Deep Learning for Medical Imaging

SU24-EG-44175-01 Ethical and Professional Issues in Engineering

Team Introductions

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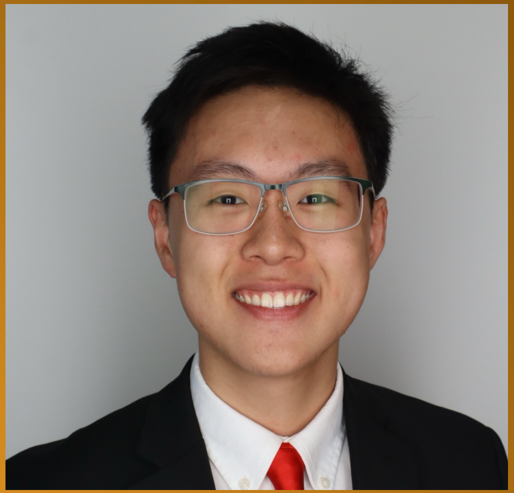
Computer Science



Derick Shi
Computer Science

Outline

- **Introduction**
- Machine Learning vs Deep Learning Overview
- How Deep Learning Works
- Musculoskeletal Fractures Case Study
- Skin Cancer Detection Case Study
- Image Detection Demonstration (Code)
- Relation to Human Cognitive and Brain Development
- Ethical Concerns
- Conclusion

Prompt Overview

Computer Learning	Machine Learning (ML) Introduction	Deep Learning (DL) Introduction	CNN
Musculoskeletal Case Study	Introduction	Fracture Detection Overview	Gray-Level Co-occurrence Matrix (GLCM)
Skin Cancer Detection Case Study	Introduction	Computer-Aided Process	Teaching Deep Learning
Image Detection Demo (Code)	GitHub	YOLOv8	Demonstration

Tasked with exploring the application of **deep learning** for **medical image** analysis and classification, we will open with a foundation in AI computer learning. With this background, we wish to explore **two** specific **case studies** before demonstrating a **code** example of medical image detection. We will close with **ethical concerns** and final comments.

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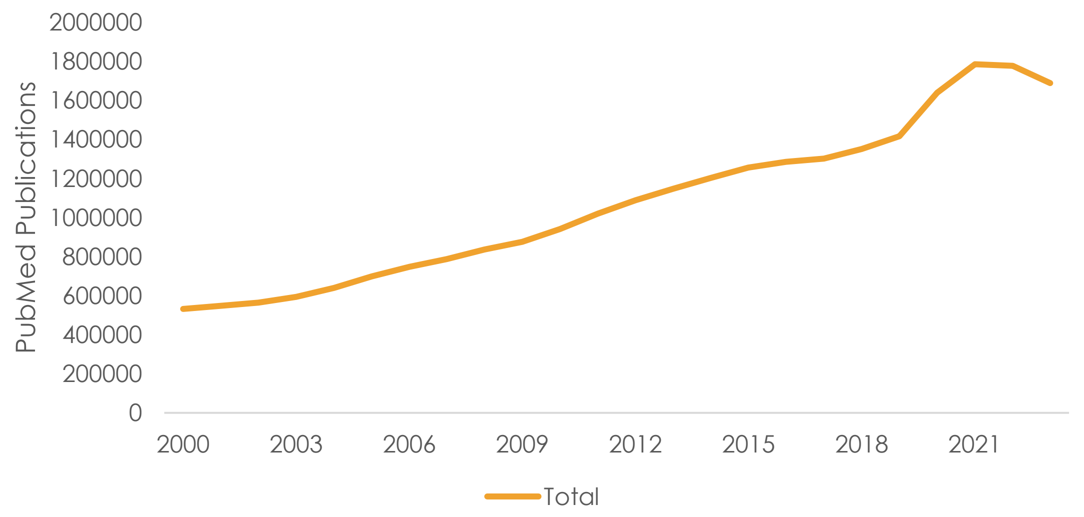
Machine and Deep Learning Overview

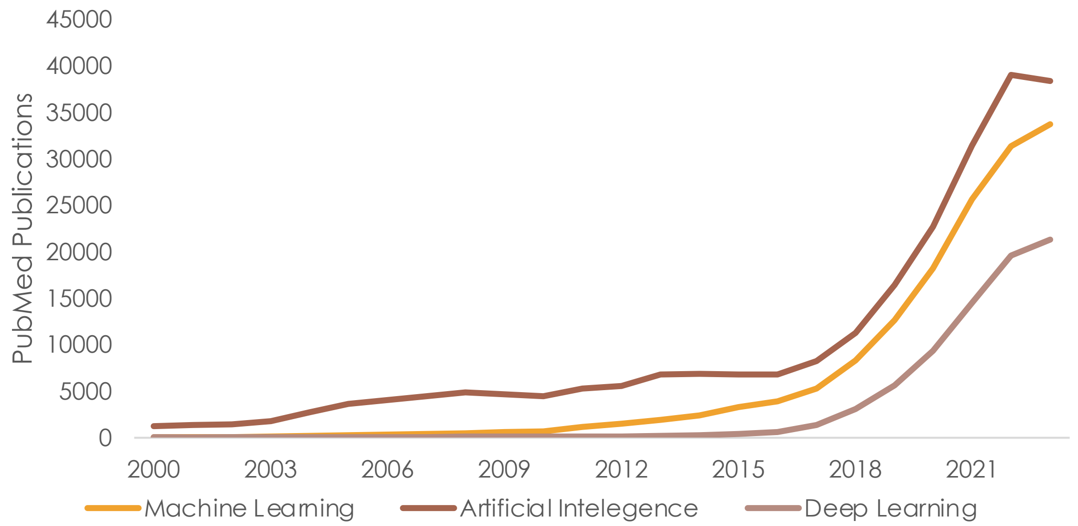
PubMed Total Publications Timeline



Linear growth of total medical publications for the past **20+ years**.

Figure 1

PubMed Publications Timeline



Exponential growth of medical publications discussing artificial learning **since 2016**.

Figure 2

Machine Learning

- Machine learning is a branch of AI where a machine learns from the data by identifying patterns and then automates decision-making with minimum human intervention

- When extracting features from medical images, machine learning requires the assistance of domain experts to identify relevant characteristics from the images, such as texture, shape, and intensity

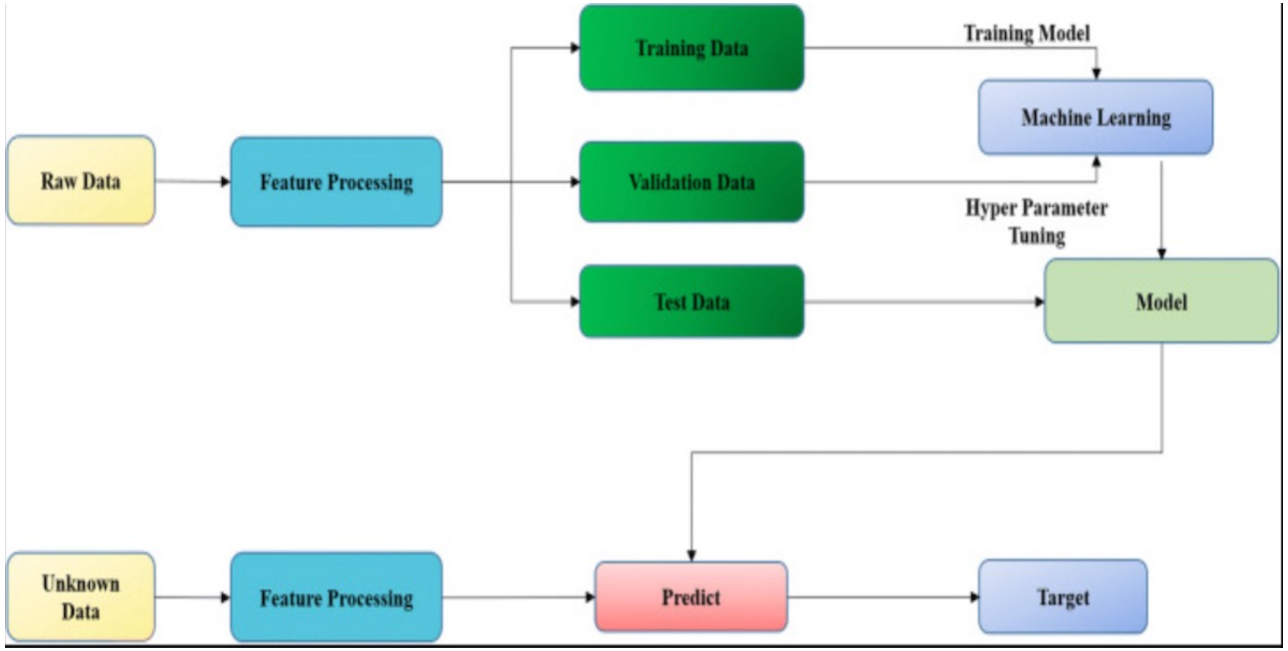


Figure 3

Deep Learning

Process of Deep Learning

Deep learning is a branch of machine learning that employs artificial neural networks comprising multiple layers to acquire and discern patterns from extensive data sets

It has the capacity to automatically learn features from raw data, along with the the capability to analyze and decipher medical images

Deep learning is modeled according to the human brain including a complex structure of algorithms enabling machines to process images and text

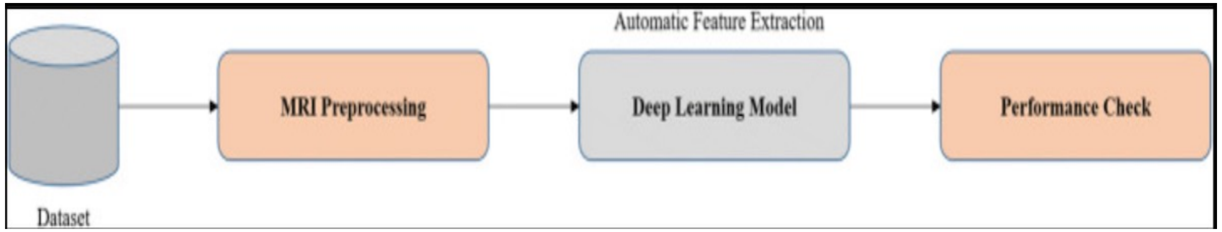


Figure 4

Comparison and Importance

Machine and Deep learning models are essential for analyzing medical images for distinctive looks and highlighting apparent areas to provide information to assist a professional’s choice

Medical images are usually the first required step for the diagnosis of disease

Early detection of disease tends to lead to a lower mortality rate

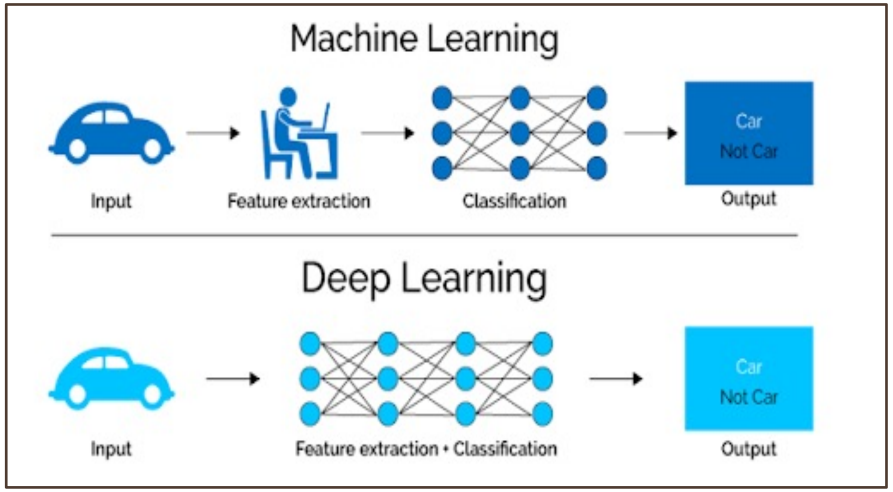


Figure 5

Comparison and Importance

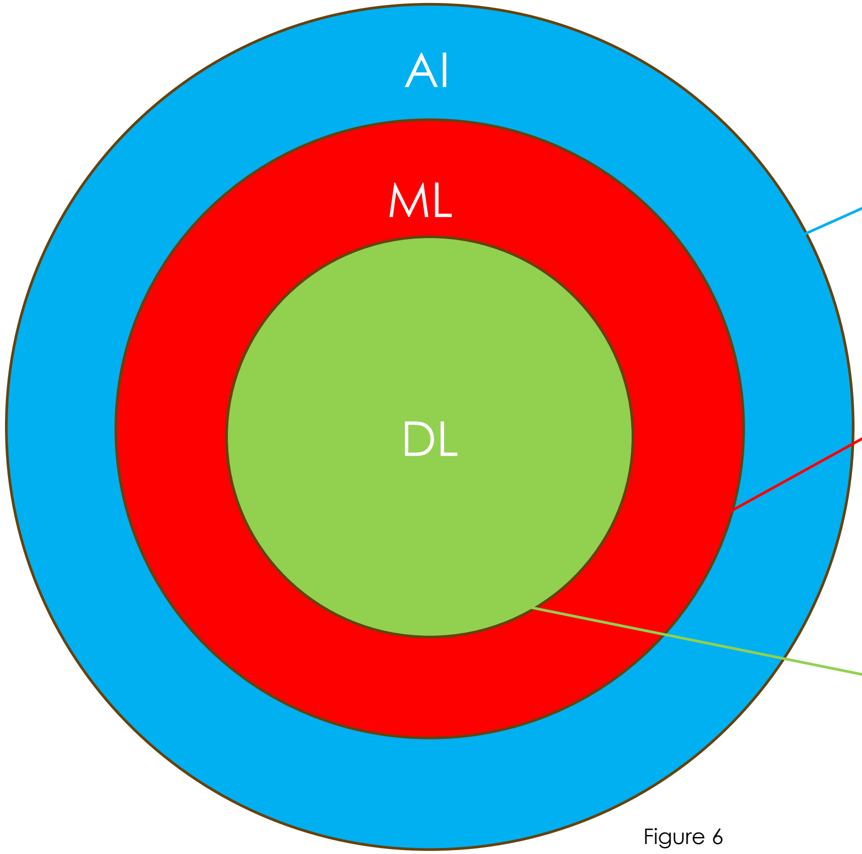


Figure 6

- Technique that enables a machine to mimic human behavior

- Technique to achieve AI through algorithms trained with data
- Requires human assistance to differentiate data

- Deep learning is inspired by the structure of the brain
- Features are picked out by the neural network without human intervention
- However, it requires a much higher volume of data to train

Outline

Convolutional Neural Networks (CNN)

- CNN is a type of Deep Neural Network
- For imaging, CNN is good for processing as well as localization and segmentation
- Contains up to hundreds of layers that are trained to identify a certain aspect of the image
- The complexity of the layers increases as the system moves on
- Conv layers are the building blocks of the CNN that do much of the computational aspects
- There are many deep learning techniques (U-NET)

Additional Networks in Medical Imaging

- Generative Adversarial Network (GAN)
- Artificial Neural Networks (ANN)

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Musculoskeletal Fractures DL Case Study

Musculoskeletal Fractures Introduction

Bone Disorders

- **Radiology** and **orthopedics**: prominent fields implementing DL to increase speed and accuracy
- X-rays, MRIs, and CTs
- Arthritis and tendinitis: long-term pain inducing diseases

Highly Consequential

- Increasing volume of images, **emergencies**, **underprivileged** and unqualified employees
- Highly complex images and highly consequential (health-related) decision making

Historical Context

- 2012: **breakthrough application** of DL in medical image analysis
- 2016-18: increased use synthetic data augmentation
- 2024 **aidoc**: prominent DL technology used in medical image analysis

Distribution of Healthcare Workers

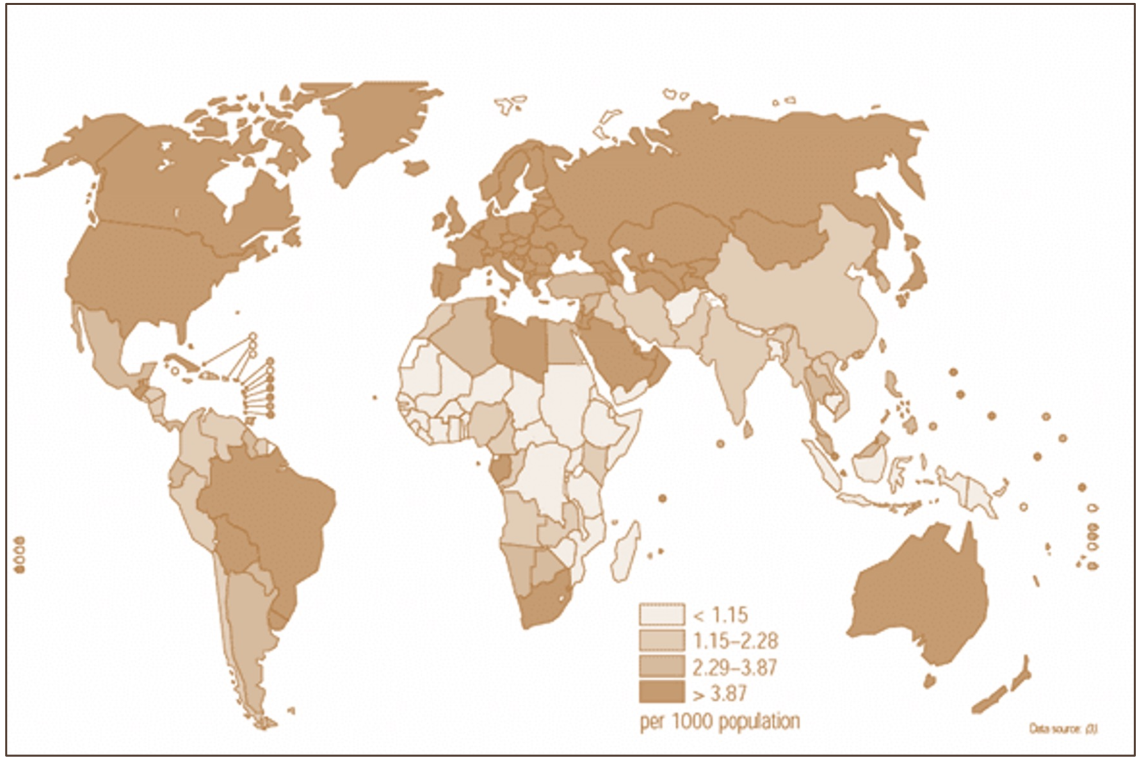

Figure 7

Sources: National Library of Medicine | Springer | Research Gate

John Castellano

Musculoskeletal Fractures DL Case Study

Fracture Detection Overview

Image Acquisition	•X-ray, MRI, CT, Mammogram, ECG
Pre-Processing	•Noise Reduction, Contrast Improvement, and Edge Detection
Detection	•Localizing fractured region
Feature Extraction	•Contrast, Correlation, Homogeneity, Energy, Dissimilarity
Performance Analysis	•Precision, Recall, Accuracy

Modalities in Medical Deep Learning

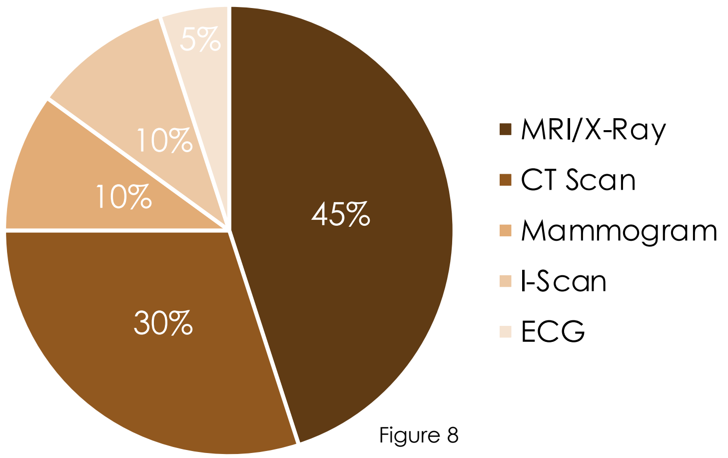

Figure 8

Although X-Rays, MRIs, and CT Scans dominate the volume of medical imaging, deep learning is used on several medical image modalities

Sources: National Library of Medicine | Springer

John Castellano

Musculoskeletal Fractures DL (cont.)

Fracture Detection Overview

Image Acquisition	•X-ray, MRI, CT, Ultrasound, PET (nuclear imaging)
Pre-Processing	•Noise Reduction, Contrast Improvement, and Edge Detection
Detection	•Localizing fractured region
Feature Extraction	•Contrast, Correlation, Homogeneity, Energy, Dissimilarity
Performance Analysis	•Precision, Recall, Accuracy

Pre-Processing

Noise Reduction: **improves quality of an image** by analyzing the intensity and color of neighboring pixels to smooth an image
$f(x, y) = g(x, y) + \mu(x, y)$ and $g(x, y) = T[f(x, y)]$ Gaussian filter for T

Contrast Improvement: Both **Gaussian filters** and **adaptive histograms** locally improve contrast

Canny Edge Detection: "a technique to **extract** useful **structural information** from different vision objects and dramatically **reduce** the amount of **data** to be processes. It is based on time-varying intensity"

Original Image

Figure 9

Gaussian Filter

Figure 10

Adaptive Histogram

Figure 11

Edge Detection

Figure 12

Musculoskeletal Fractures DL (cont.)

Fracture Detection Overview

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Steps to Construct a GCLM

1. **Quantization**: Manipulate the number of gray levels (n)

2. **Parameters**: (i) Distance (d) that co-occurrence is measured and (ii) Angle/direction (θ)

3. **Initialization**: GCLM should have same # of rows and columns as # of gray levels

4. **Population**: consider every cells' neighbor to the d distance and θ direction. Populate new GCLM

Feature Extraction

Often regarded as one of the **most important steps** for musculoskeletal deep learning analysis, feature extraction transforms the edge-detected generated x-ray into a matrix to be further analyzed. The **Gray-Level Co-occurrence Matrix (GLCM)** is one of these useful tools.

Process

Figure 13

Figure 14

0	1	0
1	2	3
3	1	0

Figure 15

0	1	0	0
2	0	1	0
0	0	0	1
0	1	0	0

Figure 16

Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

Figure 18

First, initialize a matrix of size (cols, rows) = (n, n)

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1,** meaning we need to consider cells 1 unit away from each other; and **ϴ = 0** meaning we intend to consider cells rightward

Your Turn!

Figure 19

Figure 20

Contrast

How neighboring pixels differ in their white/black concentrations

$$\sum_{i,j} |i-j|^2 p(i,j) \quad (1)$$

Correlation

A measurement of similarity between neighboring pixels

$$\sum_{i,j} \frac{(i-\mu_i)-(j-\mu_j)p(i,j)}{\sigma_i \sigma_j} \quad (2)$$

Homogeneity

Gauges the distance between pixels in an image

$$\sum_{ij} \frac{p(i,j)}{1+|i-j|} \quad (3)$$

Energy

Dictates the weight (importance) of regions in an image

$$\sum_{i,j} p(i,j)^2 \quad (4)$$

Dissimilarity

Aids in segmentation of images and quantifies whether images match

$$\sum_{i,j} p(i,j)\,|i-j| \quad (5)$$

Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

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

Figure 18

Begin by considering the top left cell (i) and the cell d = 1 and θ = 0 (j) away from it (in this case the cell one position directly right of the top left cell). Increase the value by 1 of this (i, j) position on the new GCLM

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1,** meaning we need to consider cells 1 unit away from each other; and **θ = 0** meaning we intend to consider cells rightward

Your Turn!

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Sources: Detection of Bone Fractures on Machine Learning Techniques | National Library of Medicine

John Castellano

Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

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

Figure 18

Next, consider the next pairs of cells (1,3), and increase the (1,3) position of the new GCLM by 1

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1,** meaning we need to consider cells 1 unit away from each other; and **θ = 0** meaning we intend to consider cells rightward

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Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

0	1	0	0
0	0	0	2
0	0	0	0
0	0	0	0

Figure 18

Repeat this process, increasing the value by 1 each time even if that position on the GCLM is already populated

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1,** meaning we need to consider cells 1 unit away from each other; and **ϴ = 0** meaning we intend to consider cells rightward

Your Turn!

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Figure 20

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Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

0	2	0	0
0	1	0	4
1	0	0	0
0	1	3	0

Figure 18

Index through the entire matrix until every cell has been accounted for. *NOTE that cells in column 3 **cannot be indexed** because there does not exist a cell directly right*

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1,** meaning we need to consider cells 1 unit away from each other; and **θ = 0** meaning we intend to consider cells rightward

Your Turn!

Figure 19

Figure 20

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Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

0	2	0	0
0	1	0	4
1	0	0	0
0	1	3	0

Figure 18

Index through the entire matrix until every cell has been accounted for. *NOTE that cells in column 3 **cannot be indexed** because there does not exist a cell directly right*

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1**, meaning we need to consider cells 1 unit away from each other; and **θ = 0** meaning we intend to consider cells rightward

Your Turn!

3	1	0
3	2	0
1	3	1

Figure 19

Figure 20

First, we need to determine what n = ?
Then, initialize a matrix of (rows, cols) = (n, n)

Consider the 3x3 matrix where **d = 1** and **θ = 0**. What is n?

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Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

0	2	0	0
0	1	0	4
1	0	0	0
0	1	3	0

Figure 18

Index through the entire matrix until every cell has been accounted for. *NOTE that cells in column 3 **cannot be indexed** because there does not exist a cell directly right*

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1**, meaning we need to consider cells 1 unit away from each other; and **θ = 0** meaning we intend to consider cells rightward

Your Turn!

3	1	0
3	2	0
1	3	1

Figure 19

0	0	0	0
0	0	0	0
0	0	0	0
0	0	0	0

Figure 20

Next, step through the matrix, increasing the value of each (i, j) pair on the new GCLM by 1

Consider the 3x3 matrix where **d = 1** and **θ = 0**. What is n?

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Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

0	2	0	0
0	1	0	4
1	0	0	0
0	1	3	0

Figure 18

Index through the entire matrix until every cell has been accounted for. *NOTE that cells in column 3 **cannot be indexed** because there does not exist a cell directly right*

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1,** meaning we need to consider cells 1 unit away from each other; and **θ = 0** meaning we intend to consider cells rightward

Your Turn!

3	1	0
3	2	0
1	3	1

Figure 19

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

Figure 20

Take about 20 seconds to step through the entire matrix and determining the GCLM

Consider the 3x3 matrix where **d = 1** and **θ = 0**. What is n?

Contrast

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Musculoskeletal Fractures DL (cont.)

Example of Constructing a GCLM

0	1	3	2
1	3	2	0
1	3	1	1
0	1	3	2

Figure 17

0	2	0	0
0	1	0	4
1	0	0	0
0	1	3	0

Figure 18

Index through the entire matrix until every cell has been accounted for. *NOTE that cells in column 3 **cannot be indexed** because there does not exist a cell directly right*

Consider our parameters: **n = 4** meaning we need a 4x4 GCLM; **d = 1**, meaning we need to consider cells 1 unit away from each other; and **θ = 0** meaning we intend to consider cells rightward

Your Turn!

3	1	0
3	2	0
1	3	1

Figure 19

0	0	0	0
1	0	0	1
1	0	0	0
0	2	1	0

Figure 20

Check your work!

Consider the 3x3 matrix where **d = 1** and **θ = 0**. What is n?

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Sources: Detection of Bone Fractures on Machine Learning Techniques | National Library of Medicine

John Castellano

Musculoskeletal Fractures DL (cont.)

Fracture Detection Overview

Image Acquisition	• X-ray, MRI, CT, Ultrasound, PET (nuclear imaging)
Pre-Processing	• Noise Reduction, Contrast Improvement, and Edge Detection
Detection	• Localizing fractured region
Feature Extraction	• Contrast, Correlation, Homogeneity, Energy, Dissimilarity
Performance Analysis	• Precision, Recall, Accuracy

Although researchers have experimented with several deep learning techniques in the past decade, recent trends seem to indicate that CNNs are the preferred network for analyzing medical images

Feature Extraction

Year	Type of Neural Network	Accuracy
2015	Decision Tree	0.85
2017	SVM	0.78
2017	SVM	0.84
2018	Decision Tree	0.82
2019	CNN	0.78
2019	Local-Entropy Approach	0.91
2019	SVM	0.8
2020	Back Propagation NN	0.91
2020	CNN	0.94
2020	CNN	0.92

Sources: Detection of Bone Fractures on Machine Learning Techniques | National Library of Medicine

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Skin Cancer Detection Case Study

Introduction to Skin Cancer

- One of the most dangerous and widespread cancers in the world
- Crucial to catch the cancer early
- Accounts for 5% of the cancer diagnosis in the United States per year
- Survival rate is 99.6% when the cancer is detected early

Medical Imaging and Cancer Detection

- Images are often used to help detect skin cancer
- Track progression and change over time
- Doctors can use computer-aided systems to help go through medical imaging
- To keep up with demand, doctors must look at imaging at an unreasonable rate
- Deep Learning can help doctors meet demands

Computer-Aided Skin Cancer Diagnosis

Image Acquisition	• Image artifacts of possible skin cancer
Pre-Processing	• Boundary localization, cropping, resizing, and normalization by CNN
Segmentation	• Breaking down the data of the image being used in part with the CNN
Feature Extraction	• Input the image and use of CNN
Classification	• Identify features, classify, results from the use of the CNN

Sources: Skin Cancer Detection Using Deep Learning

Jack Keller

Skin Cancer Detection DL (cont.)

Image Acquisition

- The image artifact of the possible skin cancer
- The better the image, the more accurate the result
- Must be aware of unwanted artifacts in the image

Unwanted Artifacts

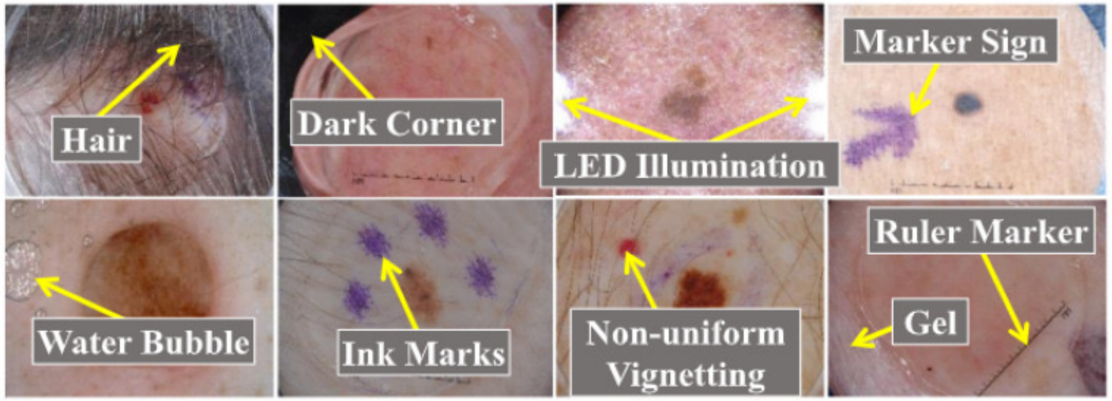


Figure 21. Unwanted Artifacts in Skin Cancer Detection

Deep Learning and Unwanted Artifacts

- Complex deep learning can have algorithms to detect these unwanted artifacts
- Can return information about the unwanted artifact or void the image analysis
- It is a varying process and not always a part of the deep learning

Pre-Processing

- Boundary localization, cropping, resizing, and normalization
- Complex deep learning identifies and/or removes unwanted artifacts
- Enhance the image for more accurate results

Skin Cancer Detection DL (cont.)

Pre-Processing

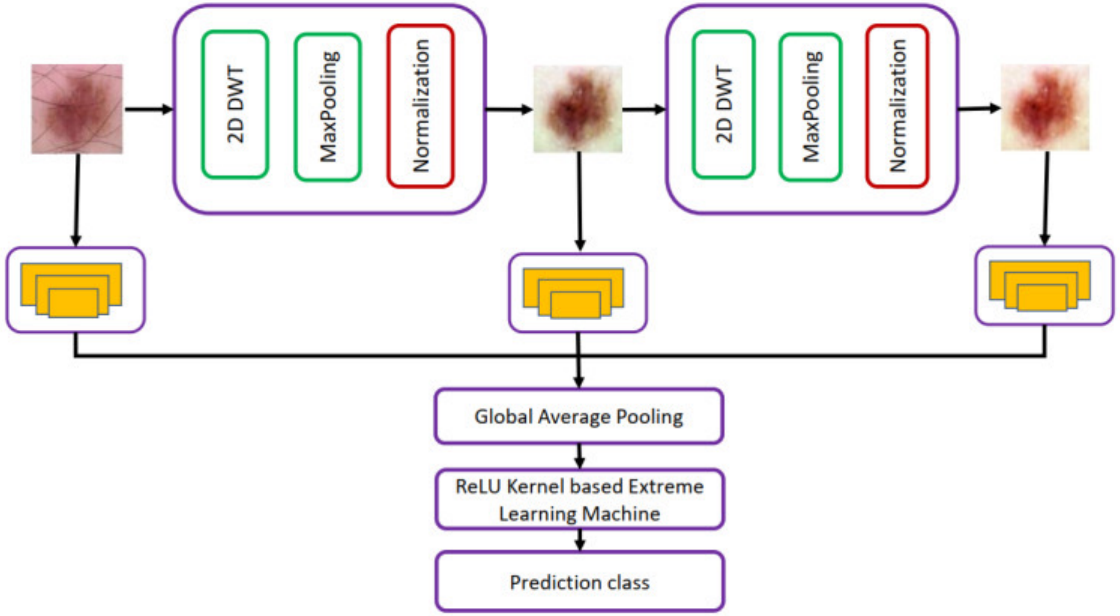


Figure 22. Flow chart of a pre-trained deep learning network to pre-process image to prepare segmentation

Segmentation

- Used to extract regions of interest (ROI) within the image
- The ROIs are then sent into the feature extraction for deeper processing within the CNN
- Process that omit this step takes longer to train
- A common practice of segmentation is U-NET, a CNN

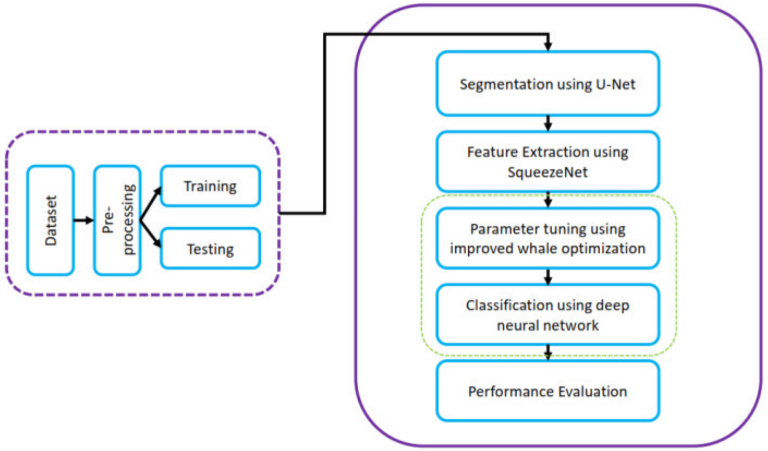


Figure 23. Flow chart of training deep learning with U-Net Segmentation

Skin Cancer Detection DL (cont.)

U-NET (Segmentation)

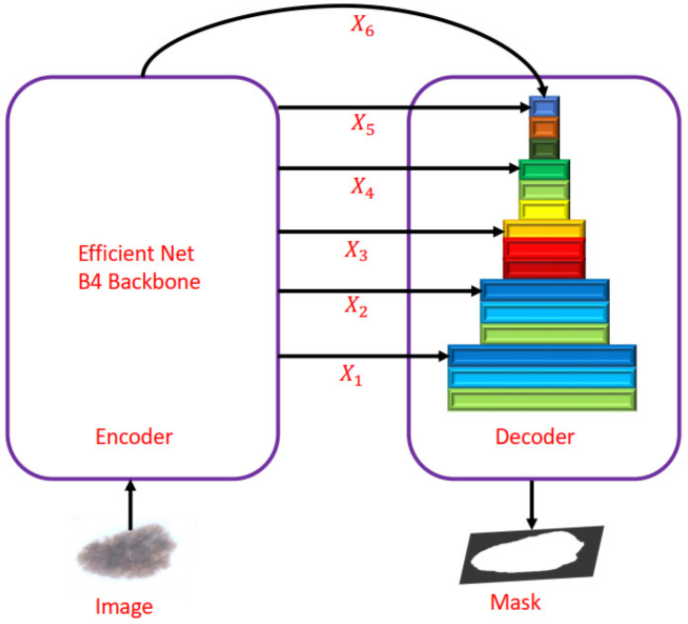


Figure 24. Flow chart of a modified U-NET, a CNN process

Feature Extraction

- CNN is used to process the image artifact
- Complex process

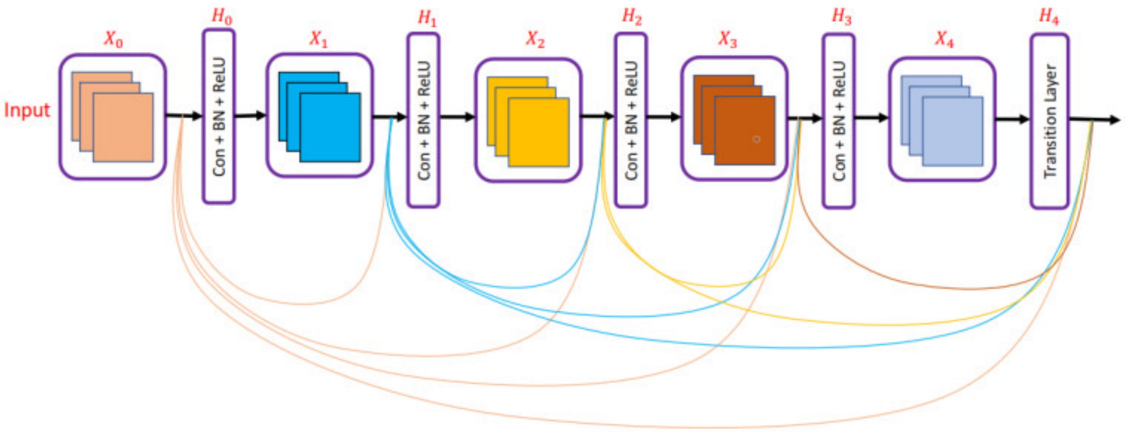


Figure 25. Complex CNN called DenseNet

Skin Cancer Detection DL (cont.)

Feature Extraction

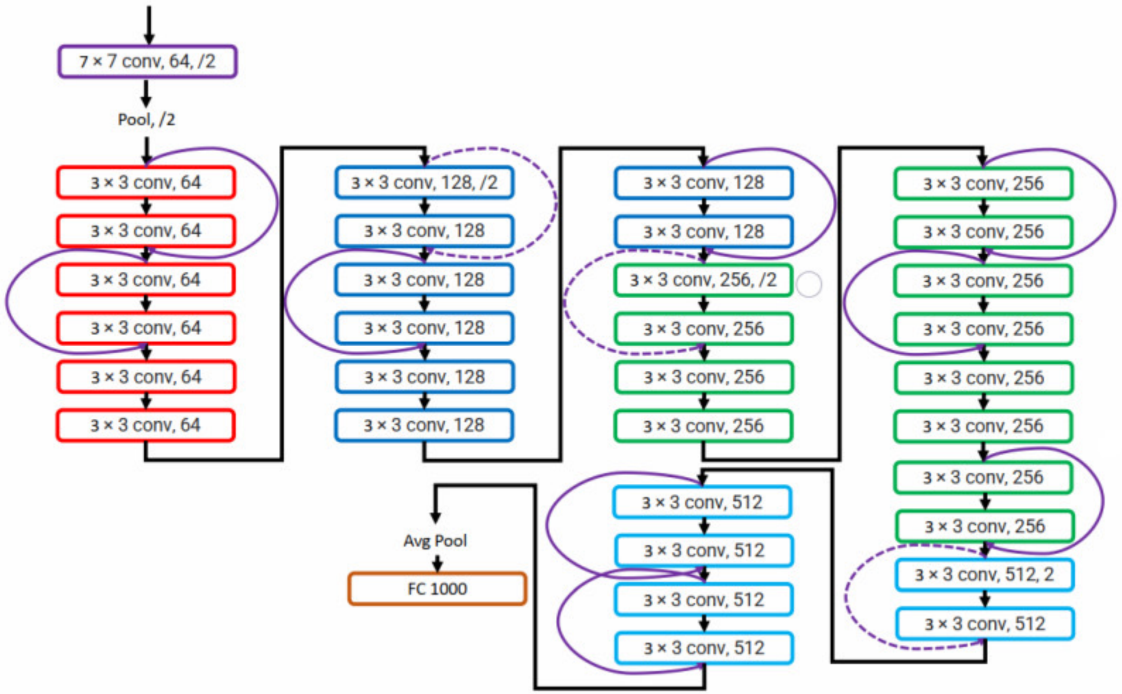
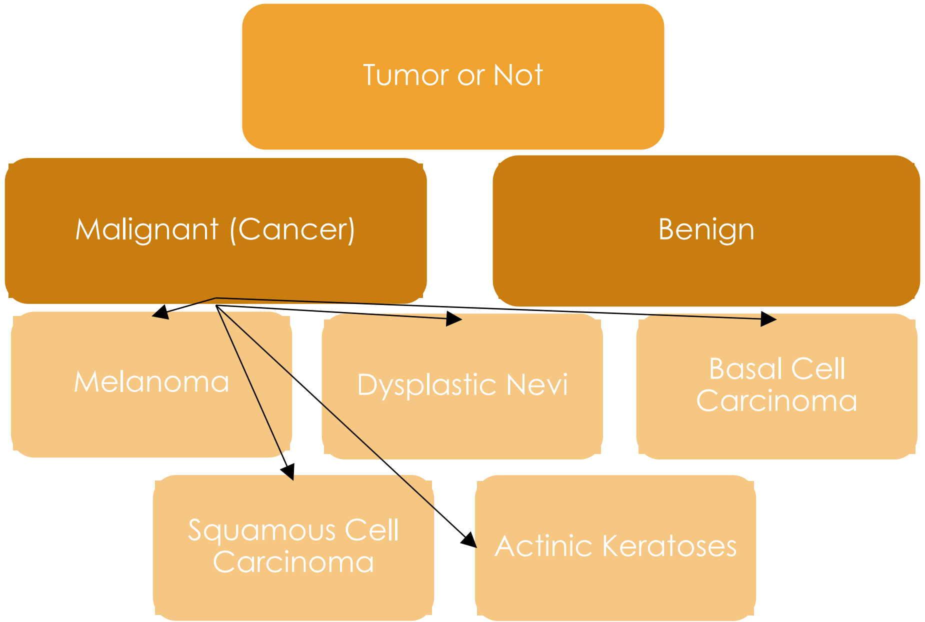


Figure 26. Another complex CNN used in feature extraction called ResNET

Classification

- The last layer of the CCN is the classification
- With the deep learning technology of today, not only can skin cancer be detected but it too can also be classified into the kind of cancer.



Skin Cancer Detection DL (cont.)

Skin Cancer Overview

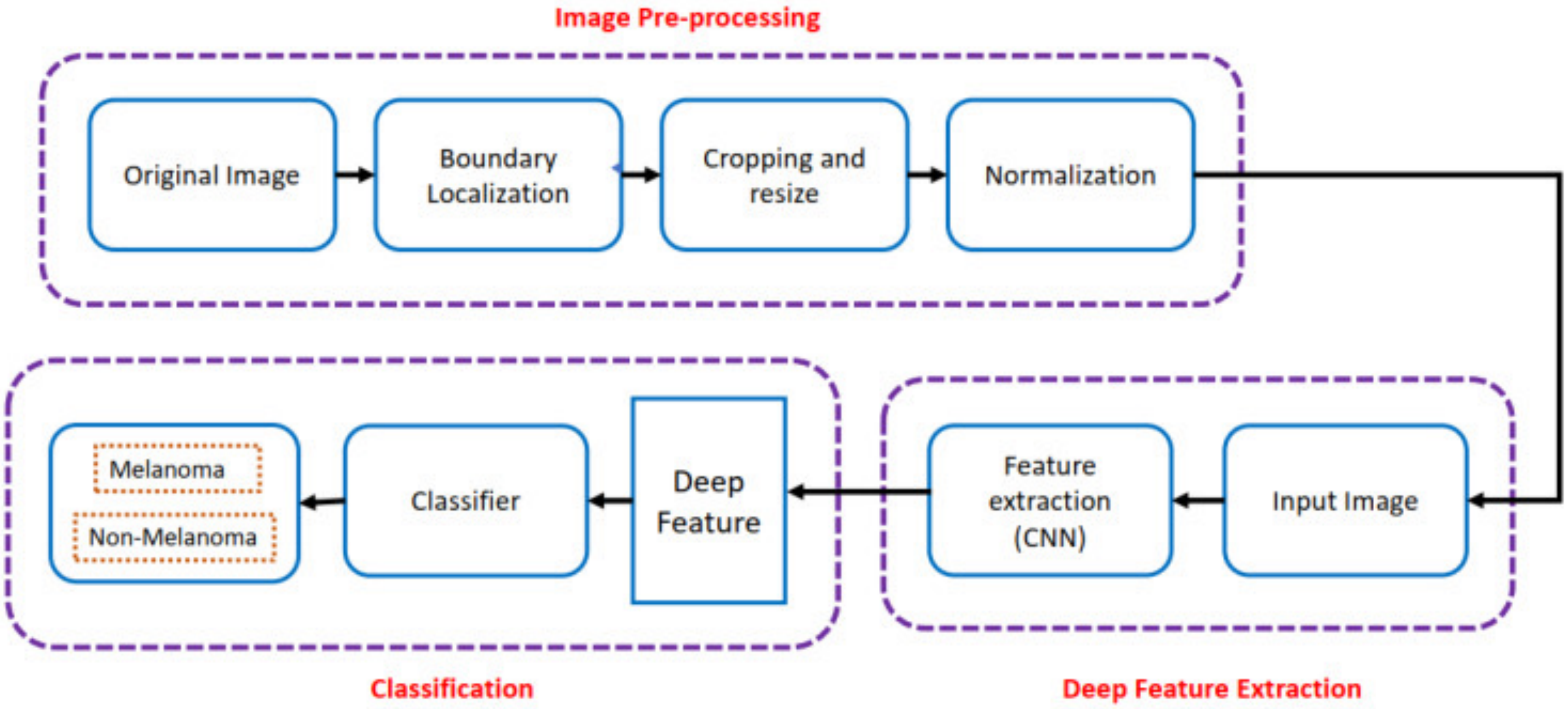


Figure 27. The brief bones of an overall flow chart of skin cancer detection

Skin Cancer Detection DL (cont.)

Skin Cancer Deep Learning

The size of the data set affects the accuracy of the deep learning system

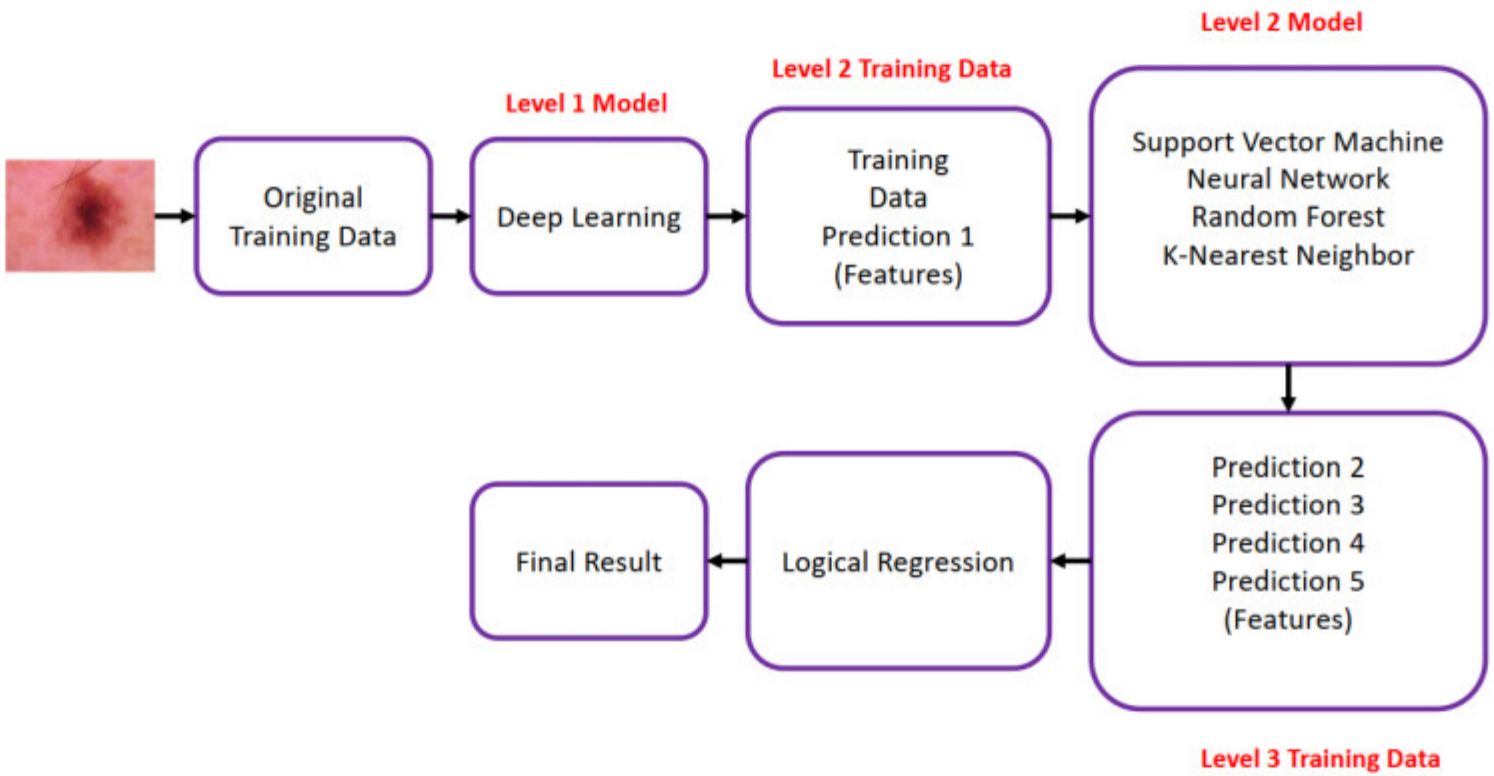


Figure 28. The brief overall flow chart of skin cancer detection deep learning

The process of teaching deep learning is an ongoing process.

Outline

Time to YOLO…

ultralytics

YOLOv8

Image Detection Demonstration (YOLOv8)

Feature Extraction, Boundary Localization, yada yada yada...

Is Deep Learning just words in bubbles and random math?

Image Detection Demonstration (YOLOv8)

NO!!!

(I mean it's partially true but not entirely)

Deep learning can also be run on **YOUR** laptop by **YOU**

Introducing…

Image Detection Demonstration (YOLOv8)

The high-level architecture has been covered previously, but we can show you something a little more interesting that we have been working on…

Outline

- Introduction
- Machine Learning vs Deep Learning Overview
- How Deep Learning Works
- Musculoskeletal Fractures Case Study
- Skin Cancer Detection Case Study
- Image Detection Demonstration (Code)
- **Relation to Human Cognitive and Brain Development**
- Ethical Concerns
- Conclusion

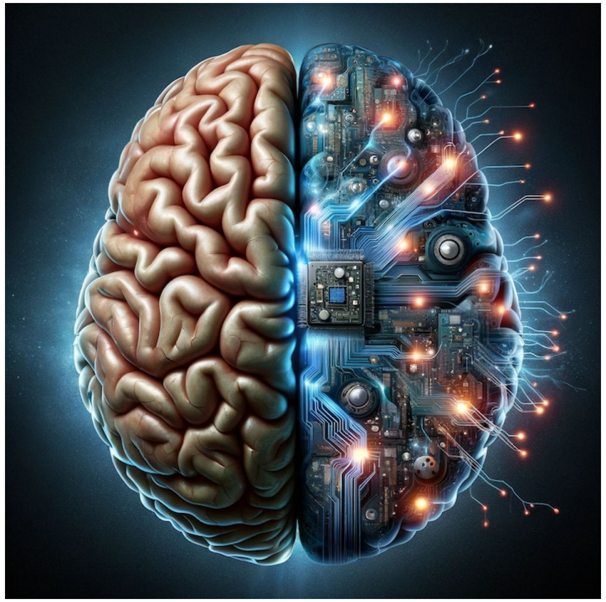
Relation to human cognitive and brain development

Deep Learning similarities to human cognition

- Time to develop basic skills (walking)
- Patients that lost medial temporal lobe usage still had past memories and skills

Complementary Learning Systems Theory

- Parts of the brain like the hippocampus provide a fast-learning system once developed.
- Learning is highly dependent on past experience and connections.



Outline

Ethical Concerns

Data bias is often the result of how the data is trained, labeled, and how representative the data are of the population of interest

Data bias can cause models to underperform on certain populations

Research has shown that there are often discrepancies in accuracy with darker-skinned females, which highlights an underlining racial and gender bias in AI systems

Inaccurate results can cause harm to patients when medical professionals use these machines for clinical decision making

Errors may also be the result of AI making decisions based on a limited dataset

Outline

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- Ethical Concerns
- **Conclusion**

Criticisms and Comments

Despite the current issues, AI with proper training and research has the ability to significantly improve patient outcomes, reduce costs, and enhance the quality of care provided to patients

Additionally, the development of deep learning has the possibility to enhance health care for patients who do not have the opportunity to go to the hospital immediately or are very far away

Deep learning for medical imaging aids medical professionals with early detection and diagnosis, accurate treatment planning, and monitoring treatment response, while making the health care system more convenient, active, efficient, and personalized

Sources: https://www.techrxiv.org/users/706380/articles/692727-advances-of-ai-in-image-based-computer-aided-diagnosis-a-review

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