training vs. Inference

- **Training:** Determine weights
  - **Supervised:**
    - Training set has inputs and outputs, i.e., labeled
  - **Unsupervised:**
    - Training set is unlabeled
  - **Semi-supervised:**
    - Training set is partially labeled
  - **Reinforcement:**
    - Output assessed via rewards and punishments

- **Inference:** Apply weights to determine output

Training Neural Networks

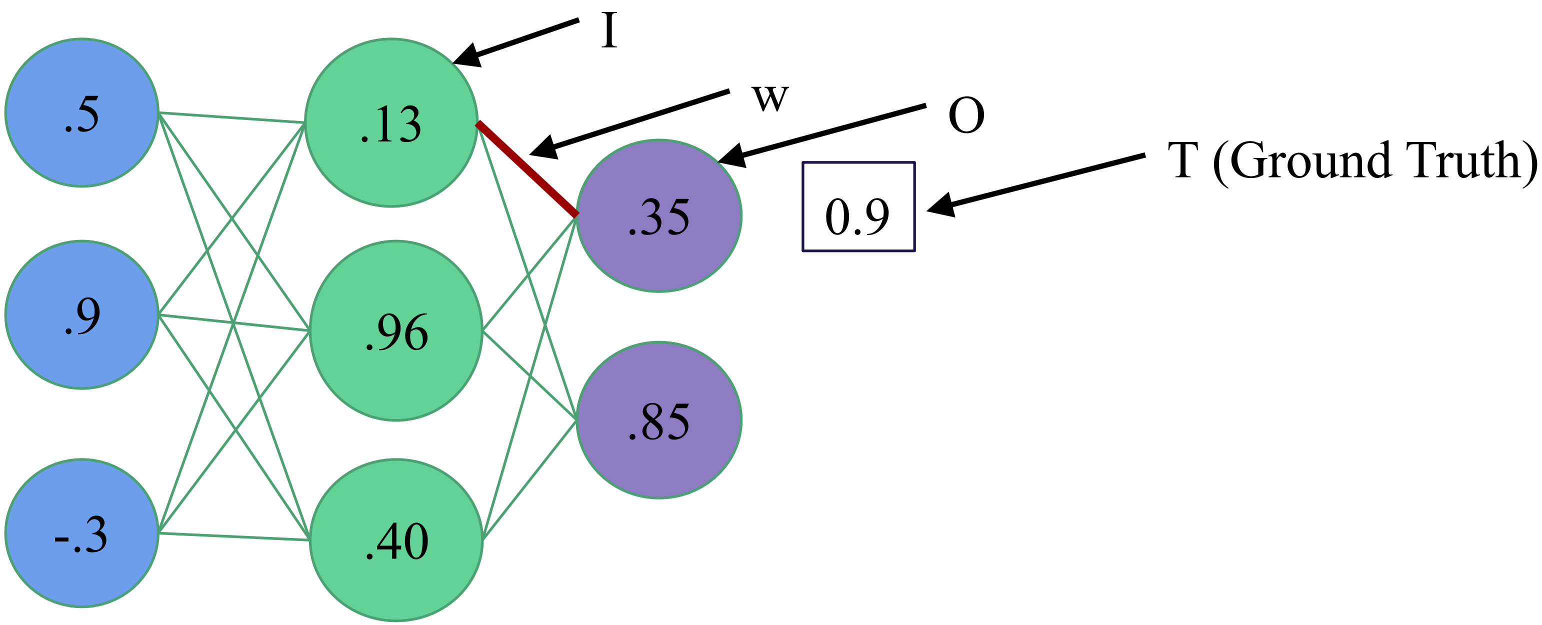
– Procedure for training Neural Networks
  – Perform inference on the training set
  – Calculate the error between the predictions and actual labels of the training set
  – Determine the contribution of each Neuron to the error
  – Modify the weights of the Neural Network to minimize the error

– Error contributions are calculated using **Backpropagation**

– Error minimization is achieved with **Gradient Descent**

Backpropagation Example

Problem: Which weights should be updated and by how much?
Insight: Use the derivative of the error with respect to weight to assign □blame□



$$\frac{\partial E}{\partial w} = I \cdot (O - T) \cdot O \cdot (1 - O)$$

$$\frac{\partial E}{\partial w} = .13 \cdot (.35 - .9) \cdot .35 \cdot (1 - .35)$$

Neural Network Playground Demo

– Live Demo

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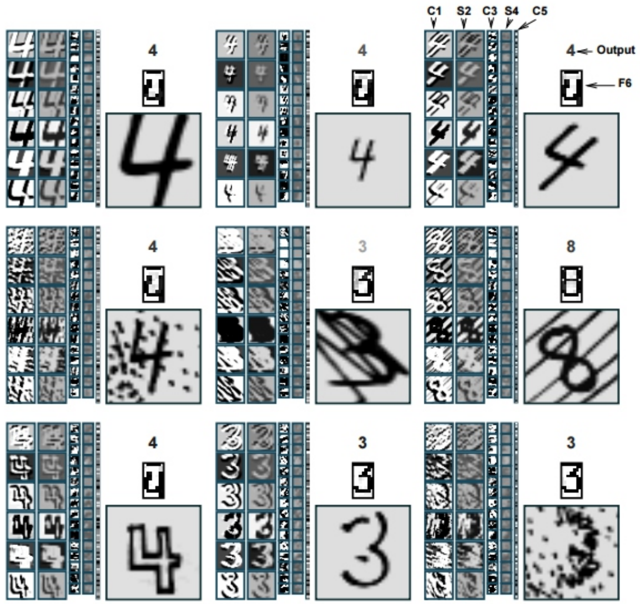
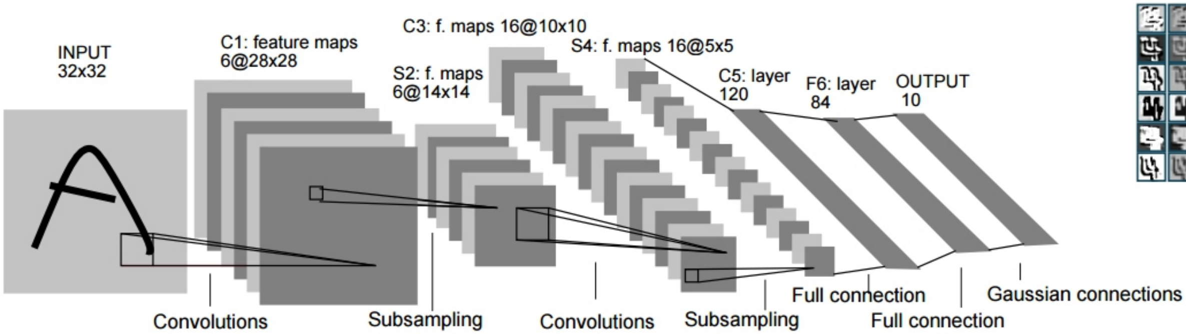
Neural Network Application

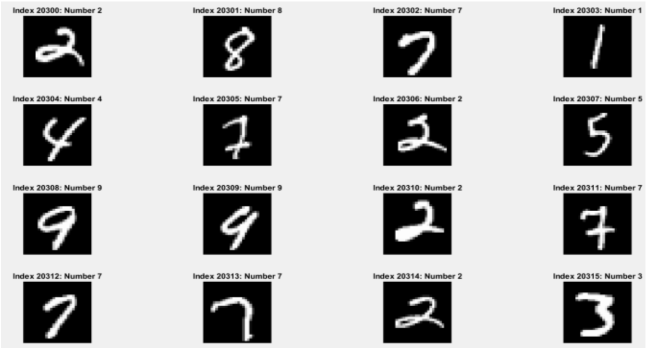
LeNet (ConvNet) 1998

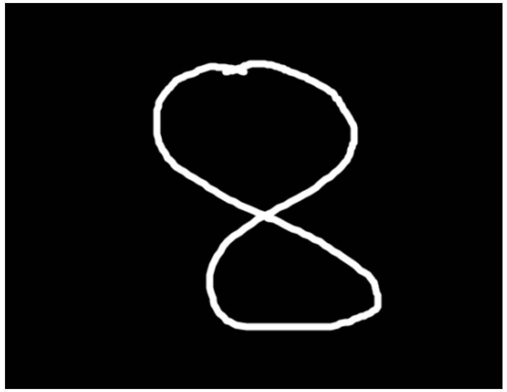
Handwriting recognition





Training the Neural Network for handwriting recognition





Handwriting data available at MNIST (Modified National Institute of Standards and Technology) web page

000	001	002	003	...	026	027
028	029	030	031	...	054	055
056	057	058	059	...	082	083
|	|	|	|	...	|	|
728	729	730	731	...	754	755
756	757	758	759	...	782	783

- MNIST handwriting images are 28 x 28 grayscale values from 0 to 255
- 60,000 training samples and 10,000 test samples

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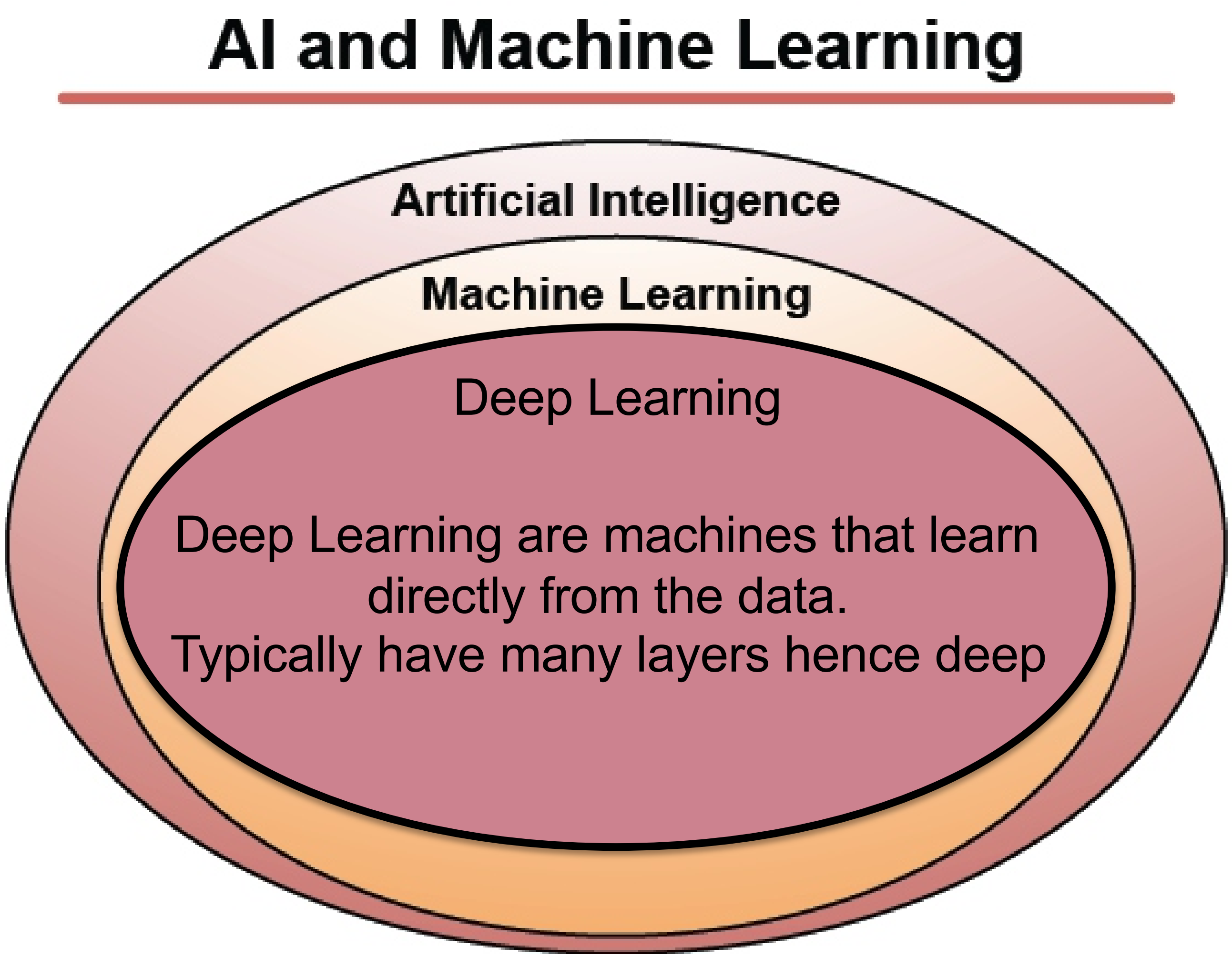
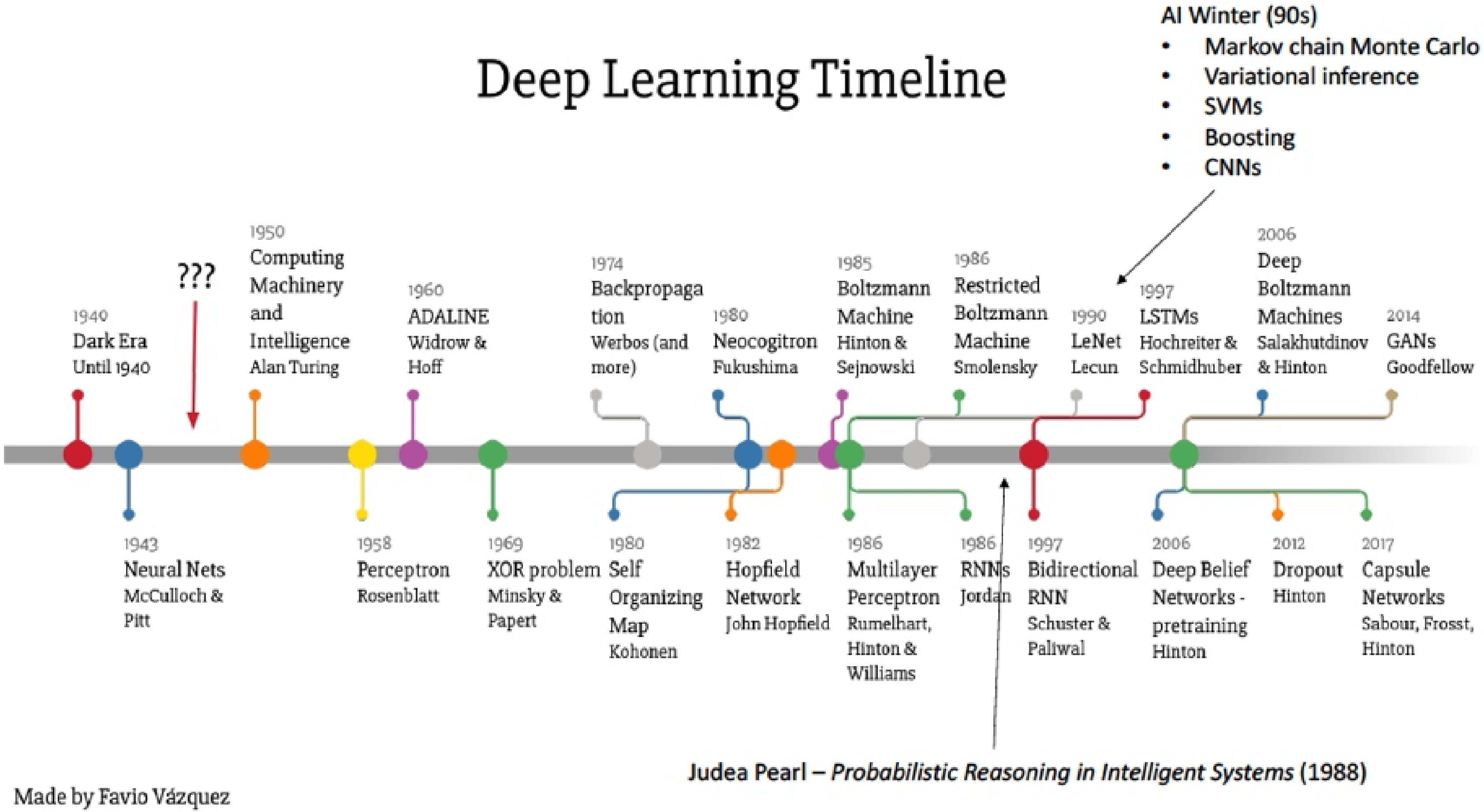
What is Deep Learning (DL) ?



Deep Learning History



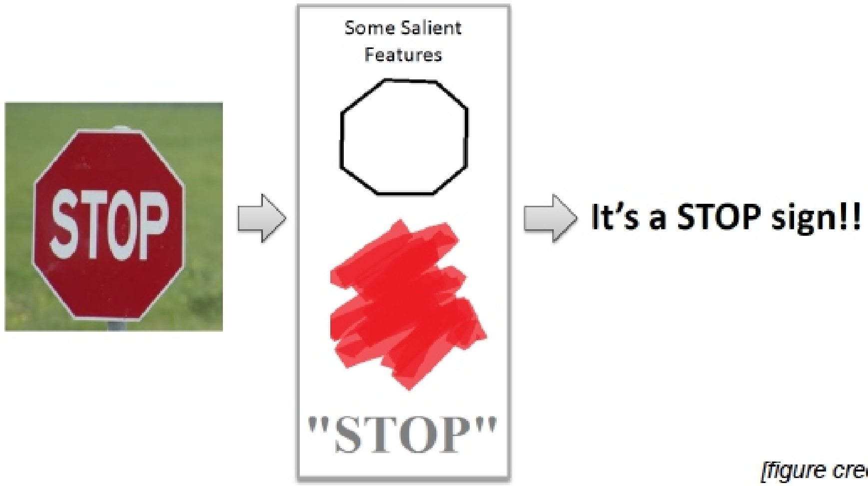
Intro to Deep Neural Networks

- Think of how to program a computer to recognize a STOP sign. What are the steps in the algorithm?
- This is the **Image Classification Problem**
- Traditional methods use Features fed into Classifier
- DNN or Deep Learning (DL) is a class of algorithms that has revolutionized **Computer Vision** in the past few years.

- Deep Learning methods **learn from the Data** !!! Instead of extracting features for a classifier.

Intro to Deep Neural Networks

- Think of how a computer can recognize a STOP sign. What are the steps in the algorithm?



[figure credit

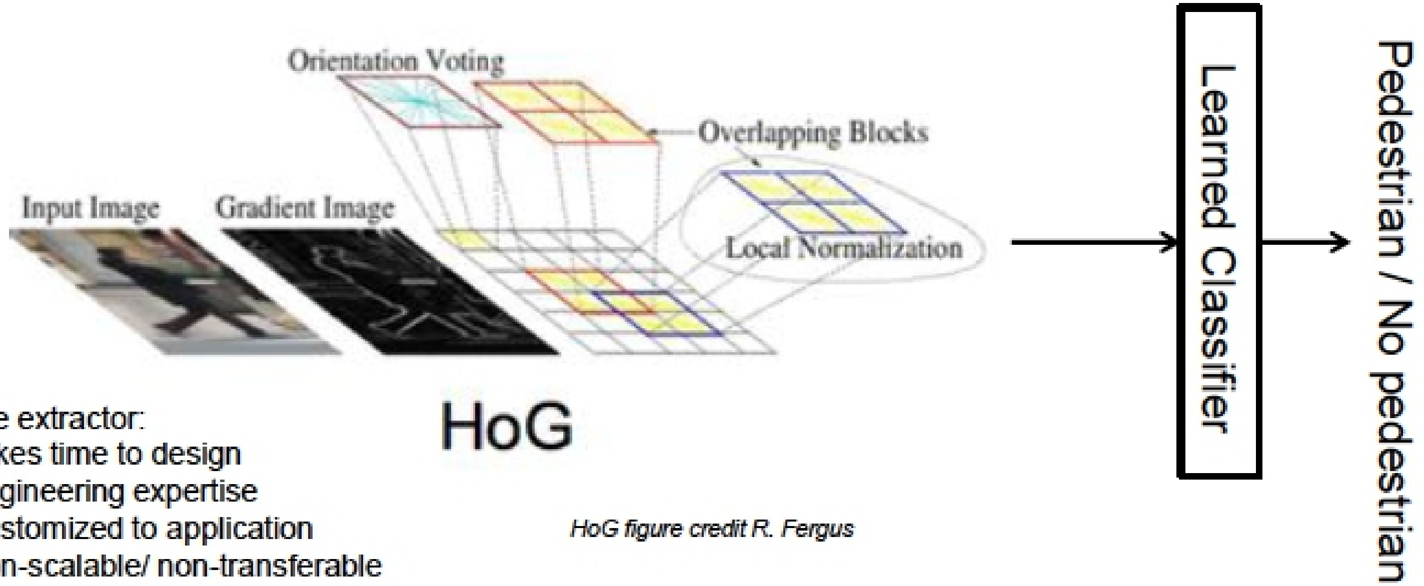
Is this a STOP sign ?

De-Mystifying Deep Neural Networks by S. Qureshi , (2017 Embedded Vision Conference).

Intro to Deep Neural Networks

- The traditional method of solving the computer vision problem of recognizing a Pedestrian or No Pedestrian involves the following steps in the algorithm:
  - Image pre-processing
  - Image segmentation
  - Contour Extraction
  - Various "undistort" operations
  - Shape reconstruction and/or Feature Extraction
  - Cascaded classifier a.k.a. "shallow learning"

Intro to Deep Neural Networks



Feature extractor:
- Takes time to design
- Engineering expertise
- Customized to application
- Non-scalable/ non-transferable

HoG

HoG figure credit R. Fergus

De-Mystifying Deep Neural Networks by S. Qureshi , (2017 Embedded Vision Conference).

Intro to Deep Neural Networks Classification Problem

- Image Classification
  - What kind of image is this?
  - What kind of object is this?
- Challenges
  - Bad Illumination, Pose, Context, etc.
  - Occlusion, Shadow, etc.
  - Clutter, etc.

- [ ] dog
- [x] car
- [x] horse
- [ ] bike
- [ ] cat
- [ ] bottle
- [x] person

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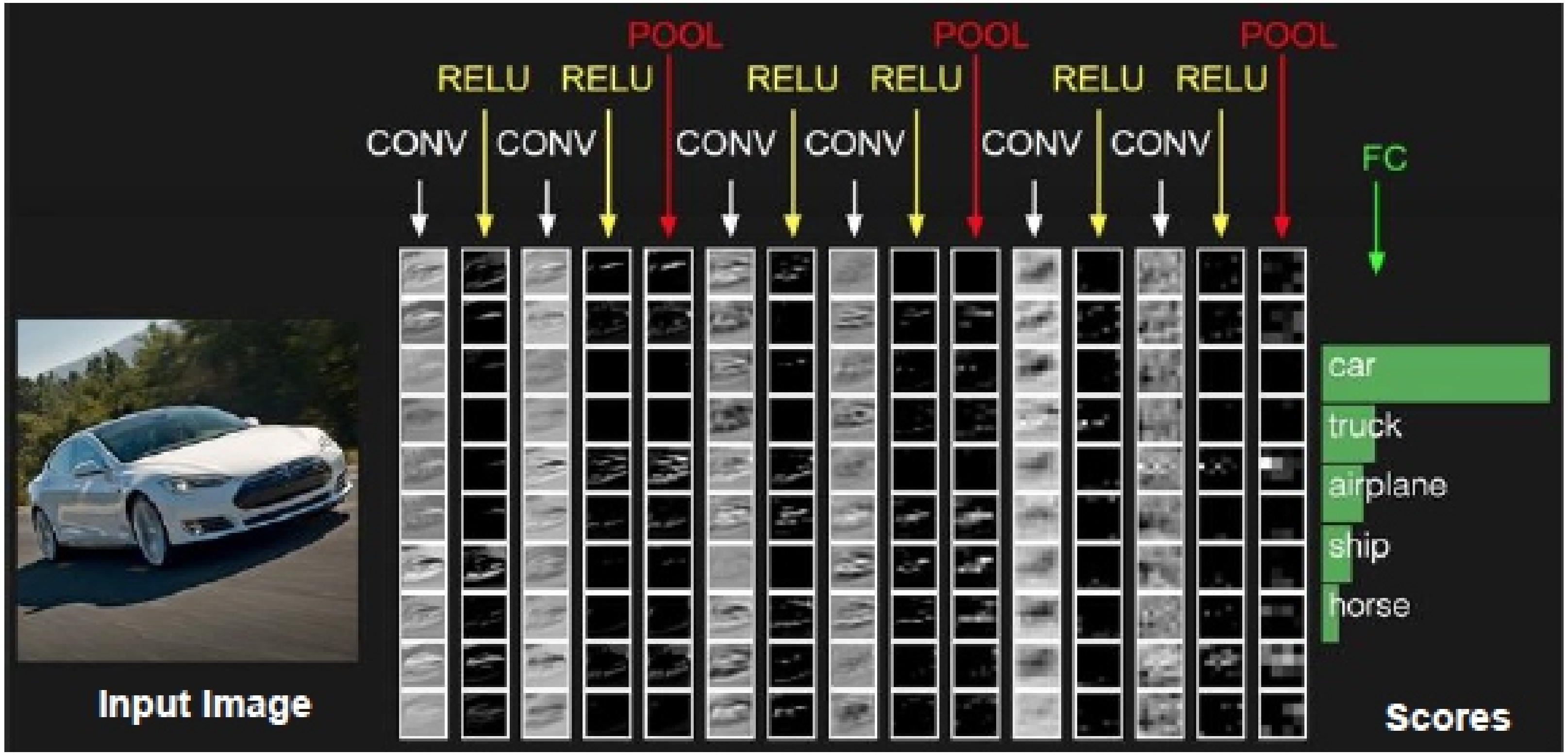
Intro to Deep Neural Networks



Deep Learning methods **learn from the Data** !!!
Instead of extracting features for a classifier.

Stanford University Course CS 261N Webpage

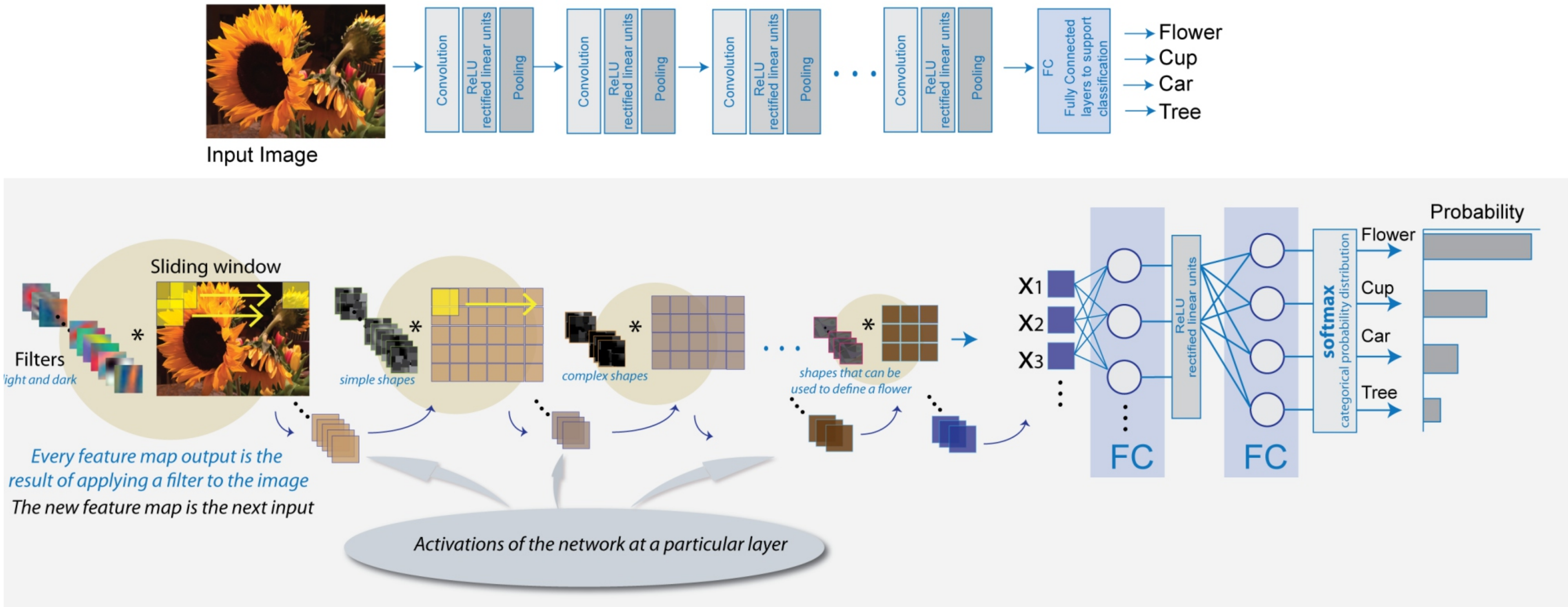
Benefits of Deep Learning

- Same toolkit to solve many different problems:
  - **Vision:** Classification, Detection, Segmentation, Image/Video Description, Activity Recognition, etc.
  - **Speech:** Recognition, Translation, Natural Language Processing (NLP)
  - **Text:** Semantic Translation
  - **Control:** Robotics, Self-driving vehicles.
  - **End-to-end learning** for many tasks from input data, i.e. learning the whole problem from input to output.
- Effective Learning of Representations
- Powerful Modelling of Relationships
- Flexible setting of networks

CNN Introduction

- A simple CNN is a sequence of layers and every layer transforms one volume of activations to another through a differentiable function.
- There are three different types of layers: **Convolutional Layer**, **Pooling Layer** and **Fully connected Layer**.
- We stack these layers to form a full **Convolutional Neural Network (CNN)**

CNN Introduction



ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) is an annual competition of image classification at large scale

History of CNN Networks

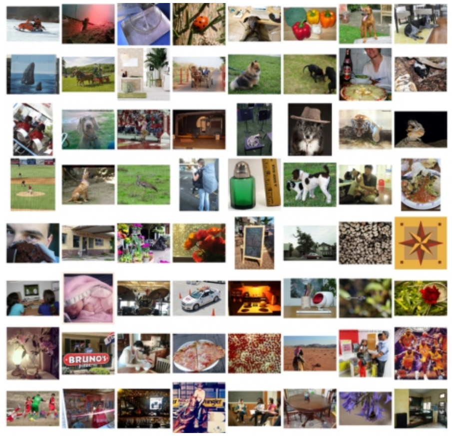
- 1990 Yann LeCun s**LeNet** Architecture, used to read zip codes and hand written digits.
- 2012 **AlexNet** won the ILSVRC challenge with top-5 error of 16% and compared to the runner up with 26% error.
- 2013 **ZFNet** won the ILSVRC challenge was an improvement on AlexNet by tweaking the hyper-parameters.
- 2014 **GoogLeNet** won ILSVRC.It has an inception module that reduced the number of parameters in the network. (4M, compared to AlexNet with 60M)

History of CNN Networks

- 2014 **VGGNet** was the ILSVRC runner up . It demonstrated the importance of depth in a network. Their final best contains 16 CONV/FC layers.
- 2015 **ResNet** won the ILSVRC 2015. It featured the special skip connections and heavy use of batch normalization. It also didn□t have fully connected layers at the end. It is considered to be the state of the art.

ImageNet Competition

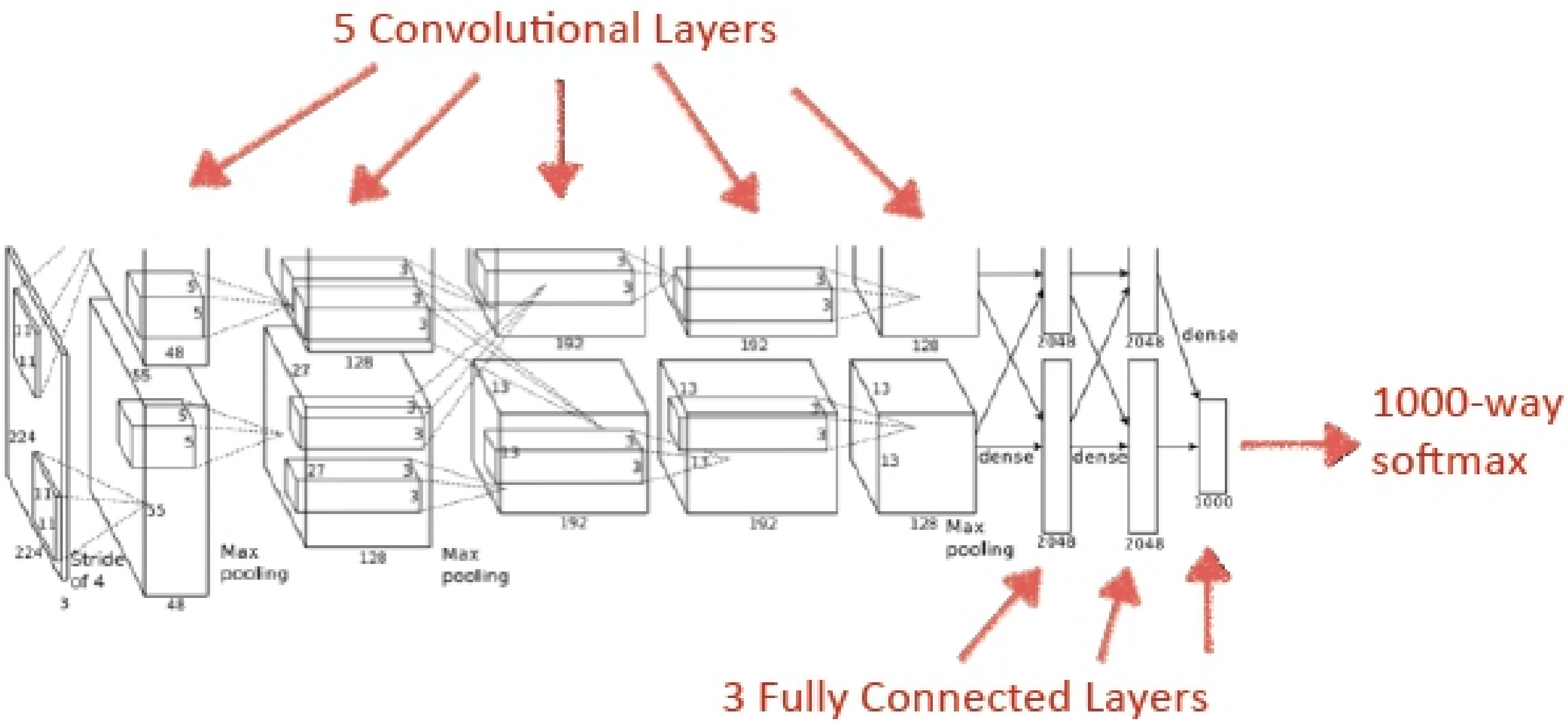
- Classify **1.2 million** ImageNet images into **1000 different classes**. ImageNet Competition for **Image Classification**
- Classification goals:
  - Make 1 guess about the label (Top-1 error)
  - Make 5 guesses about the label (Top-5 error)
- ImageNet Competition for **Image Classification:** ImageNet Large-Scale Visual Recognition Challenge (ILSVRC) is an annual competition of image classification at large scale



Y. LeCun, L. Bottou, Y. Bengio and P. Haffner, "Gradient-based learning appl
document recognition," in *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-
Nov 1998. doi: 10.1109/5.726791

AlexNet Architecture

The AlexNet neural network contains 60 million parameters and 650,000 neurons.
The state of the art performance is achieved with the error rate improving from 26.2% to 15.3%

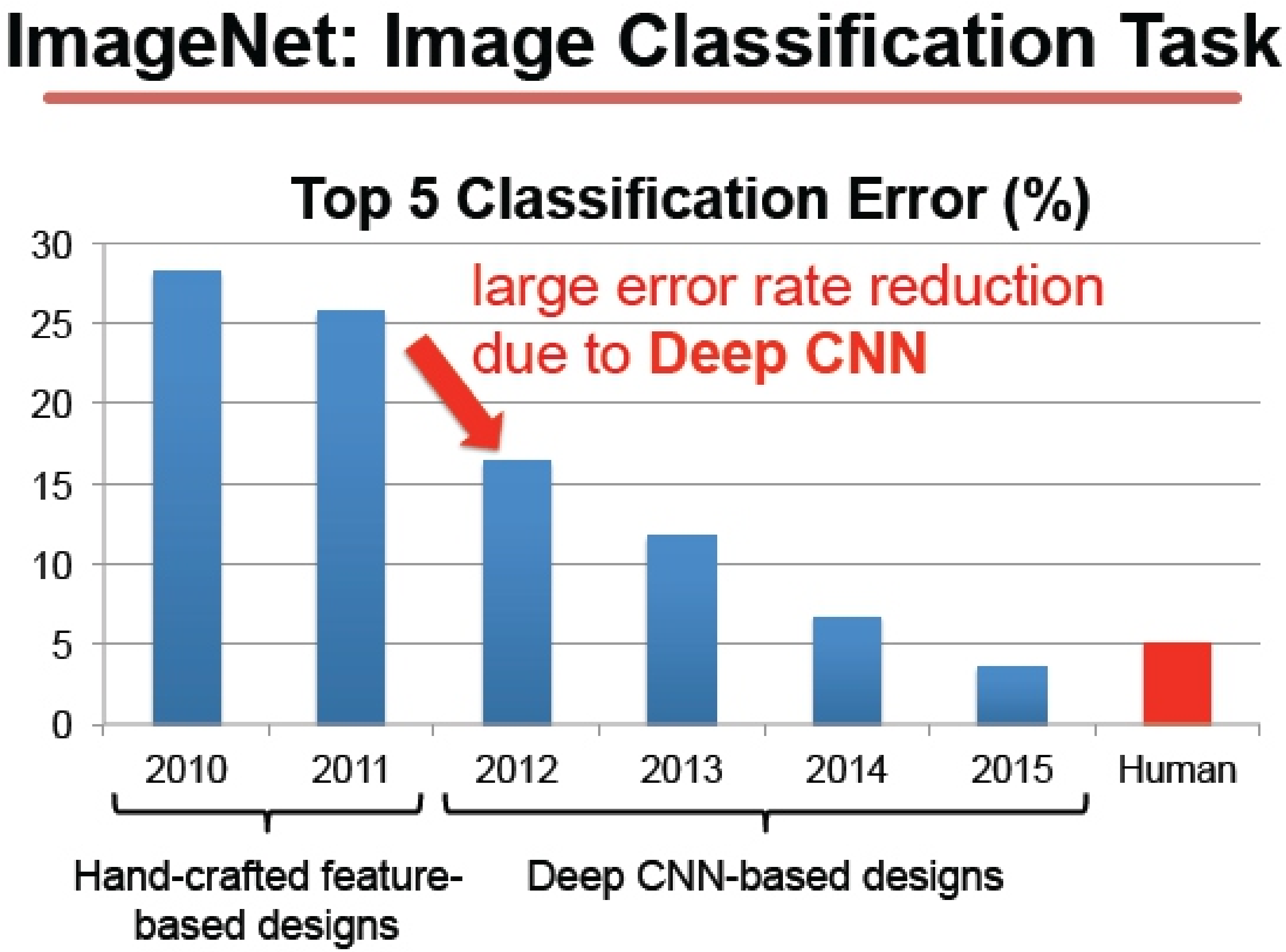


Krizhevsky, Alex, Ilya Sutskever, and Geoffrey E. Hinton. "Imagenet classification with deep convolutional neural networks." *Advances in neural information processing systems*. 2012.

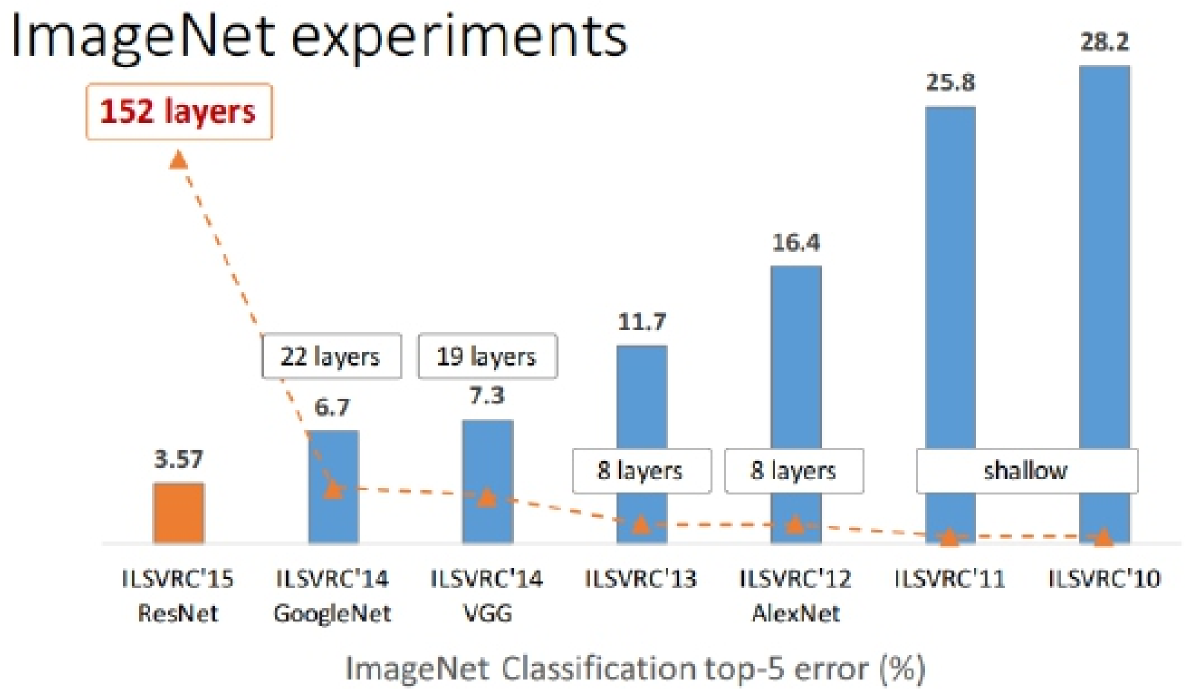
ImageNet Results: Alex Net

- AlexNet won the 2012 ImageNet LSVRC-2012 competition by a large margin (15.3% vs. 26.2% (second place) error rates).
- Paper ImageNet Classification with Deep Convolutional Neural Networks.
- **The highlights of the paper**
  - Use ReLU instead of Tanh to accelerate the speed by 6 times at the same accuracy.
  - Use dropout instead of regularization to deal with overfitting. However the training time is doubled with dropout rate of 0.5.
  - Overlap pooling to reduce the size of network. It reduces the top-1 and top-5 error rates by 0.4% and 0.3%, repectively.

ImageNet Results



ImageNet Results



He, Kaiming, et al. "Deep residual learning for image recognition." Proceedings of the IEEE conference on computer vision and pattern recognition. 2016.

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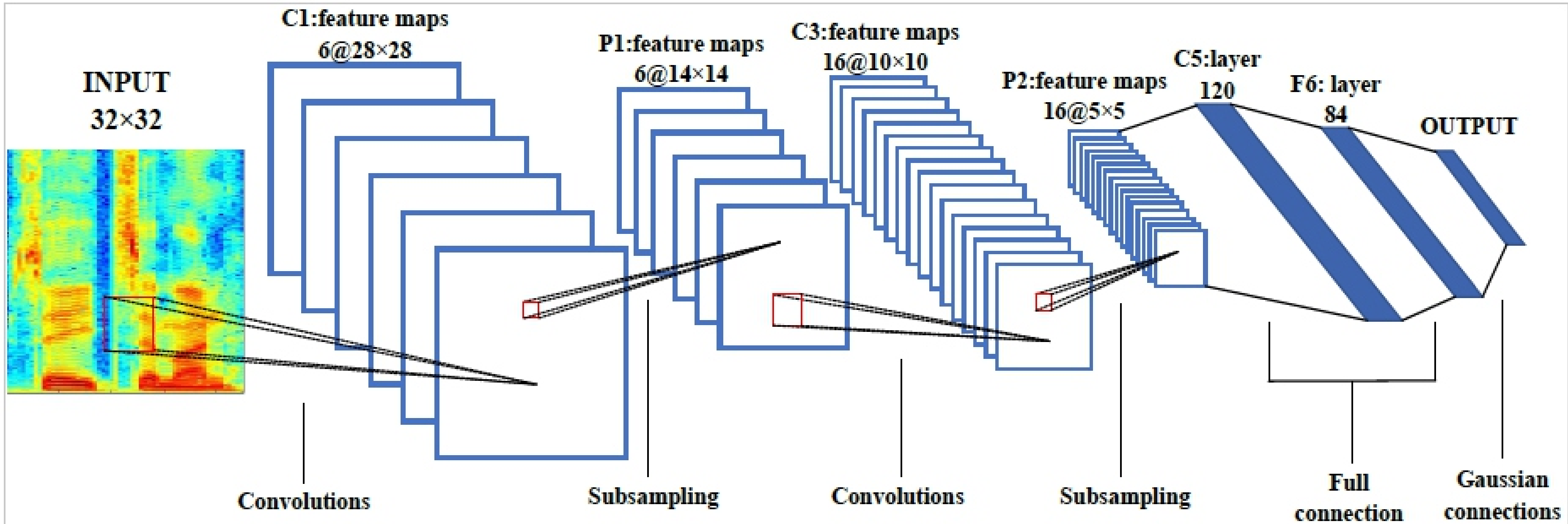
Alex Net Application



Issues with Deep Learning

- Amount of Training Data
  - Huge amounts of data are required for training
- Optimal network hyper-parameters and architectures
  - network depends on repetitive fine-tuning and empirical judgments. Network influenced by topology, training method and hyper-parameters. How to adjust these factors and avoid general traps (e.g. local optimum and over-/underfitting) simultaneously
- Hardware Implementation on portable devices
- Models with higher level perception

Outline

- Introduction
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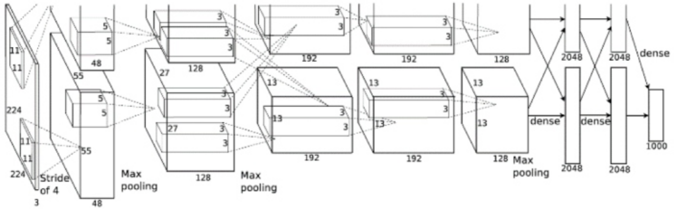
- Generative AI
- Applications (Medical, Autonomous cars, etc.)
- Concluding Remarks

CNN: Hardware Architecture

- CNNs are complex to implement in hardware.
- Some of the main challenges are
  - High memory bandwidth
  - Need for low latency
  - Optimum use of resources
  - Accommodating heterogeneous layers
  - Need for an network agnostic design.

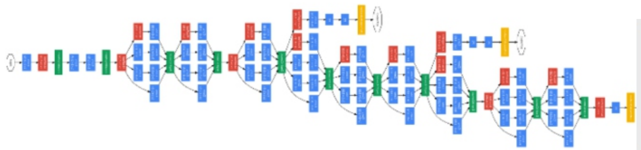
Hardware for CNN

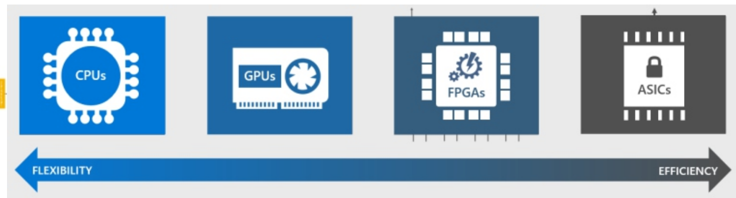


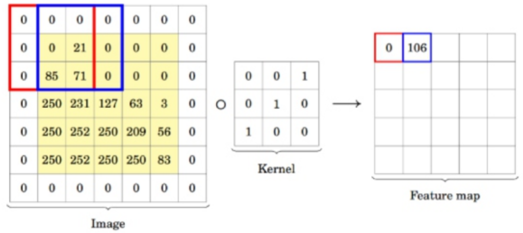
ENERGY COST OF DRAM ACCESS COMPARED TO OTHER OPERAT

Operation	Energy (pJ)	Relative Cost
32 bit int ADD	0.1	1
32 bit float ADD	0.9	9
32 bit int MULT	3.1	31
32 bit float MULT	3.7	37
32 bit 32KB SRAM	5	50
32 bit DRAM	640	6400

Han, Song, et al. "EIE: efficient inference engine on compressed deep neural network." *Computer Architecture (ISCA), 2016 ACM/IEEE 43rd Annual International Symposium on.* IEEE, 201(







Deep Deeper Deepest Networks	→	CPU FPGA GPU Embedded	→	Power Consumption Computational Complexity

Networks get deeper

Hardware plays catchup

Power and computation challenges get renewed

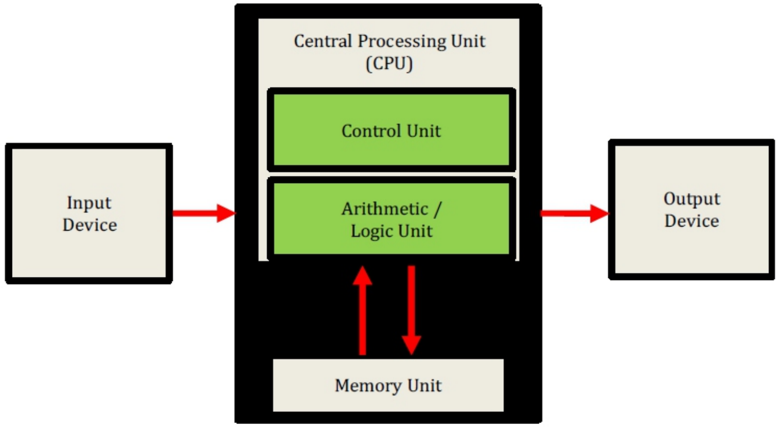
Hardware for Training and Inference Comparisons

Hardware Type	If used for Training	If used for Inference
CPU	Suitable for training as it's not on the edge	A lot of software overhead due to the compilation of instruction set architecture (ISA)
GPU	Faster than CPUs because of massively parallel operations	Overhead of the software to provide the parallelism
FPGA	Reconfigurable and high performance. More energy efficient compared to GPUs. Faster than CPUs	Flexible reconfigurable hardware. Better performance per watt than GPU for deep learning functions. Custom logic can be implemented on them in the most optimized way
DSPs	Not typically used for Training	Low power compared to FPGAs but less parallelism
ASIC	Not typically used for Training	Most efficient in terms of energy consumed however, fixed function and cannot be reconfigured easily

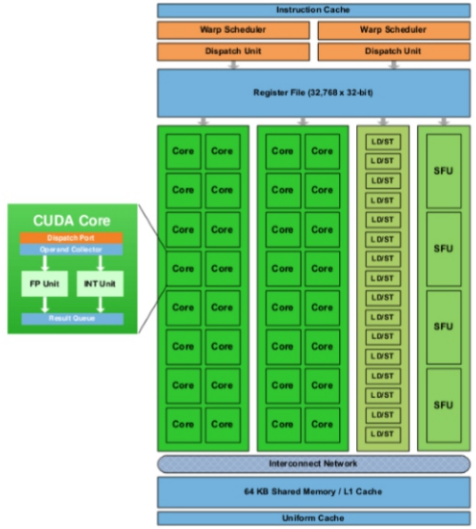
Future Challenges in Hardware Research Area

- Neuromorphic computing mimics the neuro-biological architecture of the human brain for machine learning
- Current machine learning algorithms run on systems based on the Von Neumann architecture
  - CPU, Memory unit (MU), ALU, control and data path, clock
  - Information has to be sent to different parts of the system **serially**
- Neuromorphic systems are **dynamic** where the computational elements of the system change depending on the stimuli. Computation is **parallel & asynchronous**.
- The concept was proposed by Carver Mead of Caltech in a 1990 paper.

CPU and GPU computing architecture



Von Neumann architecture

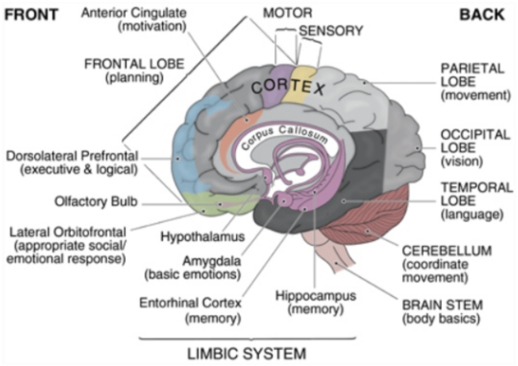


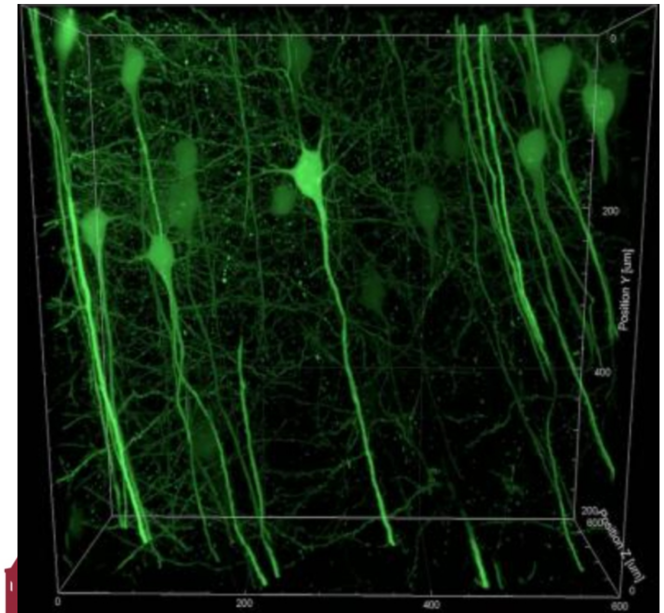
Fermi Streaming Multiprocessor (SM)

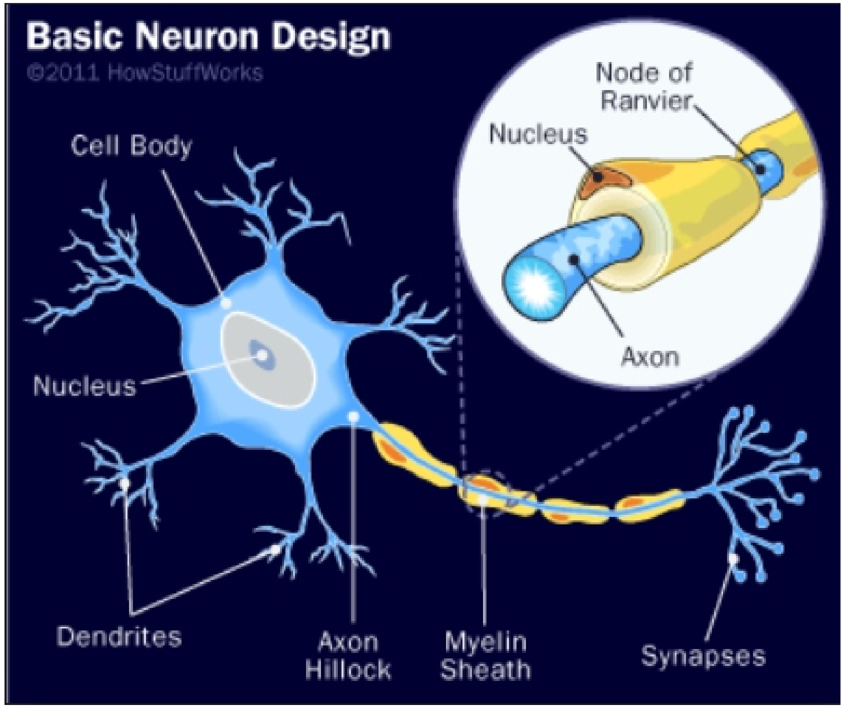
GPU

- CPU architecture (x86/ARM) in PCs still based on the Von Neumann model (proposed in 1945)
- Speed limited by "Von Neumann bottleneck"
- GPUs contain many more cores than CPU (parallelism)
- **100s of Watts of power** consumed by CPUs and GPUs

Computing architecture of the human brain

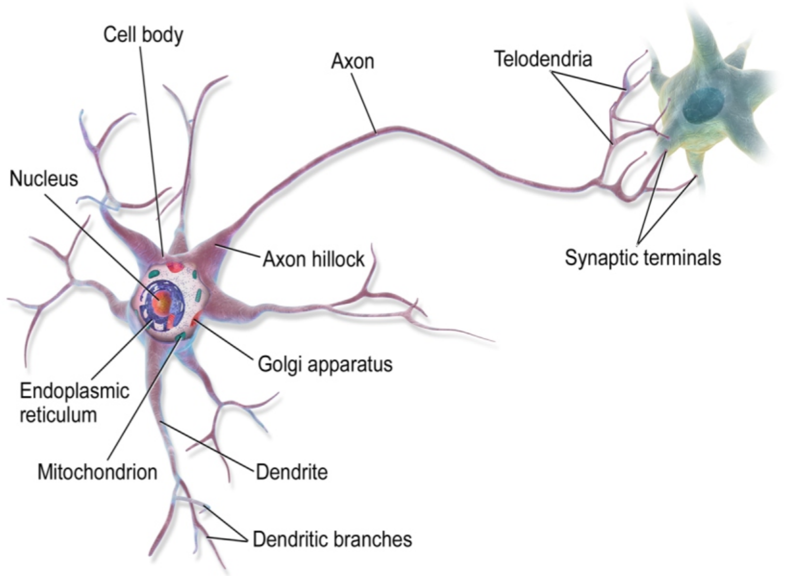


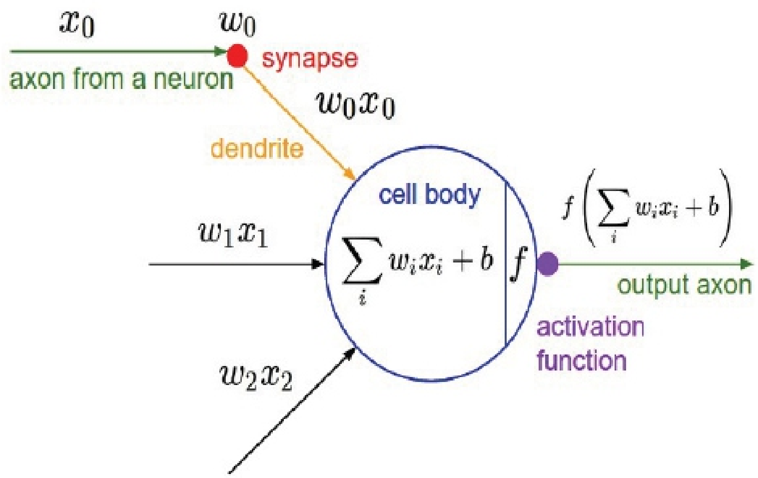




- 86 billion neurons in the human brain (257 billion in elephant brain)
- 1.5×10^{14} synapses between neurons
- **20 Watts of power** used by the brain

Neuron Model is too SIMPLE !





Neural Networks are not as Efficient as the Brain !!!

Computer vs the human brain

Feature	Computer	Human Brain	Comments
Number of computing elements	7.2 x 10^9 transistors	80 x 10^9 neurons	The brain has ~10 times more computing elements
Connectivity between computing elements	Sparse connectivity	Each neuron can be connected to 10^4 other neurons	Brain's neuron connectivity outperforms the computer
Speed	100 ps clock (10 GHz)	100 µs	Computer is 10^6 times faster!
Computing architecture	Clocked and serial (Von Neumann)	Completely parallel, asynchronous	Memory and computing elements of the brain are together
Computing capabilities	Good at crunching numbers and math	Good at solving ill-posed problems (speech, vision)	

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Generative AI

- Generative AI (GAI) is a type of artificial intelligence model or tool that is able to produce **new content** such as text, code and images in response to user-defined prompts or commands. Examples of popular GAI tools include ChatGPT, Bing Chat, Bard and Claude 2. They rely extensively on large language models for content generation. The language models collect vast amounts of online content and utilize algorithms to discern patterns.

Generative AI

TABLE I. TYPES OF GENERATIVE AI TOOLS

GAI Tool	*Model*	*Commercial Use or Not*	*Output*
UM-GPT	AI bot from the Univ of Michigan providing information and academic assistance	No	NLP (Natural Language Processing)
Ployglot	A multilingual model with higher non-English language performance	Apache 2.0 License	NLP
Jukebox AI	GAI music model to create raw audio music	No	Audio
DALLE-2	Generates images from textual descriptions	Yes	Image
Stable Diffusion	Uses text descriptions to genarate images	Yes	Image
BARD	Large language model trained on text and code	No	NLP
Climate Bert	Pretrained Language Model for Climate related text	Apache 2.0 License	NLP
LAMBDA	Good for open-ended chatbot conversations	No	NLP
LLaMA 2	Large language model (LLM) developed by Meta	Yes, but limited	NLP
ChatGPT3.5	Generates content, translate and answer questions	Yes	NLP

Source - https://midas.umich.edu/generative-ai-resources/

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Generative AI

- Any sufficiently advanced technology is simply indistinguishable from magic
  --Arthur C. Clarke

The same can be said of various applications of GAI

- See the websites
- https://www.ourworldindata.org/brief-history-of-ai
- https://www.linkedin.com/learning/what-is-generative-ai/how-generative-ai-works?

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Applications for Developing Economies SDG

SDG


9 INDUSTRY, INNOVATION AND INFRASTRUCTURE
10 REDUCED INEQUALITIES
11 SUSTAINABLE CITIES AND COMMUNITIES
12 RESPONSIBLE CONSUMPTION
13 CLIMATE ACTION
14 LIFE BELOW WATER
15 LIFE ON LAND
16 PEACE AND JUSTICE
17 PARTNERSHIPS FOR THE GOALS

Accra Newspaper Story on SDG (Friday May 10, 2019)

24 News

Daily Graphic Friday, May 10, 2019.

Ghana's commitment to achieve SDGs commendable

— UN General Assembly President

By Timothy Ngnenbe

THE President of the 73rd Session of the United Nations (UN) General Assembly, Ms Maria Fernanda Espinosa Garces, has spoken highly of the Ghana government's commitment and leadership in the global action to achieve the Sustainable Development Goals (SDGs).

She commended President Nana Addo Dankwa Akufo-Addo, in particular, for his great leadership role on the international front as co-Chair of the UN Secretary-General's Eminent Advocates on the SDGs and the structures put in place locally to achieve the global targets.

"One of the ingredients for achieving the SDGs is a high level of political will, and for President Akufo-Addo to show this commitment so far by creating an advisory unit at the Presidency and also setting up a high-level ministerial committee on the SDGs is so commendable.

"The UN Secretary-General thought it wise to reappoint him as a co-Chair of the SDGs until 2020 and this is well deserved," she added.

Meeting

Ms Garces, who arrived in the country last Wednesday on a four-day official visit, gave the commendation when she met the 15-member high-level ministerial committee on SDGs in Accra yesterday.

The meeting was meant to discuss the global efforts being made to achieve the SDGs and explore avenues for achieving the targets at the country level.

Present at the meeting were key stakeholder ministers, including those of Finance, Mr Ken Ofori-Atta; Education, Dr Mathew Opoku-Prempeh; Justice and Attorney-General, Ms Gloria Akuffo; Planning, Professor George Gyan-Baffour, and Foreign Affairs and Regional Integration, Ms Shirley Ayorkor Botchwey.

The ministers of Employment and Labour Relations, Fisheries and Aquaculture Development, Local Government and Rural Development, Health and Gender, Children and Social Protection, Mr Ignatius Baffour-Awuah, Mrs Elizabeth Afoley Quaye, Hajia Alima Mahama, Mr Kwaku Agyeman Manu and Ms Cynthia Morrison, respectively, were also at the meeting.

Commendation

Ms Garces said the government's holistic approach to achieving the SDGs by bringing together related ministries, departments and agencies (MDAs) was strategic and commendable.

She described the free senior high school, the One-district, One-factory (1D1F) and the one-village, one-dam (1V1D) policies and the other initiatives by the government as timely, since they would play a critical role in addressing most of the SDGs.

"I am ... I am encouraged by what ... here and I am ... ambassador in Ghana," she ... with a smile.

She ... government to create more ... that would make the SDGs ... by making them ... the youth and women.

Funding

Ms Garces ... stressed the need to take the issue of funding ... programmes seriously.

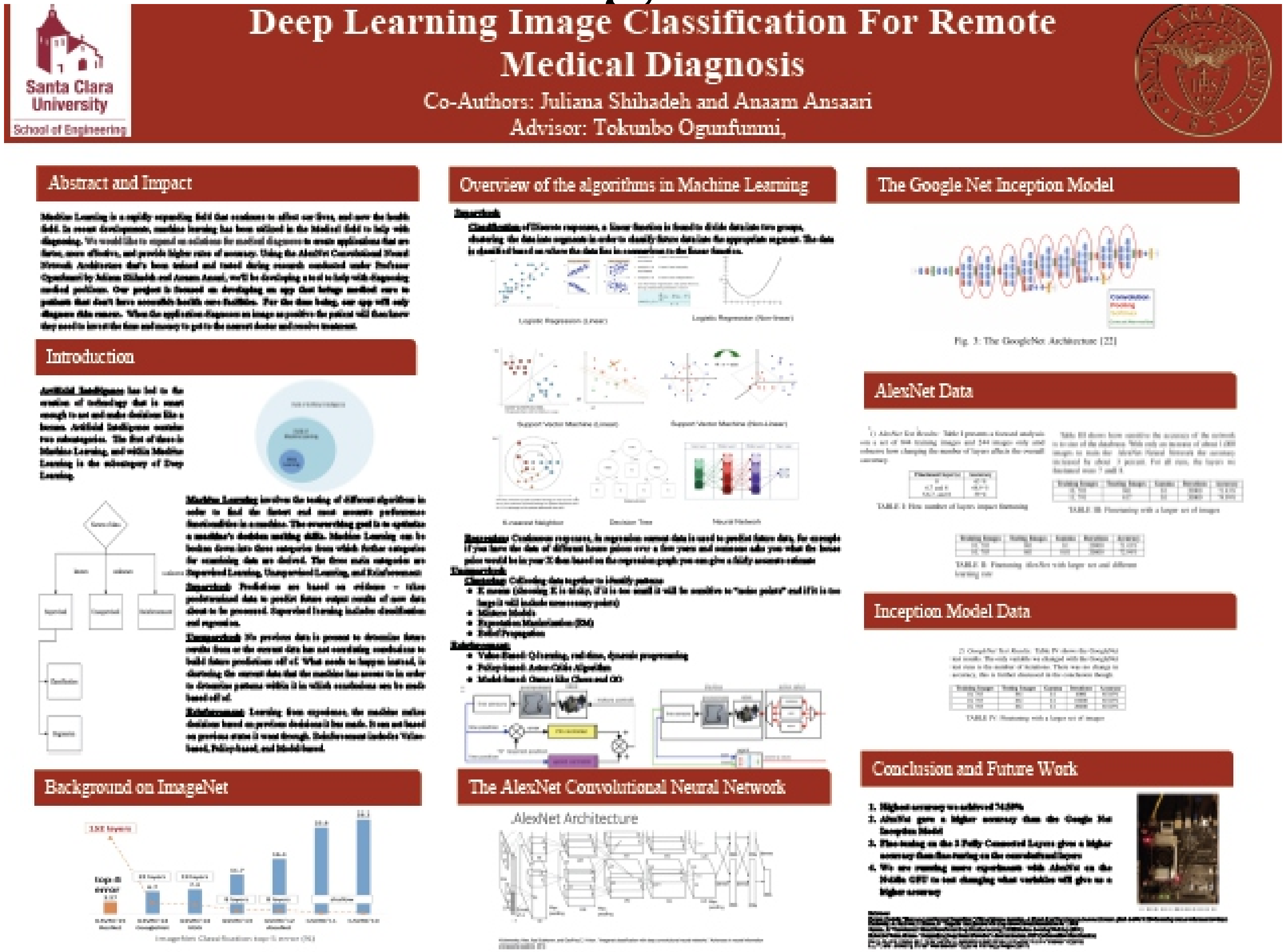
That, she said, required innovative strategies and coordinated action involving the private sector to raise funds for programmes that would achieve the SDGs.

"It is important to be encouraging and making the private sector accountable in raising funds for the SDGs, but we need to also be more innovative in exploring other avenues to raise funds," she said.

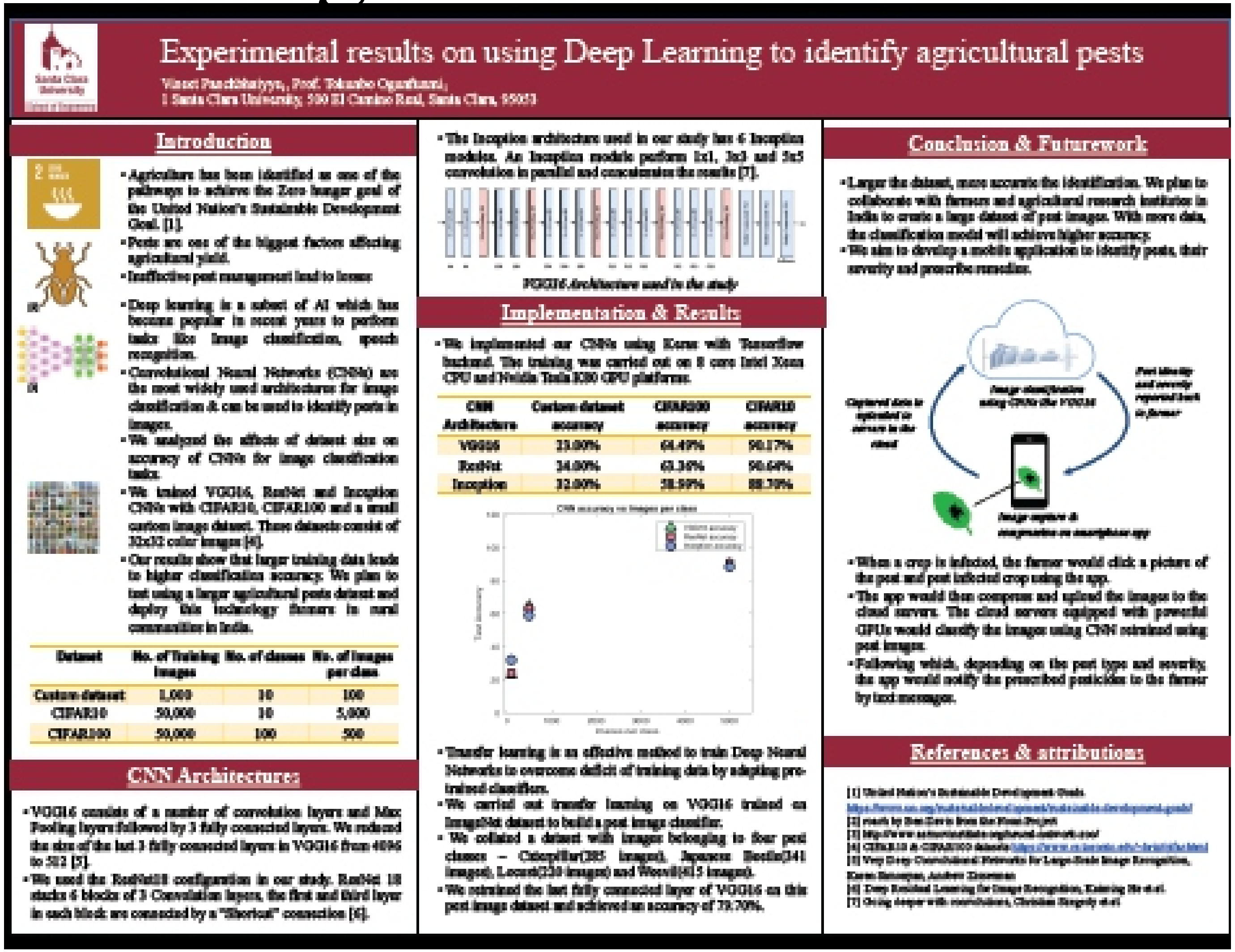
Fact Sheet

- Ms Maria Fernanda Espinosa Garces was elected President of the 73rd Session of the UN General Assembly on June 5, 2018.
- She is the first woman from Latin America to become President of the UN General Assembly.

SDG Application: Remote Medical Diagnosis



SDG Application: Identifying Agricultural Pests



Experimental results on using Deep Learning to identify agricultural pests

Vineet Panchbhaiyya, Prof. Tokunbo Ogunfunmi,
1 Santa Clara University, 500 El Camino Real, Santa Clara, 95053

Introduction

- Agriculture has been identified as one of the pathways to achieve the Zero hunger goal of the United Nation's Sustainable Development Goal. [1].
- Pests are one of the biggest factors affecting agricultural yield.
- Ineffective pest management lead to losses
- Deep learning is a subset of AI which has become popular in recent years to perform tasks like image classification, speech recognition.
- Convolutional Neural Networks (CNNs) are the most widely used architectures for image classification & can be used to identify pests in images.
- We analyzed the effects of dataset size on accuracy of CNNs for image classification tasks.
- We trained VGG16, ResNet and Inception CNNs with CIFAR10, CIFAR100 and a small custom image dataset. These datasets consist of 32x32 color images [4].
- Our results show that larger training data leads to higher classification accuracy. We plan to test using a larger agricultural pests dataset and deploy this technology farmers in rural communities in India.

Dataset	No. of Training Images	No. of classes	No. of Images per class
Custom dataset	1,000	10	100
CIFAR10	50,000	10	5,000
CIFAR100	50,000	100	500

CNN Architectures

- VGG16 consists of a number of convolution layers and Max Pooling layers followed by 3 fully connected layers. We reduced the size of the last 3 fully connected layers in VGG16 from 4096 to 512 [5].
- We used the ResNet18 configuration in our study. ResNet 18 stacks 6 blocks of 3 Convolution layers, the first and third layer in each block are connected by a "Shortcut" connection [6].
- The Inception architecture used in our study has 6 Inception modules. An Inception module perform 1x1, 3x3 and 5x5 convolution in parallel and concatenates the results [7].

VGG16 Architecture used in the study

Implementation & Results

- We implemented our CNNs using Keras with Tensorflow backend. The training was carried out on 8 core Intel Xeon CPU and Nvidia Tesla K80 GPU platforms.

CNN Architecture	Custom dataset accuracy	CIFAR100 accuracy	CIFAR10 accuracy
VGG16	23.00%	61.49%	90.17%
ResNet	34.00%	63.36%	90.64%
Inception	32.00%	58.59%	88.70%

CNN accuracy vs Images per class

- Transfer learning is an effective method to train Deep Neural Networks to overcome deficit of training data by adapting pre-trained classifiers.
- We carried out transfer learning on VGG16 trained on ImageNet dataset to build a pest image classifier.
- We collated a dataset with images belonging to four pest classes – Caterpillar(285 images), Japanese Beetle(341 images), Locust(230 images) and Weevil(415 images).
- We retrained the last fully connected layer of VGG16 on this pest image dataset and achieved an accuracy of 70.70%.

Conclusion & Futurework

- Larger the dataset, more accurate the identification. We plan to collaborate with farmers and agricultural research institutes in India to create a large dataset of pest images. With more data, the classification model will achieve higher accuracy.
- We aim to develop a mobile application to identify pests, their severity and prescribe remedies.

- When a crop is infected, the farmer would click a picture of the pest and pest infected crop using the app.
- The app would then compress and upload the images to the cloud servers. The cloud servers equipped with powerful GPUs would classify the images using CNN retrained using pest images.
- Following which, depending on the pest type and severity, the app would notify the prescribed pesticides to the farmer by text messages.

References & attributions

[1] United Nation's Sustainable Development Goals.
[2] work by Ben Davis from the Noun Project
[4] CIFAR10 & CIFAR100 datasets
[5] Very Deep Convolutional Networks for Large-Scale Image Recognition, Karen Simonyan, Andrew Zisserman
[6] Deep Residual Learning for Image Recognition, Kaiming He et al.
[7] Going deeper with convolutions, Christian Szegedy et al.

Medical and Robotics Applications

Video link

CNN Inside Africa Program

https://urldefense.com/v3/__https://www.cnn.com/videos/tv/2023/08/31/inside-africa-technology-is-disrupting-medicine-and-beyond-in-south-africa-spc-intl.cnn__;!!MLMg-p0Z!F67ottskDqmtLb3zOLkNMSGr5pUppphipjICbbGrpdITa-hhrRfvhUetxi2hWjoZi7sc8EEJYWVLs5mBNAbP$

Autonomous Vehicle Systems

Localization:
How does vehicle know where it is in the world?

Perception:
How does vehicle recognize other objects?

HD Maps:
When are traditional maps not adequate?

Integration of many different technologies.

Prediction:
How does vehicle determine intentions of pedestrians and other vehicles ?

Planning:
What route will vehicle follow from A to B?

Machine Learning:
How does vehicle adjust its knowledge in real-time?

Control:
How does vehicle steer, accelerate or break ?

Computer Vision:
How does vehicle see and understand ?

[Youtube Video on Waymo Self Driving cars]

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Concluding Remarks

- AI, ML, DL are revolutionizing our high technology lives !!!
- This Revolution is HUGE !
- African Countries must not be left behind
- There is very little barrier to entry
- You can contribute in Applications
- There are several possible applications for developing economies (UN SDG examples)
- Get involved !!!

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Questions?

PROFILE OF THE 2ND NDU PUBLIC LECTURER

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Professor of Electrical and Computer Engineering

Dept. of Electrical & Computer Engineering,

School of Engineering, Santa Clara University

California, United States of America

CITATION OF PROF. TOKUNBO OGUNFUNMI

Prof. Ogunfunmi began his formal education at ICC Primary School, Apata, Ibadan. After three years, he transferred to Ebenezer Primary School, Oke-Ado, Ibadan where he completed his primary school education as the best student in the last two of his three years there. He was admitted to Government College Ibadan (GCI) in 1971 and later graduated the West African School Certificate (Grade I with Distinction) in 1975.

He was admitted to the University of Ife, Ile-Ife (Great Ife ! now known as Obafemi Awolowo University (OAU)). He graduated with a Bachelor's degree in Electrical and Electronics Engineering (First Class Honors) in 1980. He served the mandatory one-year National Youth Service Corps (NYSC) in Sokoto State. After working as Assistant Lecturer at the newly created Dept. of Electrical Engineering at the University of Ibadan, he proceeded to Stanford University for post-graduate studies.

He graduated with Master of Science (MS) and Doctor of Philosophy (PhD) degrees in Electrical Engineering both from Stanford University, Stanford, California. While at Stanford, he was actively involved in the design of the Multichannel Spectral Analyzer (MCSA), a Digital Signal Processing (DSP) Integrated Circuit (IC) chip which was used for United States National Aeronautics and Space Agency (NASA)'s Search for Extra-Terrestrial Intelligence (SETI) program in the late 1980's and early 1990's. Two versions of the IC chips are used by NASA for its continuing search for extra-terrestrial intelligence. After Stanford, he joined the faculty at Santa Clara University (SCU). Since being at SCU, he has established a vibrant research lab (Information Processing and Machine Learning Research Lab (IPML)) where new algorithms are developed and new implementation methods are introduced. He has mentored and supervised several Post-docs, PhDs, Engineer's (MPhil) and MS degrees in this research area.

He is Full Professor of Electrical and Computer Engineering and the David Packard Endowed Faculty Fellow professor in the School of Engineering at SCU. His research interests include the areas: machine learning and deep learning, digital signal processing, adaptive and nonlinear signal processing, video and speech, artificial neural networks and DSP/FPGA/VLSI design with applications in wireless communications, internet of things, etc.
He has published extensively in these areas: 4 advanced graduate level books, over 250+ journal and conference papers, several book chapters and invited lectures.

From 2010-2014, he served as the Associate Dean for Research and Faculty Development in the School of Engineering at SCU overseeing all the research activities of the School of Engineering. Currently, he is serving as the co-Associate Dean for Mission, Culture and Inclusion in the School of Engineering at SCU.

He has held the following Visiting Professorships:

- Carnegie Foundation Visiting Professor, Covenant University, Ota, and Obafemi Awolowo University, Ife, Nigeria (2015, 2019, 2021).
- Visiting Professor, The University of Texas, Dallas, (2014)
- Visiting Professor, The University of Texas, Arlington, (2007-2008)
- Visiting Professor, Stanford University, (1999-2000)

He has worked in industry and consulted for the following companies among many others: AT&T Bell Labs, NIKON, Broadcom, AMD, NEC, etc.
He is a Senior Member of the Institution of Electrical and Electronic Engineers (IEEE). The IEEE is the largest professional engineering society in the world (about 340,000 members across 10 geographical areas), a Member of Sigma Xi (the Scientific Research Society), and a Member of the American Association for the Advancement of Science (AAAS).

He served as Associate Editor or Senior Associate Editor of the journals:
IEEE Transactions on Circuits and Systems: I-Regular Papers,
IEEE Transactions on Circuits and Systems: II-Express Briefs
IEEE Signal Processing Letters journal,
Circuits, Systems and Signal Processing journal.
IEEE Transactions on Signal Processing.

He was appointed as a Distinguished Lecturer for the IEEE Circuits and Systems Society for 2012-2014. A distinguished lecturer position is awarded by the IEEE to very senior and highly qualified IEEE members to travel around the world to deliver high-quality technical lectures to its members.

He has served and continues to serve the IEEE in many other capacities including:
• Technical Program Chair, IEEE ISCAS Conference, 2019
• General Chair, IEEE SIPS Conference, Capetown, South Africa, 2018
• Special Sessions Chair, IEEE World Congress on Internet of Things (IoT), Seoul, Korea, 2014
• Chair, IEEE Circuits and Systems Society (CASS) Technical Committee on Circuits and Systems for Communications (CASCOM), 2014-date.
• Chair, IEEE CASS Technical Committee on Education and Outreach (CASEO), 2012-2014.
• Tutorial Chair, IEEE ICME Conference, 2013
• General Co-Chair, IEEE ICAST Conference, 2011
• Technical Program Chair, ICAST 2009 Conference,
• Chair, IEEE Signal Processing Society Santa Clara Valley chapter (2007-2009),
• Chair, IEEE GOLD Committee (2009),
• Chair, IEEE PACE Committee (2010),
• Delegate, IEEE Sections Congress, Quebec, Canada, 2008,
• Member, IEEE Circuits and Systems Society (CASS) Technical Committee on Digital Signal Processing (DSP),
• Member, IEEE Signal Processing Society Technical Committee on Digital Signal Processing Systems Implementation (DISPS).

He is also a Registered professional engineer in the state of California. He has received the following recognitions for his work:
• Best paper award, IEEE Signal Processing Workshop (SiPS) 2005,
• Best Paper Award, Information Systems, ASEE Annual Conference, 2009
• IEEE Meritorious Service Award, 2009
• Researcher of the Year (2002),
• Wilmot Nicholson Fellow (1995),
• Carnegie Foundation Professorship (2015-2021)
• David Packard Endowed Faculty (2021-date)

He has organized several special sessions and workshops at many IEEE and non-IEEE conferences. He also delivered keynote talks at several conferences.

Finally, he is very passionate about educating the next generation of engineers. He has supervised several BS, MS, Engineers (MPhil) Theses and Ph.D. dissertations. He has served as external examiner for several PhD candidates in other countries e.g. Nigeria, India, Ghana, etc.

He is married to Teleola and the marriage is blessed with two wonderful children.

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