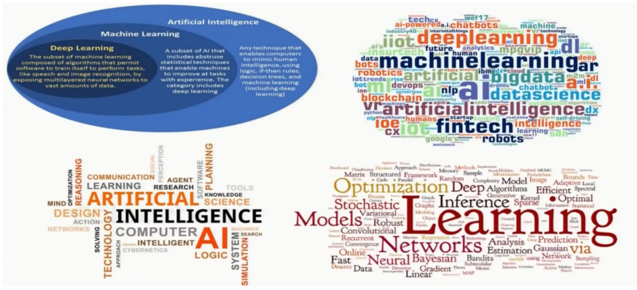
Motion Analytics & Diabetic Foot Ulcer using Deep Learning Models

Dr. Chandra Prakash

AI- ML Terminology

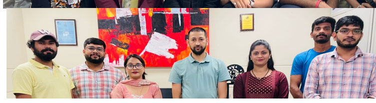


Slide credit : Dr. Partha Pratim Chakrabarti

Artificial Intelligence

Source: https://www.youtube.com/watch?v=e2_hsjpTi4w&t=67s

Computational Intelligence and Smart Motion Research (CISMR) @SVNIT



PROJECTS UNDER CISMR

Project Title: Computational Techniques based investigation for Diabetic foot ulcers complications (CISMR)
Funding Agency: DST- Science and Engineering Research Board (SERB) under EMEQ scheme, GoI
Project Duration : Three (03) years
Objective: The aim of the project is to explore Foot pressure plate and Thermogram Images for diabetic foot ulcer

Pose Estimation and Human Gait Analysis
Objective: The aim of the project is to exploring pose techniques for gait/motion analysis.

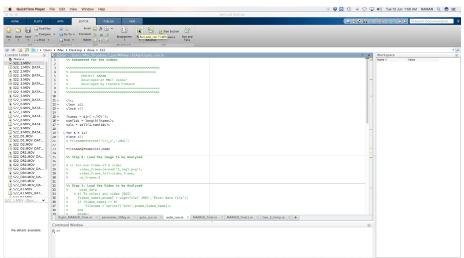
Sign Language Interpreter Using machine learning techniques
Objective: The aim of the project is to exploring techniques for Sign Language Interpreter

Emotion Classification Using Human Gait Analysis
Objective: The aim of the project is to gauge emotion via their gait is a key component in enabling machines to understand people in real-time.

Path Planning Techniques for Mobile Robots
Objective: The aim of the project is to exploring path planning methods for mobile robots both on simulation and real time environment.

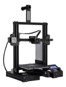
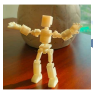
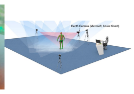
Prediction of Freezing of Gait in Parkinson's Disease
Objective: The aim of the project is to exploring techniques for predicting proactively FOG condition

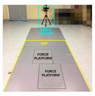
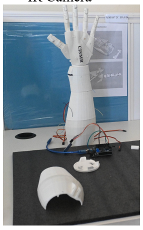
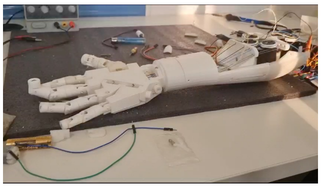
Motion Rehabilization



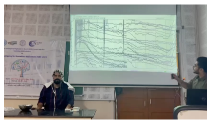
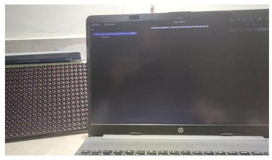
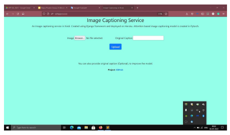
Computational Intelligence and Smart Motion Robotics (CISMR)

- 3 D Printer
- Bipedal Robot
- Foot pressure sensor
- IR Camera

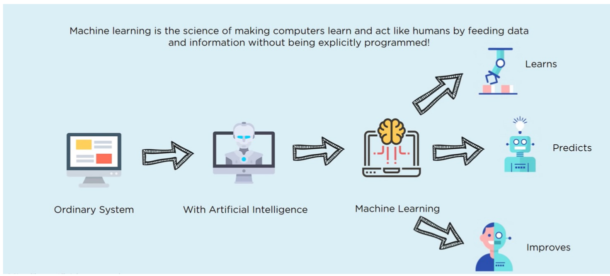





Projects @ CISMR

- Let's Deep Dive into Motion analytics and Deep learning models

What is Machine learning

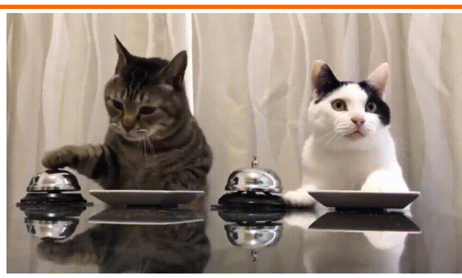


Can You Recognize these Pictures ?


Portrait or a sculpture ???

- If Yes, How do you Recognize it?

Learning



Learning is constructing or modifying representations of what is being experienced.
-- McCarthy, 1968

Machine learning Type:

With respect to the feedback type to learner:

- **Supervised learning** :
  - Task Driven (Classification)
- **Unsupervised learning** :
  - Data Driven (Clustering)
- **Reinforcement learning**
  - Self learning (reward based)

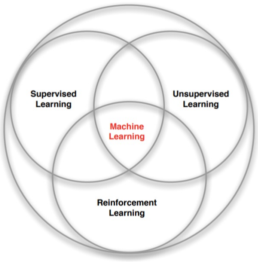
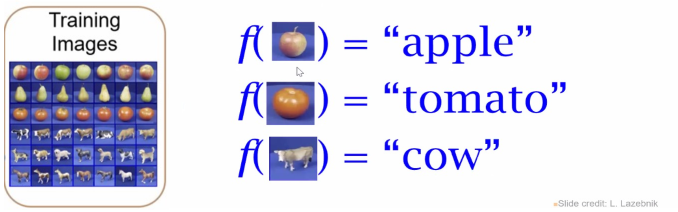


Image credit : UCL Course of RL

Supervised Learning

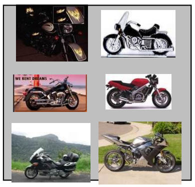
- Apply a prediction function to a feature representation of the image to get the desire output



Slide credit: L. Lazebnik

Supervised Learning

Cars

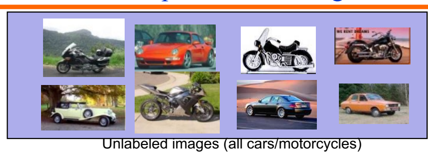


Motorcycles

Testing:
What is this?

- Linear regression
- Logistic regression
- Perceptron
- Naive Bayes
- Neural Networks
- Decision trees; K-Nearest Neighbor
- Support Vector Machine (SVM)

Un-Supervised learning

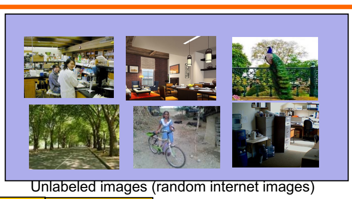


Unlabeled images (all cars/motorcycles)

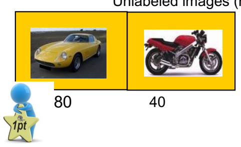
Clustering

Which Group
It belongs to ??

Reinforcement / Self Learning



Unlabeled images (random internet images)



80 40

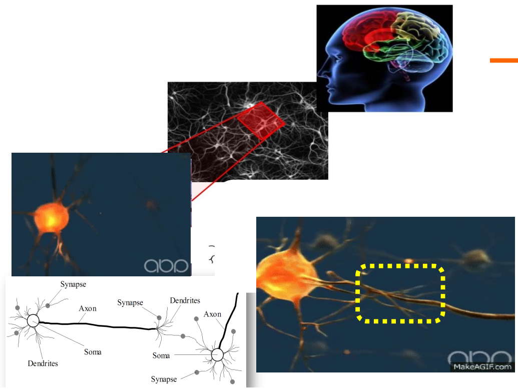
Testing:
What is this?

Human Learning Process

Locate people in this photo

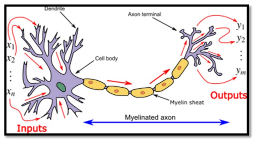
Add these numbers

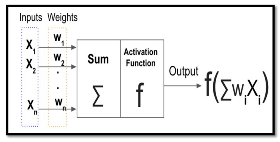
2403343781289312
\+ 2843033712837981
\+ 2362142787897881
\+ 3256541312323213
\+ 9864479802118978
\+ 8976677987987897
\+ 8981257890087988
= ?



Artificial Neural Network

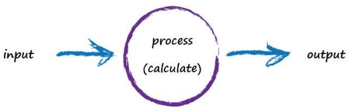
- Consists of a number of very simple processors, also called **neurons**,
  - Analogous to the biological neurons in the brain.
- Neurons are connected by weighted links passing signals from one neuron to another.
- The output signal is transmitted through the neuron's outgoing connection.
- The outgoing connection splits into a number of branches that transmit the same signal.
  - The outgoing branches terminate at the incoming connections of other neurons in the network.





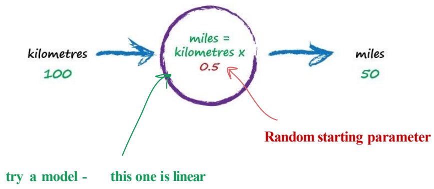
Source: Wikipedia

Example : Learning in a Human Way

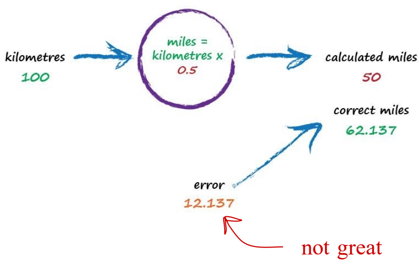


f() = "apple"

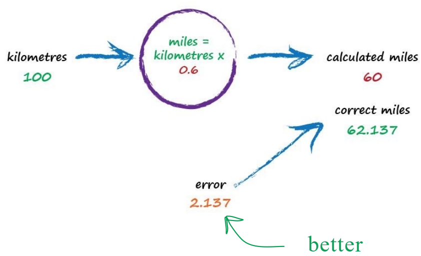
Example : Learning in a Human Way



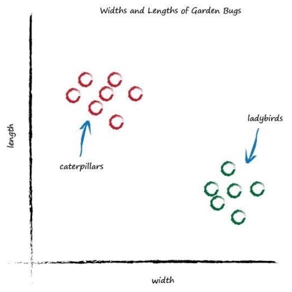
Example : Learning in a Human Way



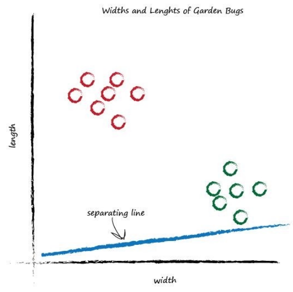
Example : Learning in a Human Way



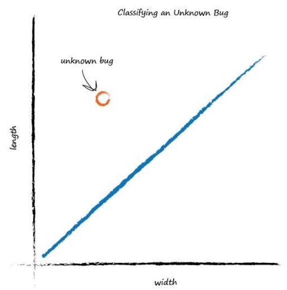
Example : Learning in a Machine Way



Example : Learning in a Machine Way



Example : Learning in a Machine Way

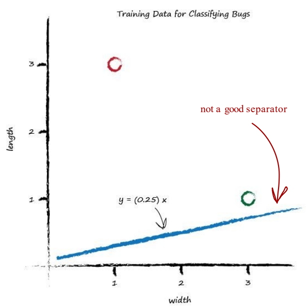


Example : Learning in a Machine Way

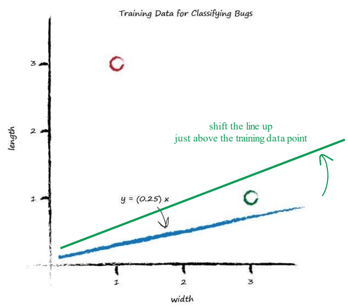
Classifying things is kinda like **predicting** things.

Example	Width	Length	Bug
1	3.0	1.0	ladybird
2	1.0	3.0	caterpillar

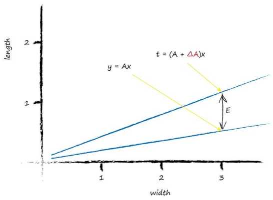
Example : Learning in a Machine Way



Example : Learning in a Machine Way



Example : Learning in a Machine Way



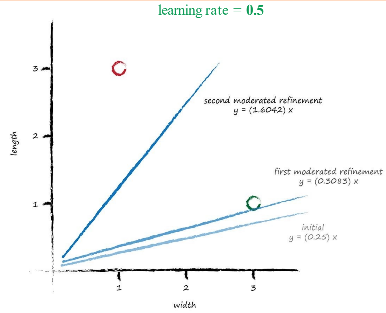
error = target - actual

E= (A +ΔA)x - Ax

ΔA = E/ x

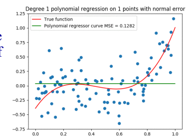
Example : Learning in a Machine Way

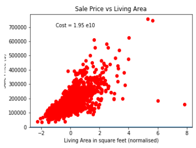
learning rate = 0.5

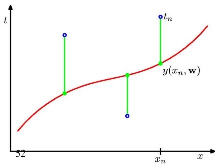


Example : Learning in a Machine Way

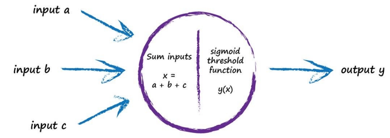
- How to choose ??
  - Loss function : measures the squared error in the prediction of y(x) from x.





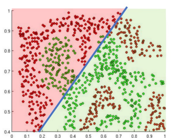


When we have more than one input?

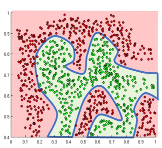


Need of Activation functions

- The purpose of activation functions is to introduce non-linearities into the network
- A neural network without an activation function is essentially just a linear regression model.

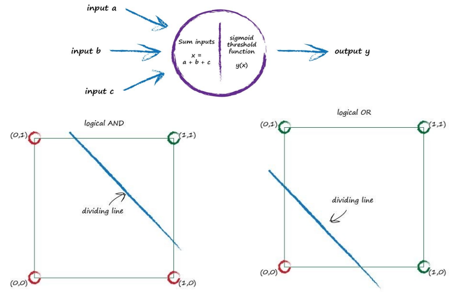


Linear Activation functions produce linear decisions no matter the network size



Non-linearities allow us to approximate arbitrarily complex functions

Single Neuron /Perceptron

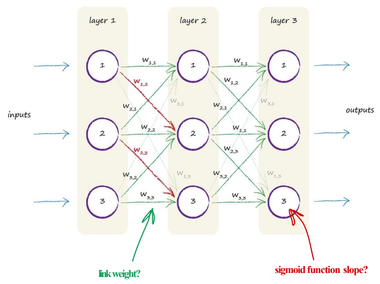


Features

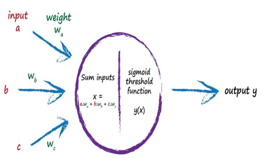
- The features are the elements of your input vectors.
- The number of features is equal to the number of nodes in the input layer of the network

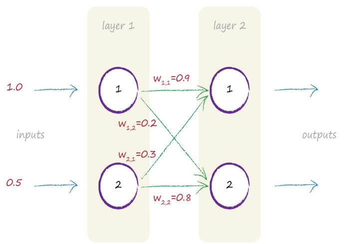
Category	Features
Housing Prices	No. of Rooms, House Area, Air Pollution, Distance from facilities, Economic Index city, Security Ranking etc.
Spam Detection	presence or absence of certain email headers, the email structure, the language, the frequency of specific terms, the grammatical correctness of the text etc.
Speech Recognition	noise ratios, length of sounds, relative power of sounds, filter matches
Cancer Detection	Clump thickness, Uniformity of cell size, Uniformity of cell shape, Marginal adhesion, Single epithelial cell size, Number of bare nuclei, Bland chromatin, Number of normal nuclei, Mitosis etc.
Cyber Attacks	IP address, Timings, Location, Type of communication, traffic details etc.
Video Recommendations	Text matches, Ranking of the video, Interest overlap, history of seen videos, browsing patterns etc.
Image Classification	Pixel values, Curves, Edges etc.

Where Does The Learning Happen?

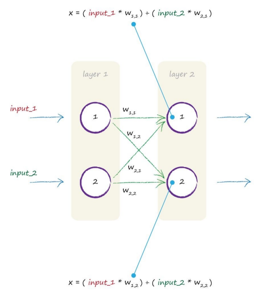


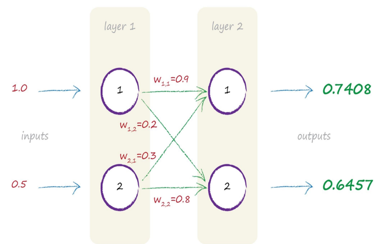
Feeding Signals Forward



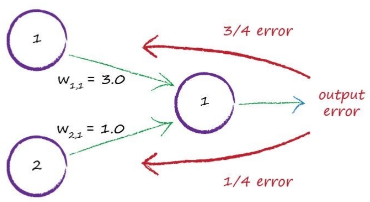


Feeding Signals Forward

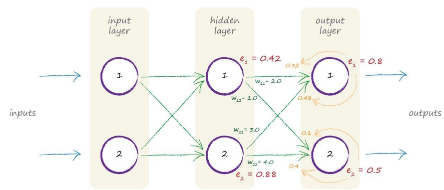




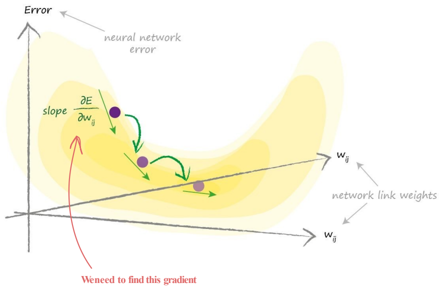
Network Error



Internal Error



Climbing Down the Network Error Landscape



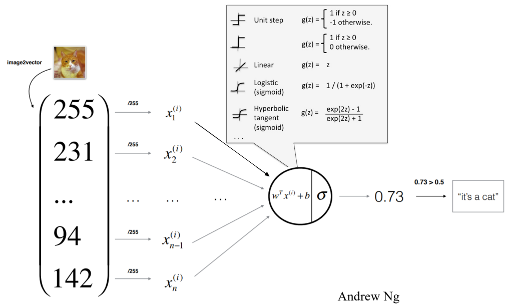
Updating the Weights

move w_{jk} in the opposite direction to the slope

$$\text{new } w_{jk} = \text{old } w_{jk} - \alpha \cdot \frac{\partial E}{\partial w_{jk}}$$

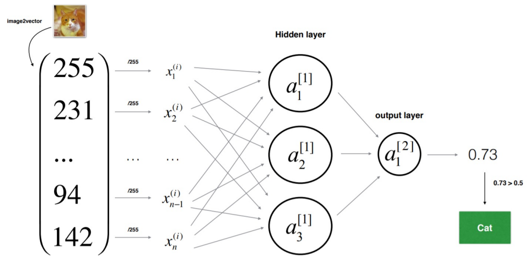
remember that learning rate

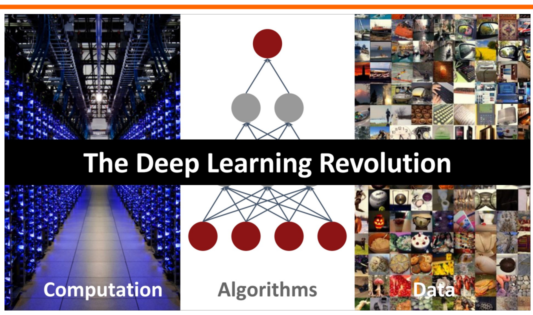
Logistic Regression as a Neural Network



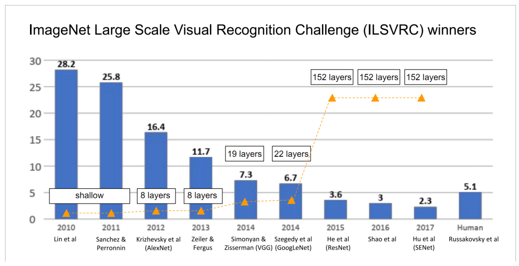
Andrew Ng

Neural Network (1 hidden layer)

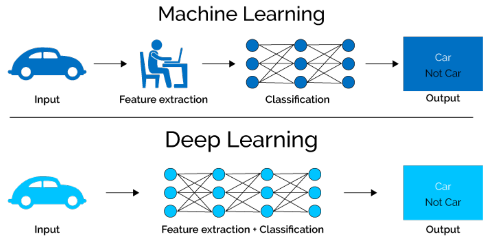




Vision and Deep Learning

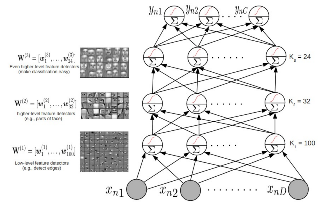


Traditional ML vs Deep Learning



Neural Networks: The Features Learned

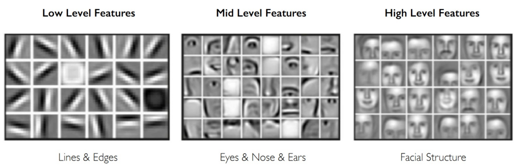
- Deep neural networks are good at detecting features at multiple layers of abstraction
- The connection weights between layers can be thought of as feature detectors or filters



- Lowest layer weights detect generic features, higher level weights detect more specific features
- Features learned in one layer are composed of features learned in the layer below

Why Deep Learning ?

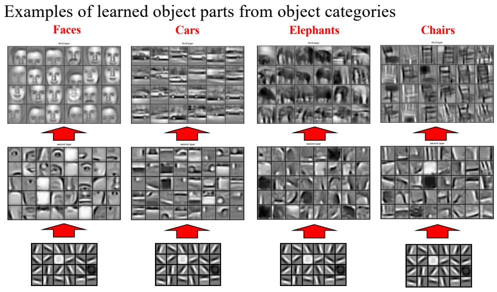
- Hand engineered features are time consuming, brittle and not scalable in practice.
- Can we learn the underlying features directly from data?



Learning of object parts

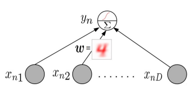
In deep learning, feature learning replaces feature engineering

Examples of learned object parts from object categories



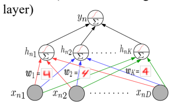
Why Are Deep Neural Network Learned Features Helpful?

- A single layer model will learn an average feature detector



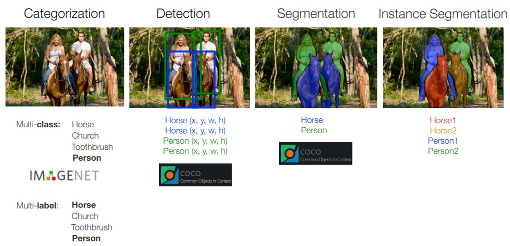
- Can't capture subtle variations in the inputs

- An MLP can learn multiple feature detectors (even with a single hidden layer)

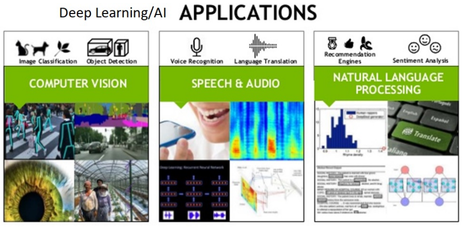


- Therefore even a single hidden layer helps capture subtle variations in the inputs

Computer Vision Problems

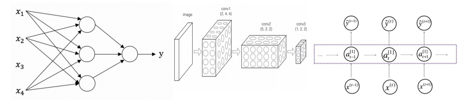


Applications



Few Popular Applications: Precision Agriculture, Learner Profiling, Video Captioning, Exploring Patterns from Satellite images, Image detection in Healthcare, Identifying specific markers in Genomes, Creating Art and Music, Recommendations, behavior prediction,

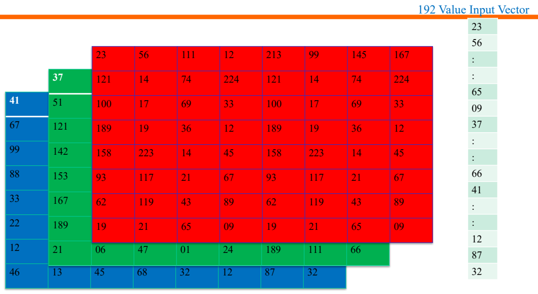
Deep Network Examples



Standard NN   Convolutional NN   Recurrent NN

- Stacked Autoencoders (multilayer neural net with target output = input)
- Stacked restricted Boltzmann machine

Color Image (8X8X3) pixels



Shape of Your Input: **X** (n x m)

← Number of IO pairs available for training the network →

No of *Data Points* in Single Input

$x_1^{(1)}$	$x_1^{(2)}$	$x_1^{(3)}$	$x_1^{(4)}$	..	..	..	..	$x_1^{(m-1)}$	$x_1^{(m)}$
$x_2^{(1)}$	$x_2^{(2)}$	$x_2^{(3)}$	$x_2^{(4)}$	..	..	..	..	$x_2^{(m-1)}$	$x_2^{(m)}$
$x_3^{(1)}$	$x_3^{(2)}$	$x_3^{(3)}$	$x_3^{(4)}$	..	..	..	..	$x_3^{(m-1)}$	$x_3^{(m)}$
$x_4^{(1)}$	$x_4^{(2)}$	$x_4^{(3)}$	$x_4^{(4)}$	..	..	..	..	$x_4^{(m-1)}$	$x_4^{(m)}$
:	:	:	:	..	..	..	..	:	:
:	:	:	:	..	..	..	..	:	:
:	:	:	:	..	..	..	..	:	:
:	:	:	:	..	..	..	..	:	:
:	:	:	:	..	..	..	..	:	:
:	:	:	:	..	..	..	..	:	:
$x_{n-1}^{(1)}$	$x_{n-1}^{(2)}$	$x_{n-1}^{(3)}$	$x_{n-1}^{(4)}$	..	..	..	..	$x_{n-1}^{(m-1)}$	$x_{n-1}^{(m)}$
$x_n^{(1)}$	$x_n^{(2)}$	$x_n^{(3)}$	$x_n^{(4)}$	..	..	..	..	$x_n^{(m-1)}$	$x_n^{(m)}$

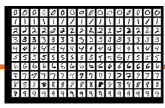
Shape of Your Output: Binary Classification

← Number of Outputs corresponding to inputs for training the network →

$y^{(1)}$	$y^{(2)}$	$y^{(3)}$	$y^{(4)}$	..	..	..	..	$y^{(m-1)}$	$y^{(m)}$

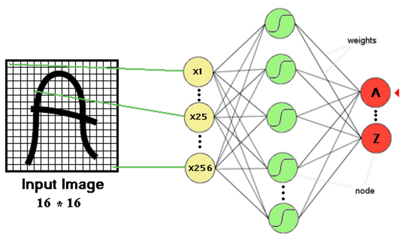
Y.Shape = (1 , m)

MNIST Dataset



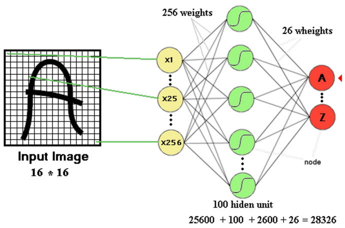
- MNIST dataset of handwritten digits
  - Categories: 10 digit classes
  - Source: Scans of handwritten zip codes from envelopes
  - Size: 60,000 training images and 10,000 test images, grayscale, of size 28 x 28
  - Normalization: centered within in the image, scaled to a consistent size
    - The assumption is that the digit recognizer would be part of a larger pipeline that segments and normalizes images.
- In 1998, Yann LeCun and colleagues built a conv net called LeNet which was able to classify digits with 98.9% test accuracy.
  - It was good enough to be used in a system for automatically reading numbers on checks.

Multi-layer perceptron and Vision



Even a simple 16x16 image

- **256x100 + 100 bias + 100x26 output neurons + 26 bias = 28236**
- the number of trainable parameters becomes extremely large



ImageNet

- ImageNet is the modern object recognition benchmark dataset. It was introduced in 2009, and has led to amazing progress in object recognition since then. [http://image-net.org/download]
- Used for the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), an annual benchmark competition for object recognition algorithms
- Design decisions
  - Categories: Taken from a lexical database called WordNet
    - WordNet consists of synsets, or sets of synonymous words
    - They tried to use as many of these as possible; almost 22,000 as of 2010
    - Of these, they chose the 1000 most common for the ILSVRC
    - The categories are really specific, e.g. hundreds of kinds of dogs
  - Size: 1.2 million full-sized images for the ILSVRC
  - Source: Results from image search engines, hand-labeled by Mechanical Turkers
    - Labeling such specific categories was challenging; annotators had to be given the WordNet hierarchy, Wikipedia, etc.
  - Normalization: none, although the contestants are free to do preprocessing

With Deep Neural Network

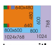
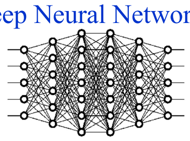


Image with
28 x 28 x 3
pixels



Number of weights in the first hidden layer will be 2352

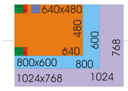
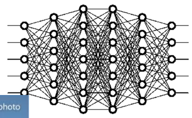
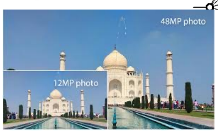


Image with
200 x 200 x 3
pixels



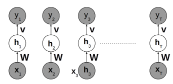
Number of weights in the first hidden layer will be 120,000



» We have Larger size image in todays era

Some Limitations of Feedforward Networks

- Require a huge number of parameters
  - The consecutive layers are fully connected)
- **Not ideal for data that exhibit locality structure, e.g., (e.g., images, sentences)**
  - Kind of works but would be better to exploit locality in the data more explicitly
- **Doesn't have a memory, so not ideal when modeling sequence of observations**

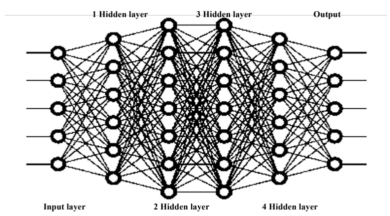


Motivation

WHY WE NEED CONVOLUTIONAL NEURAL NETWROKS?

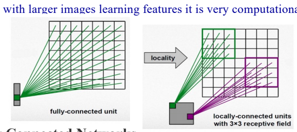
Deep NN: Too many parameters

- **We know it is good to learn a small model.**
- **From this fully connected model, do really need all the edges?**
- **Can some of these be shared?**



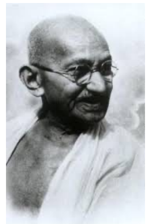
Feature Extraction Using Convolution

- **Fully Connected Networks**
  - Fully connect all the hidden units to all the input units.
  - With small images it was computationally feasible to learn features on the entire image.
  - But, with larger images learning features it is very computationally expensive



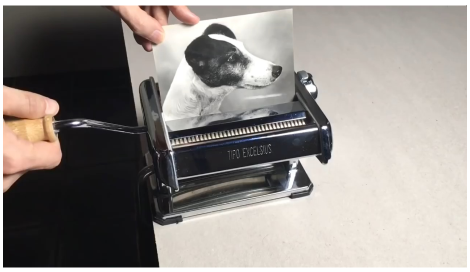
- **Locally Connected Networks**
  - Restrict the connections between the hidden units and the input units,
    - Allow each hidden unit to connect to only a small subset of the input units.
    - Each hidden unit connects to only a small contiguous region of pixels.
  - This idea of having locally connected networks also draws inspiration from how the early visual system is wired up in biology.
    - Neurons in the visual cortex have localized receptive fields (i.e., they respond only to stimuli in a certain location).

Can you recognize ??



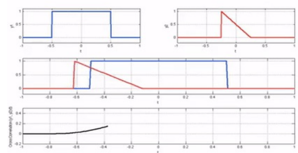
learned features over small patches sampled randomly from the larger image

Basic Idea of Convolution



What is Convolutions ????

- Dictionary meaning
  - a thing that is complex and difficult to follow.
- In mathematics convolution is a *mathematical operation on two functions that produces a third function expressing how the shape of one is modified by the other*. The term convolution refers to both the result function and to the process of computing it. [Wikipedia]



$x[n] \rightarrow$ Linear System $h[n]$ $\rightarrow y[n]$

$x[n] * h[n] = y[n]$

$$(f * g)(t) \triangleq \int_{-\infty}^{\infty} f(t-\tau)g(\tau)\,d\tau.$$

Convolutional Neural Networks (CNN)

Deep Learning on large images

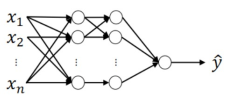
64x64 x 3

$\rightarrow$ Cat? (0/1)

1288

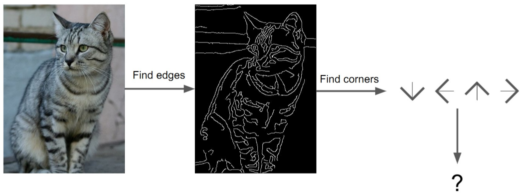
1000x1000x3

~= 3 million

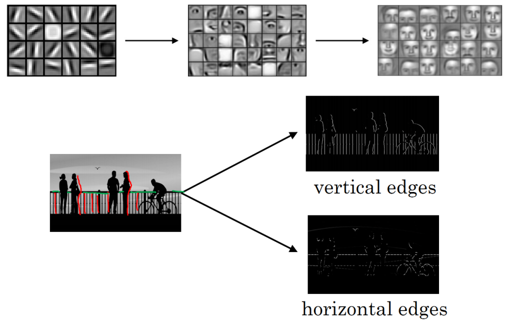


Andrew Ng

Attempts have been made though edge detection



Computer Vision Problem



Vertical Edge Detection

1	1	1	0	0
0	1	1	1	0
0	0	1	1	1
0	0	1	1	0
0	1	1	0	0

5X5 Matrix

1	0	1
1	0	1
1	0	1

3x3 Filter

4x4

Vertical Edge Detection

$1_{\times1}$	$1_{\times0}$	$1_{\times1}$	0	0
$0_{\times0}$	$1_{\times1}$	$1_{\times0}$	1	0
$0_{\times1}$	$0_{\times0}$	$1_{\times1}$	1	1
0	0	1	1	0
0	1	1	0	0

Image

*

4		

Convolved Feature

Vertical Edge Detection

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

=

Vertical and Horizontal Edge Detection

1	0	-1
1	0	-1
1	0	-1

Vertical

1	1	1
0	0	0
-1	-1	-1

Horizontal

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
0	0	0	10	10	10
0	0	0	10	10	10
0	0	0	10	10	10

*

1	1	1
0	0	0
-1	-1	-1

=

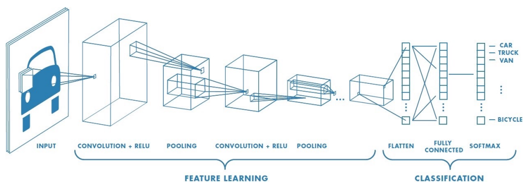
This is convolution function in image processing

CNNs Vs. ANNs

- ANNs suffer from curse of dimensionality when it comes to high resolution images
- We use filters (receptive fields) to exploit spatial locality by enforcing a local connectivity pattern between neurons of adjacent layers
  - Parameter Sharing
  - Sparsity of connection

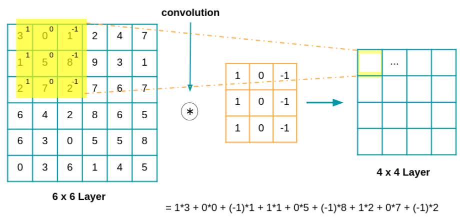
Neural network with many convolutional layers

- Natural images have the property of being ”‘stationary’”, meaning that the statistics of one part of the image are the same as any other part.
- This suggests that the features that we learn at one part of the image can also be applied to other parts of the image, and we can use the same features at all locations.

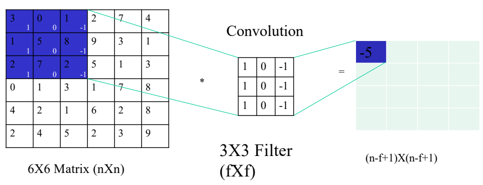


- 3 Layer in a convolutional network:
  - Convolution (CONV) - Pooling (POOL)
  - Fully connected (FC)

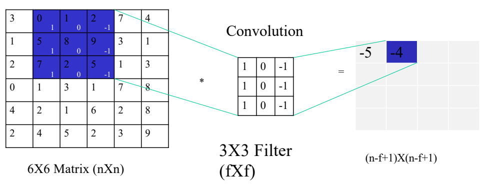
Convolution Example: Vertical Edge Detection



Convolution Example



Convolution Example



Convolution Example

3	0	1 (1)	2 (0)	7 (-1)	4
1	5	8 (1)	9 (0)	3 (-1)	1
2	7	2 (1)	5 (0)	1 (-1)	3
0	1	3	1	7	8
4	2	1	6	2	8
2	4	5	2	3	9

6 X 6 Matrix (n X n)

*

Convolution

1	0	-1
1	0	-1
1	0	-1

3 X 3 Filter (f X f)

=

-5	-4	0	8
-10	-2	2	3
0	-2	-4	-7
-3	-2	-3	-16

(n-f+1) X (n-f+1)

Convolution: Detecting Vertical edges

6*6 = 36

10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0
10	10	10	0	0	0

*

1	0	-1
1	0	-1
1	0	-1

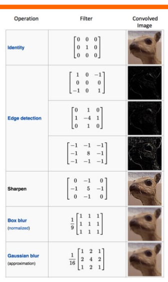
4*4=16

0	30	30	0
0	30	30	0
0	30	30	0
0	30	30	0

- In case of ANN # parameter to train = 36*16 = 576
- In case of CNN # parameter to train = 9

The role of the ConvNet is to reduce the images into a form which is easier to process, without losing features which are critical for getting a good prediction.

Convolution : Filter Weights



1	0	-1
2	0	-2
1	0	-1

Sobel Filter

3	0	-3
10	0	-10
3	0	-3

Schorr Filter

w_1	w_2	w_3
w_4	w_5	w_6
w_7	w_8	w_9

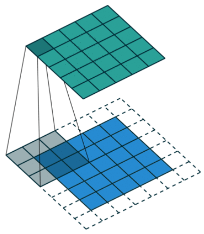
45º
70º
…
85º
…
…

Convolutional Neural Networks automatically estimates the weights of the filter

- **Learn them**

Padding

- **Two problems**
  - Shrinking output
  - Through away info from edges: Pixel at the corner are used much lesser then the pixel at middle
- Padding is used to preserve the original dimensions of the input
- Zeros are added to outside of the input
- Number of zero layers depend upon the size of the kernel



0	0	0	0	0	0	0
0	1	1	1	0	0	0
0	0	1	1	1	0	0
0	0	0	1	1	1	0
0	0	1	1	1	0	0
0	0	1	1	0	0	0
0	0	0	0	0	0	0

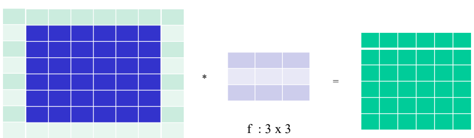
5 x 5 (with padding)

×1	×0	×1
×0	×1	×0
×1	×0	×1

2	2	3	1	1
1	4	3	4	1
2	2	4	3	3
1	2	3	4	1
1	2	3	1	1

5 x 5

Padding



n x n - *6x6* to *8x8* Padding (p)=1

f : 3 x 3

(n-f+1) x *(n-f+1)* to *(n+2p-f+1)* x *(n+2p-f+1)*
Valid to same

4x4 – 6x6

Valid and Same convolutions

- **Valid convolutions**
  - No padding
  - *(n x n) * (f x f) = (n-f+1)* x *(n-f+1)*
  - *(6x6) * (3x3) = 4 x 4*
- **Same convolutions**
  - Pad so that output size is the same as the input size.
  - *(n+2p-f+1)* x *(n+2p-f+1)*
  - *(n+2p-f+1) =n*

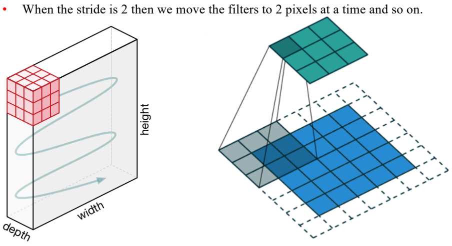
$$p=\frac{f-1}{2}$$

If f=5 ; 5x5 therefor p=2

f is usually odd.

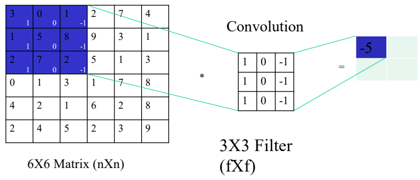
Strided Convolutions

- Stride defines the number of nodes a filter moves between two consecutive convolution operations
- Likewise, we have a stride to define the same when applying pooling
  - When the stride is 1 then we move the filters to 1 pixel at a time.
  - When the stride is 2 then we move the filters to 2 pixels at a time and so on.



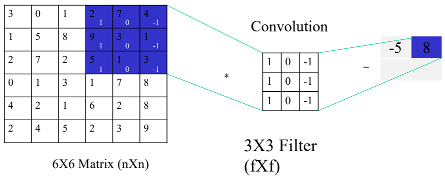
Stride

Stride=s (3 Here)



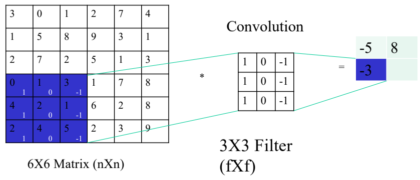
Stride

Stride=s (3 Here)



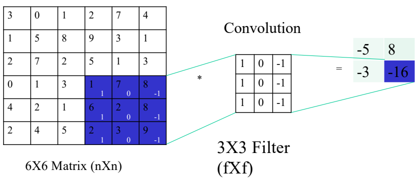
Stride

Stride=s (3 Here)



Stride

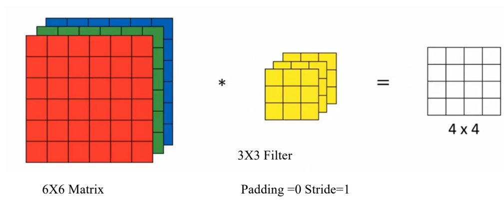
Stride=s (3 Here)



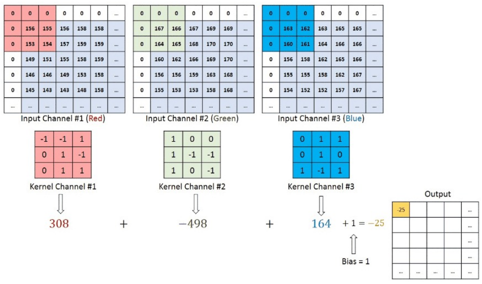
Floor($\frac{n+2p-f}{s}+1$) X Floor ($\frac{n+2p-f}{s}+1$)

$= \frac{6+2*0-3}{3} + 1 = 2$

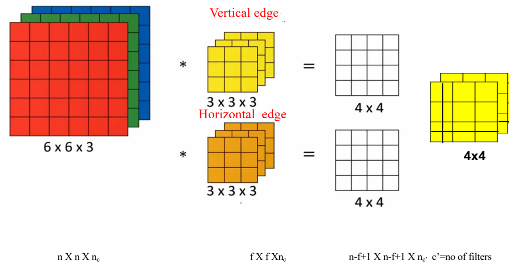
Channels: Convolutions over volumes

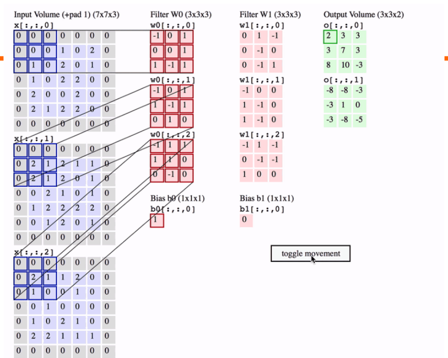


Convolutions on RGB image

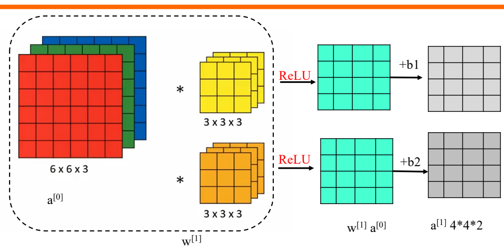


Convolutions with Multiple filter (depth/channels)





One layer of a convolutional network



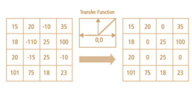
2 filters means two units here

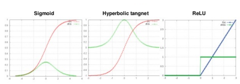
$z^{[1]} = w^{[1]} a^{[0]} + b^{[1]}$

$a^{[1]} = g(z^{[1]})$

Non Linearity (ReLU)

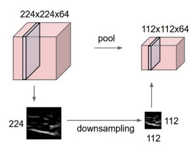
- ReLU stands for Rectified Linear Unit for a non-linear operation. The output is $f(x) = \max(0,x)$.
- Why ReLU is important :
  - ReLU's purpose is to introduce non-linearity in our ConvNet.
  - Result should be non-negative linear.
- Other non linear functions
  - tanh or
  - sigmoid

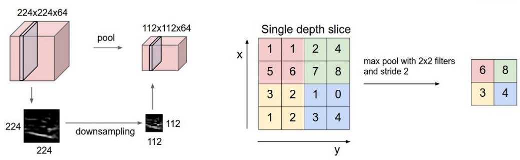




Pooling [Downsampling] Layer

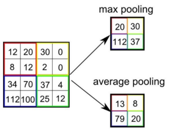
- Used to downsample the representation-size after convolution step
- Pooling layers section would reduce the number of parameters when the images are too large.
- Spatial pooling also called subsampling or downsampling which reduces the dimensionality of each map but retains important information.
- Ensures robustness against minor rotations, shifts, corruptions in the image
- Popular approaches:
  - Max-pooling , Average Pooling, Sum Pooling, etc

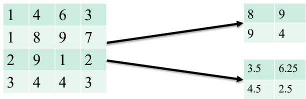




Pooling Layer

One example of pooling layer :
- Max and Average Pooling



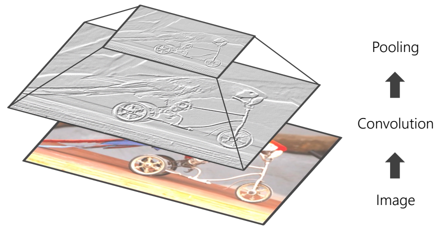


f=2
s=2
4X4 converted to 2X2

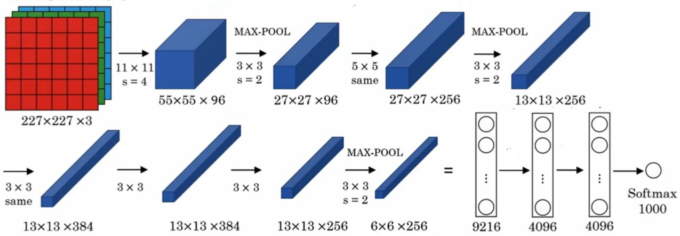
Function of Pooling is to progressively reduce the spatial size of the representation to reduce the amount of parameters and computation in the network.

No parameter to learn

A Basic Module of the CNN



AlexNet



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Other Deep Learning Modules

- **Oxford VGG Model**
- **Google Inception Model**
- **Microsoft ResNet Model**
- **Xception**: Deep Learning with Depthwise Separable Convolutions
  - **[Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1251-1258).]**
- **EfficientNet**: Rethinking Model Scaling for Convolutional Neural Networks
  - **[Tan, M., & Le, Q. V. (2019). Efficientnet: Rethinking model scaling for convolutional neural networks. arXiv preprint arXiv:1905.11946.]**
- **Google's word2vec Model**
- **Stanford's GloVe Model**

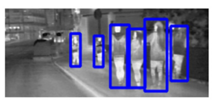
"You need a lot of a data if you want to train/use CNNs"

if **less data how to proceed** ??

Exercise

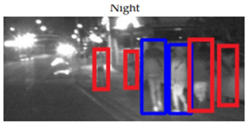
<u>Design a model to detect pedestrians on night-time images</u>





What we have discussed so far

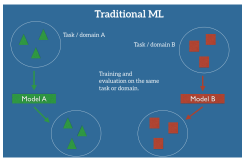
- In the classic supervised learning scenario
  - If we want to train a model for some task A and Domain A
  - Eg: **Task/Domain A** : Train a model to detect pedestrians on night-time images
    - we assume that we are provided with labeled data for the same task and domain.
    - We train a model A on this dataset and expect it to perform well on unseen data of the same task and domain.
  - On another occasion, when given data for some other task or domain B,
  - Eg: **Task/Domain B:** Train a model to detect pedestrians on day-time images
    - we require again labeled data of the same task or domain that we can use to train a new model B so that we can expect it to perform well on this data.

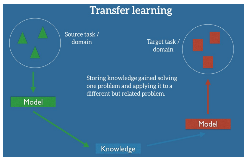


Eg: Cycle riding

What can be done

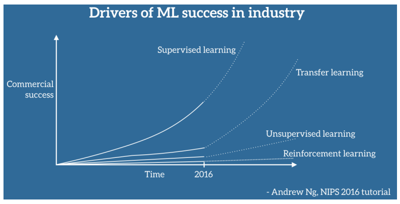
- If we want to train a model to detect pedestrians on night-time images,
- We could **apply a model that has been trained on a similar domain**, e.g. on day-time images.
- **Transfer learning**
  - allows us to deal with these scenarios by leveraging the already existing labeled data of some related task or domain.
  - We try to store this knowledge gained in solving the source task in the source domain and apply it to our problem of interest .
  - Try to exploit what has been learned in one task to improve generalization in another.
  - We transfer the weights that a network has learned at "task A" to a new "task B."





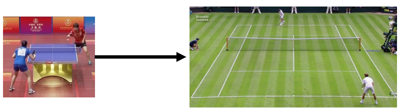
Why it is popular

- It can train deep neural networks with comparatively **little data.**
- Useful in the data science field as most real-world problems typically do not have millions of labeled data points to train such complex models.
  - million examples for image recognition task, lot of data to learn a low level features, while for the radiology task we have 100 examples , lot of knowledge learned from image recognition task may be helpful to transferred for radiology task.



When to Use Transfer Learning?

- Situation where what has been learned in one setting is exploited to improve generalization in another setting.

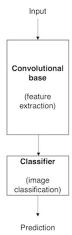


- **Task A and B have the same input x**
- **You have a lot more data for Task A than Task B.**
- **Low level features from A could be helpful for learning B.**

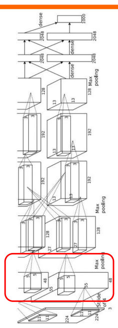
Convolutional neural networks

A typical CNN has two parts:

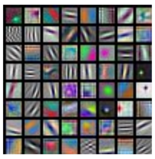
1. **Convolutional base**:
   - Composed by Stack of convolutional and pooling layers.
   - The main goal of the convolutional base is to generate features from the image.
2. **Classifier**:
   - Composed by fully connected layers.
   - The main goal of the classifier is to classify the image based on the detected features.
   - A fully connected layer is a layer whose neurons have full connections to all activation in the previous layer.



Transfer Learning with CNNs



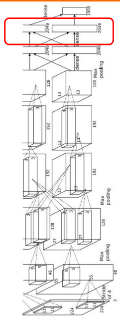
- **Convolutional base** its lower layers
  - refer to general features,



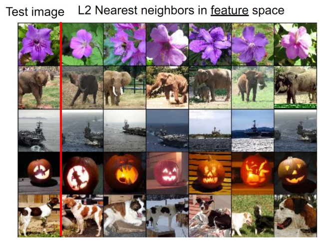
AlexNet:
64 x 3 x 11 x 11

Source : Fei-Fei Li , CS231n Convolutional Neural Networks for Visual Recognition, 2020

Transfer Learning with CNNs

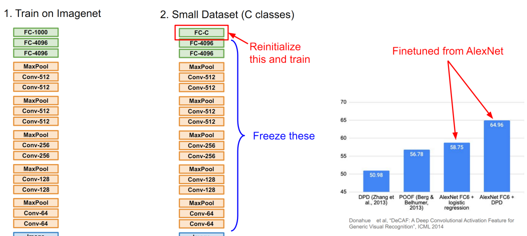


- **Classifier part-** higher layers of
  - specialised features



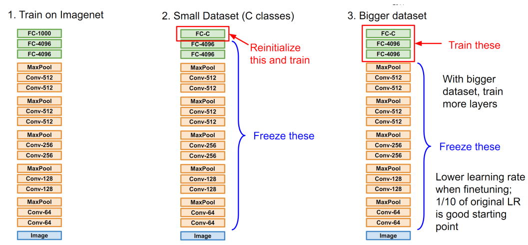
Source : Fei-Fei Li , CS231n Convolutional Neural Networks for Visual Recognition, 2020

Transfer Learning with CNNs



Source : Fei-Fei Li , CS231n Convolutional Neural Networks for Visual Recognition, 2020

Transfer Learning with CNNs

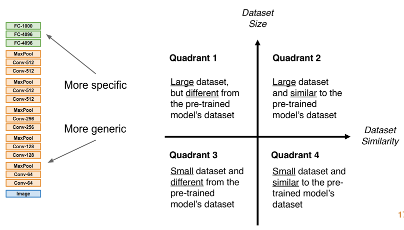


Donahue et al, "DeCAF: A Deep Convolutional Activation Feature for Generic Visual Recognition", ICML 2014
Razavian et al, "CNN Features Off-the-Shelf: An Astounding Baseline for Recognition", CVPR Workshops 2014

Source : Fei-Fei Li , CS231n Convolutional Neural Networks for Visual Recognition, 2020

Transfer Learning Process

1. Select a pre-trained model
   - https://keras.io/api/applications/
2. Classify your problem according to the Size-Similarity Matrix
3. Fine-tune model.
4. Classifiers on top



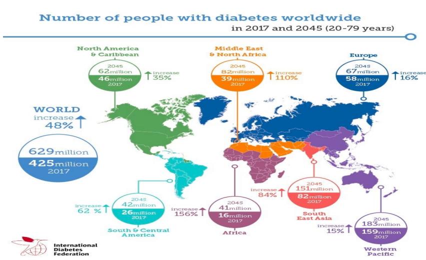
RESEARCH PROJECT

- **Project Title:** Computational Techniques based investigation for Diabetic foot ulcers complications
- **Funding Agency:** Department of Science and Technology (DST) - Science and Engineering Research Board (SERB)
- **Duration:** 3 Years

विज्ञान एवं प्रौद्योगिकी विभाग
DEPARTMENT OF
SCIENCE & TECHNOLOGY

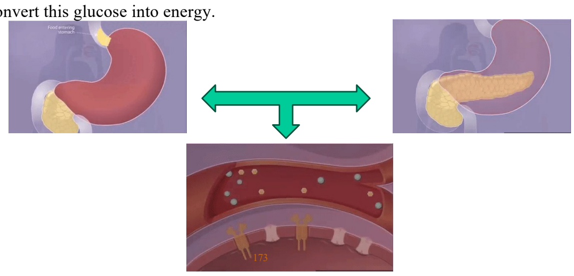
Science and Engineering Research Board
Statutory Body Established through an Act of Parliament: SERB Act 2008
Government of India

Diabetes : Facts and Figure

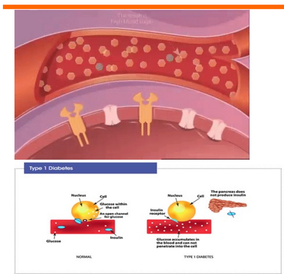


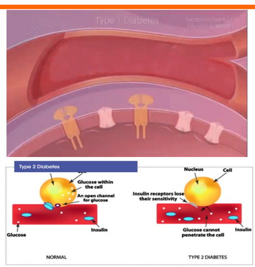
INTRODUCTION: Diabetes

- Diabetes mellitus (DM): Diabetes is a disorder of metabolism, in which there is Glucose in the bloodstream in enormous amounts and the body is not able to convert this glucose into energy.



TYPES OF DIABETES



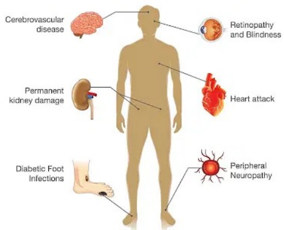


Type 1 Diabetes:
Insulin- producing cell become dysfunctional or are destroyed by Immune System.

Type 2 Diabetes:
Body either resist the effect of insulin or does not produce enough insulin.

COMPLICATIONS OF DIABETES MELLITUS

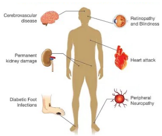
- **Microvascular** → Physiology Difficult to deal with
  - **Retinopathy**
  - **Nephropathy**
  - **Neuropathy**
- **Macrovascular** → Can see It Can treat It
  - **Coronary Macrovascular Disease (CAD)**
  - **Stroke risk**
  - **Peripheral Artery Disease (PAD)**



Physiology: The chemistry and physics behind basic body functions, from how molecules behave in cells to how systems of organs work together

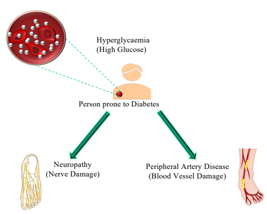
Extent: Diabetic

- Long-term complications of diabetes include nephropathy leading to
  - Renal (kidneys) failure
  - Retinopathy with potential loss of vision
  - Peripheral neuropathy with risk of foot ulcers
  - Amputations
  - Charcot disease
  - etc.



- 20 million DM patients in India (2 Crore)
- DM largest cause of neuropathy
- Half don't know
- Foot ulcerations is most common cause of hospital admissions for Diabetics
- Expensive to treat, may lead to amputation and need for chronic institutionalized care
- After amputation 30% lose other limb in 3 years
- After amputation 2/3rds die in five years
- Type II can be worse
- 15% of diabetic will develop a foot ulcer
- Diabetes is a serious chronic disease that needs attention.

- One of the major complications patients with poorly managed long-term DM face is developing a Diabetic Foot Ulcer (DFU).
- 19% to 34% of diabetics will develop a DFU during their lives.
- Up to 20% of patients with a DFU will require lower limb amputation.
- Up to 80% of these patients will die within 5 years of amputation.[4]
- Major factors that predispose individuals to DFUs.[5]
  - Diabetic Peripheral Neuropathy (DPN)
  - Peripheral Arterial Disease (PAD)

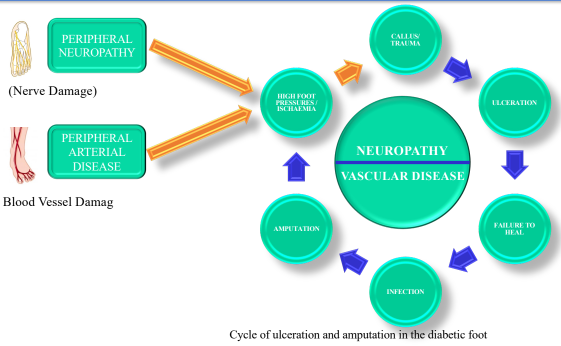


Major risk factors of Diabetic Foot

- Diabetic foot is characterized by a classical triad of neuropathy, ischemia, and infection. [6]
  - **Peripheral Arterial Disease (PAD):**
    - PAD leads to ischemia by narrowing or blocking arteries in the lower limbs, which reduces blood flow to the feet.
      - Impaired tissue healing
      - Increases the risk of infection
      - Development of diabetic foot ulcers.

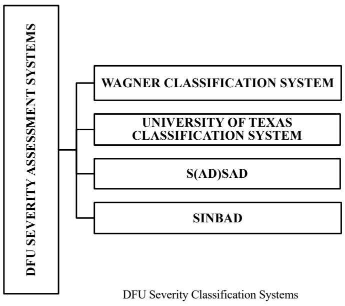
Peripheral Arterial Disease
Risk Factors of Diabetic Foot Ulcers

CYCLE OF ULCERATION AND AMPUTATION IN THE DIABETIC FOOT



Cycle of ulceration and amputation in the diabetic foot

SYSTEMS TO ASSESS SEVERITY OF DFU



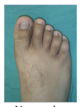
DFU Severity Classification Systems

FOOT RISK CATEGORIES

CATEGORY 0

No Pathology

CATEGORY 1



Neuropathy
2 times more likely to ulcerate
1-2 years

CATEGORY 4

4a: Neuropathic Ulcer

4b: Acute Charcot's Arthropathy

CATEGORY 2

Neuropathy with Deformity
12 times more likely to ulcerate
6 months

CATEGORY 3

History of Pathology
36 times more likely to ulcerate
2 months

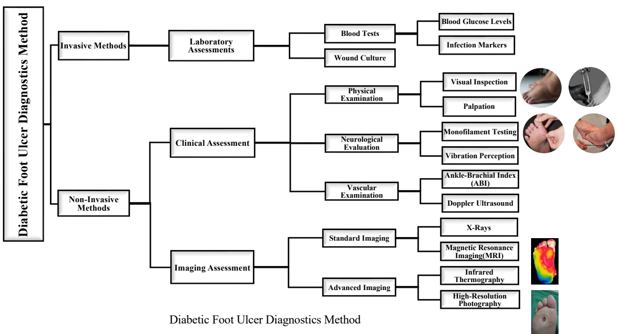
CATEGORY 5

Active Infection

CATEGORY 6

Ischaemic Limb

LITERATURE SURVEY: DIABETIC FOOT ULCER DIAGNOSIS METHOD



Diabetic Foot Ulcer Diagnostics Method

ADVANCED IMAGING TECHNIQUE FOR EARLY DETECTION OF DIABETIC FOOT

Infrared Thermography: What the human eye cannot see[10]

THERMOGRAPHY

- Infrared thermography is a noncontact tool that maps surface temperature of an object in a non contact and remote manner [9].
- The image generated by IR radiation is referred to as thermogram.
- Medical IR diagnostics uses the fact that many pathological processes in the human organs manifest themselves as local changes in heat production and also as changes in blood flow pattern of affected organs or tissues [9].

ADVANCED IMAGING TECHNIQUE FOR EARLY DETECTION OF DIABETIC FOOT

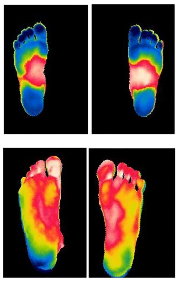


Fig 12: Thermal image of the foot–control, Thermal image of the foot – Diabetic [11]

The use of IRT can be divided in four different categories [11]:

1. Independent limb temperature analysis- temperature analysis is performed on each limb separately;
2. Asymmetric analysis- in healthy subjects there is a contralateral symmetry in the skin temperature distribution and consider that an asymmetry in this distribution can be an indicator of an abnormality;
3. Temperature distribution analysis- similar skin temperature distribution on the feet of healthy individuals comparing to varying temperature variation on diabetic individuals;
4. External stress analysis- the reaction of the body thermoregulation system under the application of thermal and/or physical stress, such as putting the feet into cold water or running.

DFU ANALYSIS ML APPROACHES

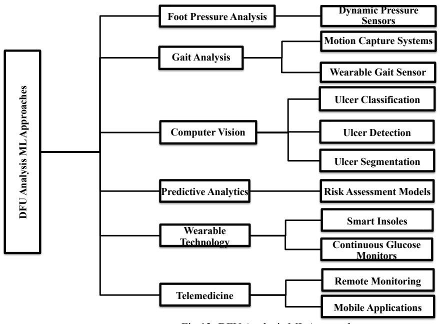


Fig 13: DFU Analysis ML Approaches

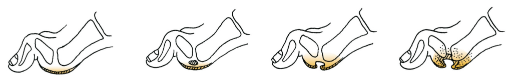
Diabetic Foot Ulcer (DFU)

- Approximately 15% of all people with diabetes will be affected by a foot ulcer during their lifetime.
- Foot ulceration is very common in Diabetic Mellitus. As the tissue doesn't get enough energy and oxygen so as to heal wounds, this complicates the situation and later leads to amputation.
- This can be avoided if we can detect it at an early stage and provide the patient the required treatment.

Wound and Diabetic

- Diabetic foot ulcers typically have a thick rim of keratinized tissue surrounding the wound

- Mechanism of ulcer developing from repetitive or excessive mechanical stress

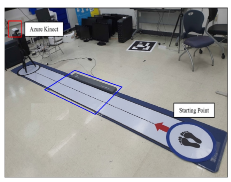


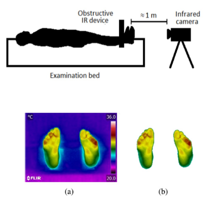
Diabetic foot

- >60% of all amputations involve diabetes in US
- 9-20% of ulcerations end in amputation
- ~84% of lower extremity amputations are preceded by ulceration
- Every year around 1,00,000 legs are amputated due to diabetes in India
- Indications for Amputation
  - Uncontrollable infection or sepsis
  - Inability to obtain a plantar grade, d
    foot that can tolerate weight bearing
  - Non-ambulatory patient
- Decision not always straightforward
- Early detection of diabetic foot prevent amputation.

- Conclusion
  - Multi-disciplinary approach needed
  - Going to be an increasing problem
  - High morbidity and cost
  - Solution is probably in prevention
    - Diabetic control
    - Foot care

A) FOOT PRESSURE B) VISION BASED C) THERMOGRAPHY





Research Paper


Robotics, Control and Computer Vision pp 67–80 | Cite as

Home > Robotics, Control and Computer Vision > Conference paper

A Pilot Study for Profiling Diabetic Foot Ulceration Using Machine Learning Techniques

Irena Tigga, Chandra Prakash & Dhiraj

Conference paper | First Online: 26 May 2023

130 Accesses

Part of the Lecture Notes in Electrical Engineering book series (LNEE,volume 1009)

Abstract

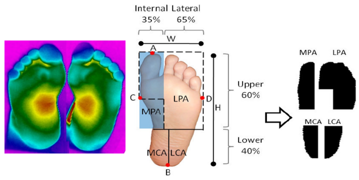
Early diagnosis of risk of diabetic foot ulceration (DFU) may allow for earlier care to avoid foot ulcers, amputation, and death. Thermography is a non-invasive imaging technique that is used to detect thermal changes in the diabetic foot. This study illustrates the comparative analysis of ML techniques (KNN, Naïve Bayse, Decision Tree, Random Forest, Logistic Regression, SVM, Ada Boost) when performed on the publicly available thermogram database with 122 diabetic and 45 non-diabetic subjects. SVM and Random forest surpass other

Dataset

- **Plantar Thermogram Database** for the Study of Diabetic Foot Complications
- Avaiable on IEEE dataport
  - **Source :** https://ieee-dataport.org/open-access/plantar-thermogram-database-study-diabetic-foot-complications

- composed of 167 plantar thermograms
  - 122 diabetic subjects and
  - 45 non-diabetic subjects.

- The dataset consist of features
  - Age,
  - Weight,
  - Height,
  - IMC,
  - General (for both left and right foot),
  - LCA (for both left and right foot),
  - LPA (for both left and right foot),
  - MCA (for both left and right foot),
  - MPA(for both left and right foot),
  - TCI (for both left and right foot)



Proportional foot division into plantar angiosomes.

Methodology

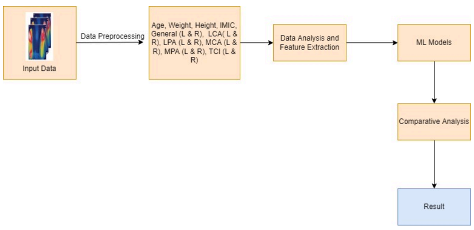


Fig: Approach first which work on detailed Thermogram dataset for subjects

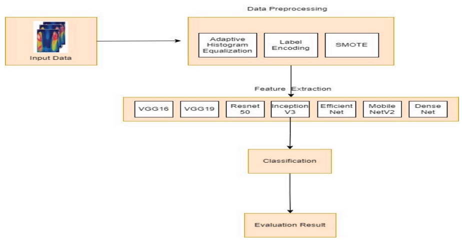
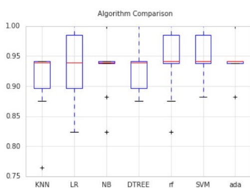


Fig: Approach second which work on Plantar Thermal Image dataset of subjects

Traditional Machine Learning Approach :Result

ML Technique	Accuracy	Accuracy with 10 fold	Parameter
KNN	95.68	93.49	n_neighbors=16, metric= euclidean
Naive Bayes	76.47	93.41	-
Decision Tree	97.39	93.41	criterion=gini , max_depth=11
Random Forest	95.65	95.18	criterion=gini , max_depth=7
Logistic Regression	93.93	93.45	-
SVM	98.25	95.22	C=1, gamma=0.1, Kernel= sigmoid



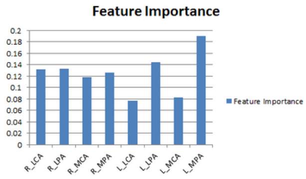
Result

- Study also include work on different train-test ratio to compare and find optimal split and corresponding accuracy.

CASE 1		CASE 2		CASE 3		CASE 4		CASE 5	
Training	Testing	Training	Testing	Training	Testing	Training	Testing	Training	Testing
10	90	30	70	50	50	70	30	90	10

	CASE 1	CASE 2	CASE 3	CASE 4	CASE 5
KNN	72.84	93.16	94.04	88.25	94.11
Naïve Bayse	86.09	**95.72**	92.85	76.47	88.23
Decision Tree	92.71	92.3	**96.42**	**94.11**	88.23
RandomForest	**94.03**	92.3	95.23	**94.11**	**100**
Logistic Regression	**94.03**	**95.72**	92.85	92.15	**100**
SVM	92.05	94.87	91.66	92.15	91.66

Results



- The analysis done on the Plantar thermogram data set, it can be inferred that Random forest is giving better accuracy results and MPA angiosome region can be taken for finding early DFU symptoms for future work.

Result

- Second approach implementation of Deep Learning Model on Plantar Thermogram dataset

Model with Softmax	Precision	Sensitivity	F1- Score	Accuracy
VGG16	97	85	91	91
VGG19	95	87	91	93
ResNet50	77	92	84	96
InceptionV3	78	78	78	77
EfficientNet	80	78	76	71
MobileNetV2	81	85	81	83
DenseNet	78	78	81	83

Conclusion and Future Work

- The best approach detect the diabetic foot at an early stage is the Random Forest, SVM and Ada Boost compared to the Deep Learning Models implemented by Transfer Learning using Imagenet followed by classifier.
- The study also shows the region with higher feature importance that can further be worked to detect early DFU in particular angiosome

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