Identifying the Maker of Shoulder Implants From Radiographs

Rick Hutchison

Shoulder Implants (Prostheses)

53,000 placed in US every year

Indications:

- Trauma
- Arthritis
- Tumor
- Infection

Project Goal

To classify the manufacturer of shoulder implants from shoulder radiographs.

Significance-

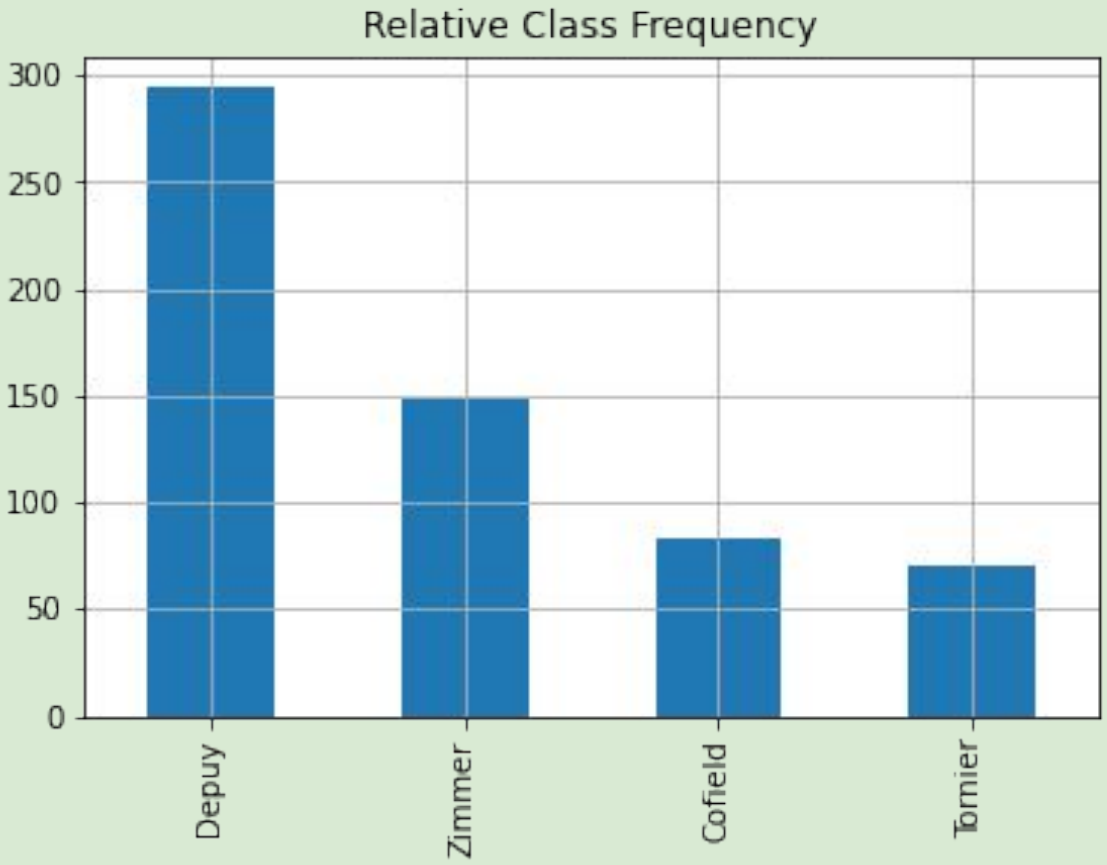
Removal or replacement requires brand specific information for surgical approach and equipment. Medical records may be unavailable.

Data

- 597 shoulder radiographs
    - 4 manufacturers - 16 models
    - jpeg format
    - 250 x 250 pixels
    - 8-bit grayscale
    - various dimensions
    - Not preprocessed
    - Collected for Master’s thesis

https://archive.ics.uci.edu/ml/datasets/Shoulder+Implant+X-Ray+Manufacturer+Classification

Distribution




Cofield - 88

Zimmer - 151

Tornier - 71

Depuy - 295

Benchmark

Computational and Structural Biotechnology Journal 18 (2020) 967–972

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COMPUTATIONAL ANDSTRUCTURAL BIOTECHNOLOGY JOURNAL

journal homepage: www.elsevier.com/locate/csbj

Classifying shoulder implants in X-ray images using deep learning

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A B S T R A C T

Total Shoulder Arthroplasty (TSA) is a type of surgery in which the damaged ball of the shoulder is replaced with a prosthesis. Many years later, this prosthesis may be in need of servicing or replacement. In some situations, such as when the patient has changed his country of residence, the model and the manufacturer of the prosthesis may be unknown to the patient and primary doctor. Correct identification of the implant's model prior to surgery is required for selecting the correct equipment and procedure. We present a novel way to automatically classify shoulder implants in X-ray images. We employ deep learning models and compare their performance to alternative classifiers, such as random forests and gradient boosting. We find that deep convolutional neural networks outperform other classifiers significantly if and only if out-of-domain data such as ImageNet is used to pre-train the models. In a data set containing X-ray images of shoulder implants from 4 manufacturers and 16 different models, deep learning is able to identify the correct manufacturer with an accuracy of approximately 80% in 10-fold cross validation, while other classifiers achieve an accuracy of 56% or less. We believe that this approach will be a useful tool in clinical practice, and is likely applicable to other kinds of prostheses.

G. Urban et al. / Computational and Structural Biotechnology Journal 18 (2020) 967–972

Goal

improve accuracy

using the same data.

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Check for updates

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ABSTRACT

Total Shoulder Arthroplasty (TSA) is a type of surgery in which the damaged ball of the shoulder is replaced with a prosthesis. Many years later, this prosthesis may be in need of servicing or replacement. In some situations, such as when the patient has changed his country of residence, the model and the manufacturer of the prosthesis may be unknown to the patient and primary doctor. Correct identification of the implant's model prior to surgery is required for selecting the correct equipment and procedure. We present a novel way to automatically classify shoulder implants in X-ray images. We employ deep learning models and compare their performance to alternative classifiers, such as random forests and gradient boosting. We find that deep convolutional neural networks outperform other classifiers significantly if and only if out-of-domain data such as ImageNet is used to pre-train the models. In a data set containing X-ray images of shoulder implants from 4 manufacturers and 16 different models, deep learning is able to identify the correct manufacturer with an accuracy of approximately 80% in 10-fold cross validation, while other classifiers achieve an accuracy of 56% or less. We believe that this approach will be a useful tool in clinical practice, and is likely applicable to other kinds of prostheses.

UC-I   Image Pre-processing and Augmentation

Augmentation-

Random shifting

Zooming

Rotations

Random flipping

Optimized the hyperparameters

UC - I

Shallow Learning Approaches:

- Gradient Boosting
- K-nearest Neighbors
- Random Forests

Deep Learning Approaches:

CNN - ReLu, softmax

- 6 conv layers,3 max pooling layers
- 1 fully connected layer

Transfer learning CNN-

- VGG-16, VGG-19
- ResNet - 152, Resnet - 50
- Densenet
- NASNET

UC-I Results

Classifier	Accuracy [%]
Random Forest	56 (1.)
Logistic Regression	53 (1.)
Gradient Boosting	55 (1.)
KNN	52 (1.)

Classifier	Accuracy [%]
VGG-16	74.0 (2.3)
VGG-19	76.2 (1.6)
ResNet-50	75.4 (1.5)
ResNet-152	75.6 (2.0)
NASNet	80.4 (.8)
DenseNet-201	79.6 (.9)

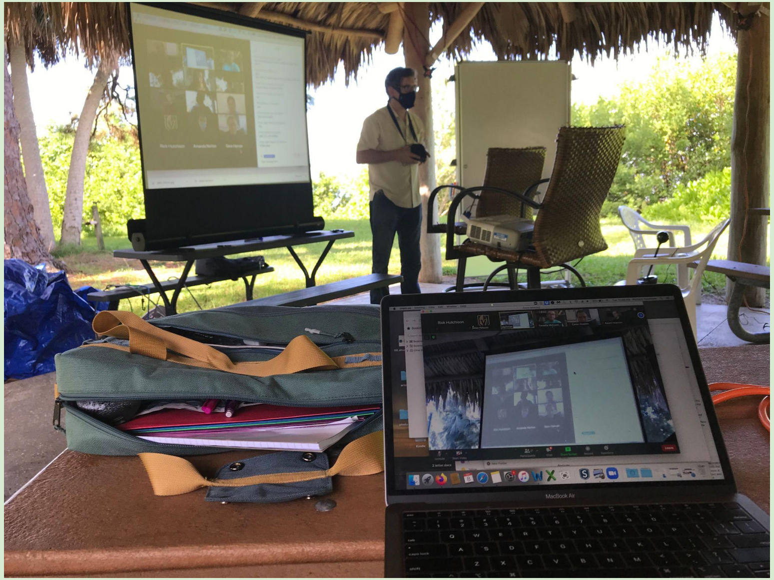
Custom CNN 56.0 (1.4)

Note - Transfer learning models were fine tuned and used data augmentation

NCF

Models tested:

- SVM
- Vanilla CNN
- Transfer learning:
  - ResNet - 18
- Vision Transformer



SVM - 2 largest groups Depuy and Zimmer

Hyperparameters:

C=1

gamma = auto

kernel = poly

Accuracy = 56%

5-fold cross - validation

Hyperparameters:

C=5

gamma = .01

kernel = poly

Accuracy = 60%

CNN   all 4 groups

accuracy = 63%

(UC -I   CNN-   accuracy = 56%)

tensorflow

Data - standardized

epochs - 50 **

Activation - relu

Optimizer - Adam   (sparse gradients on noisy problems.)

Batch size - 32

rescaling layer

Conv layers - 3

Maxpool layers - 3

Dropout layers - 1   **rate = .4 ****

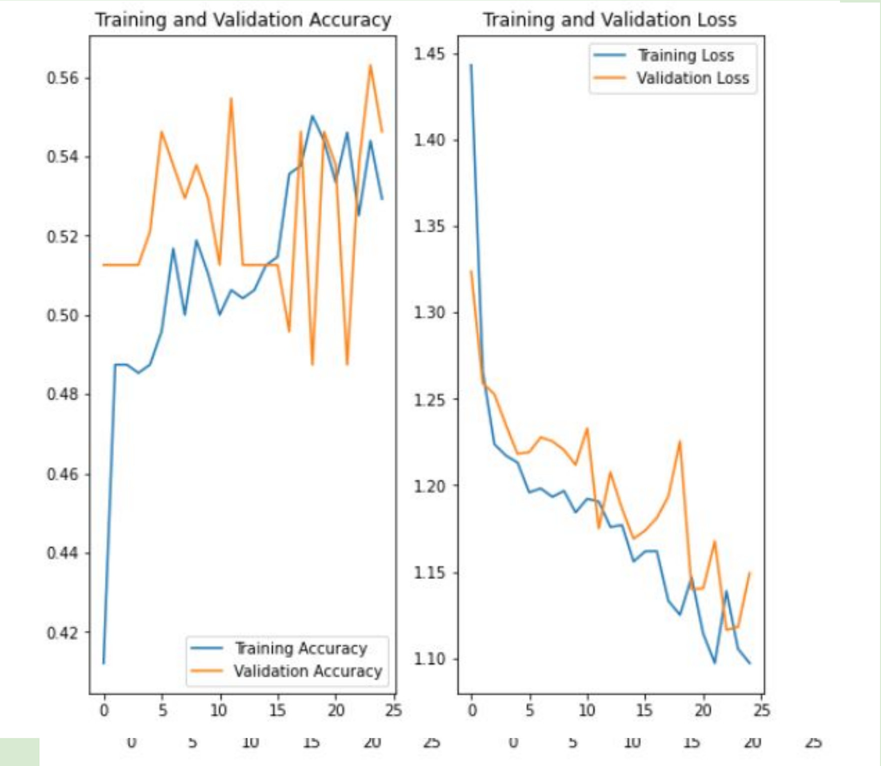
Flatting layers - 1

Dense layers - 2

Augment - random flip,rotation and zoom

- *overfitting*

Before and After Data Augmentation, Dropout, Tuning



CNN Transfer Learning

CNN - Resnet 18 accuracy 77%

Data preprocessing - crop, flip, normalize

Fine tuned

UC-I CNN-transfer learning - 74 - 80%

Optimizer - SGD

Decay learning rate

step size 7, gamma ..01

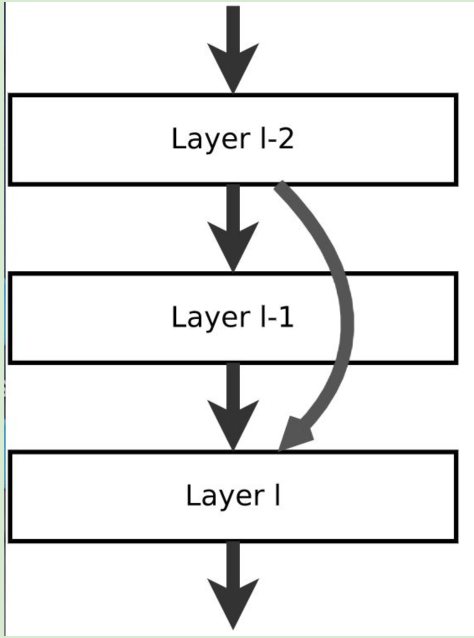
Resnet-18

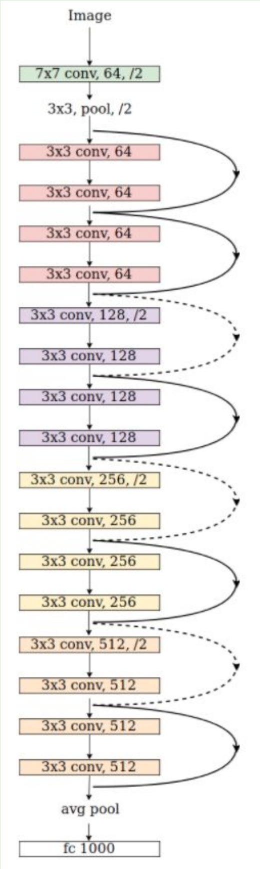
Ancient circa 2015- 2016 CE

Trained on imagenet

18 layers deep

Innovation - identity shortcut connection





CNN Model Problems

Overfitting-

Data -

large intra-class variability - manufacturer offers multiple models

low inter-class variability - implants look roughly alike ,no trivial features (e.g. color)

high variability in image size, quality, and device used to generate it

class and sub-class imbalance

Vision Transformer

Vision Transformer - accuracy = 76%

torch

epochs = 25

lr = 3e-5 (3e-6)

gamma = 0.7 (discount factor) (.5)

Train 449 Validation 113 Test 36

criterion = CrossEntropyLoss()

optimizer = Adam

Data - resize and flip

Best UC-I CNN-transfer learning - 74 - 80%

Transformer

Released in 2017 for NLP   Google researchers

SOTA for NLP

Constructs transformers

based on attention
  self - attention   relates different position of input to get representation
  Attends to all the tokens in the previous layer for contextual mapping O(n^2)

not sequential - allows parallel processing

Treats tokens as sets, not one after another

More efficient than RNNs - faster training process

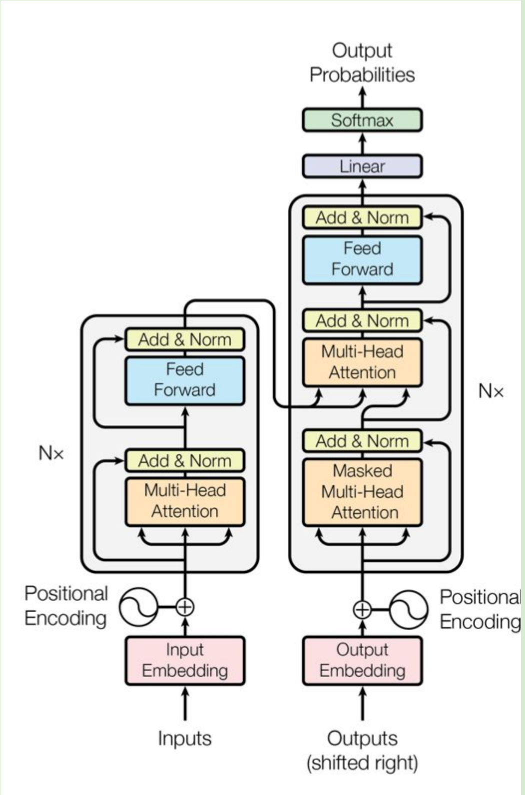
arXiv:1706.03762 [cs.CL]

Attention Is All You Need

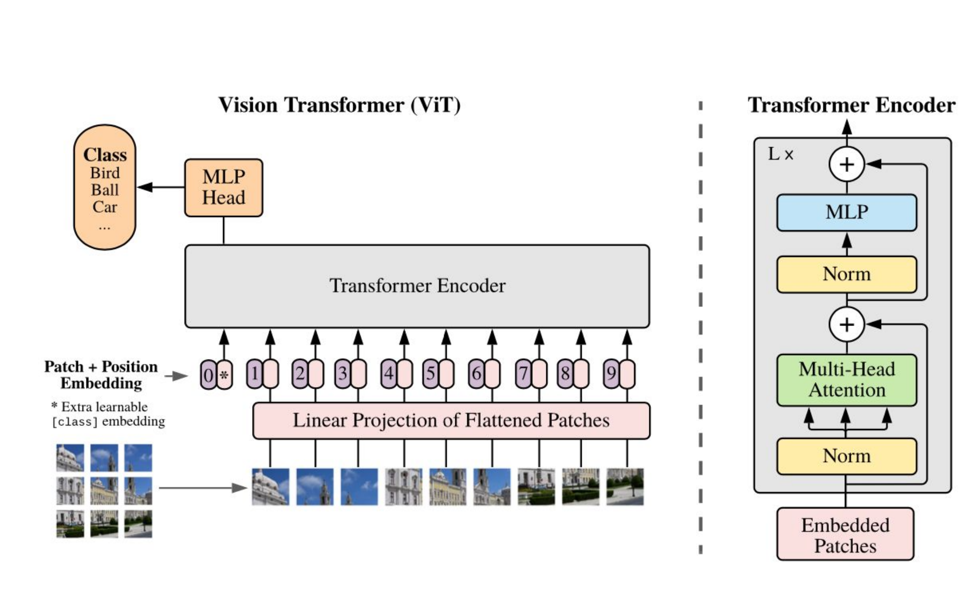
Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, Illia Polosukhin

The dominant sequence transduction models are based on complex recurrent or convolutional neural networks in an encoder-decoder configuration. The best performing models also connect the encoder and decoder through an attention mechanism. We propose a new simple network architecture, the Transformer, based solely on attention mechanisms, dispensing with recurrence and convolutions entirely. Experiments on two machine translation tasks show these models to be superior in quality while being more parallelizable and requiring significantly less time to train. Our model achieves 28.4 BLEU on the WMT 2014 English-to-German translation task, improving over the existing best results, including ensembles by over 2 BLEU. On the WMT 2014 English-to-French translation task, our model establishes a new single-model state-of-the-art BLEU score of 41.8 after training for 3.5 days on eight GPUs, a small fraction of the training costs of the best models from the literature. We show that the Transformer generalizes well to other tasks by applying it successfully to English constituency parsing both with large and limited training data.

Transformer



Vision Transformer



Vision Transformer

Released in Oct 2020   Google researchers

Vision Transformer (ViT)

-based on Transformer architecture

-outperforms CNN on larger data sets

-better performance per computational unit

Problem with CNN

specifically designed for images

can be computationally expensive

Published as a conference paper at ICLR 2021

AN IMAGE IS WORTH 16X16 WORDS: TRANSFORMERS FOR IMAGE RECOGNITION AT SCALE

Alexey Dosovitskiy[*,†], Lucas Beyer[*], Alexander Kolesnikov[*], Dirk Weissenborn[*], Xiaohua Zhai[*], Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, Neil Houlsby[*,†]

[*]equal technical contribution, [†]equal advising

Google Research, Brain Team

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Vision Transformer

Series of patches

Flattened into interconnected channels

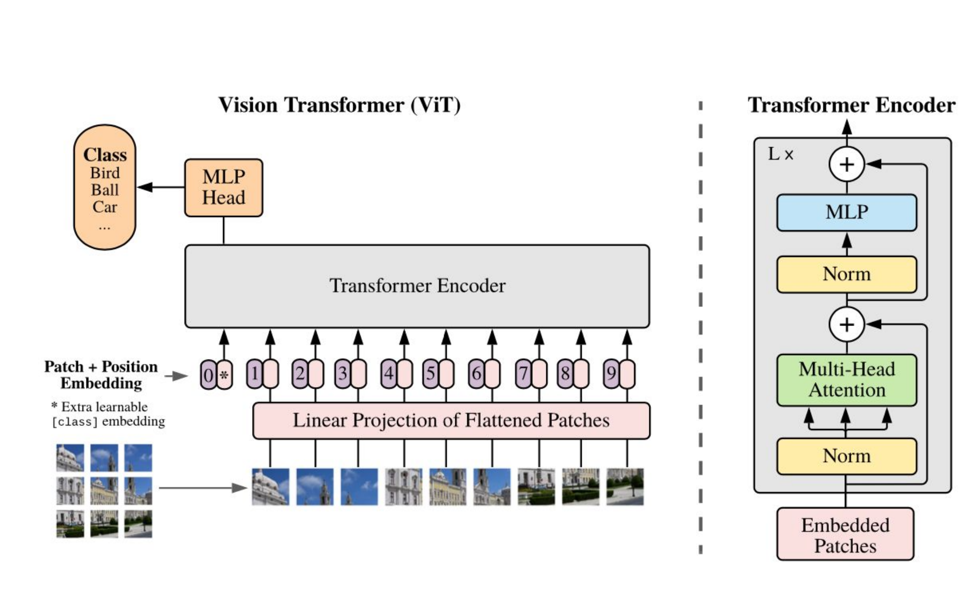
Relationship in original image not known ->

learns relevant features not dependent on order

Uses low-rank matrices   O(n)

Classification tokenoken added to represent entire image

Absolute position embedings



Future plan

Experiment with data augmentation

Test versus automated deep learning systems

Explore more about vision transformer

- Pretrained model

Apply to different medical problems-

- Pediatric hand fractures
- Forearm fracture prostheses

Selected References and Data:

Maya Belen Stark, Automatic detection and segmentation of shoulder implants in X-ray images, MS thesis, San Francisco State University, 2018, [Web Link]

Gregor Urban, Saman Porhemmat, Maya Stark, Brian Feeley, Kazunori Okada, Pierre Baldi, Classifying Shoulder Implants in X-ray Images using Deep Learning, Computational and Structural Biotechnology Journal, 2020: e-pub: [Web Link]

https://archive.ics.uci.edu/ml/datasets/Shoulder+Implant+X-Ray+Manufacturer+Classification

https://www.kaggle.com/redwankarimsony/uci-shoulder-implant-x-ray-manufacturer/code

Attention is All You Need 2017 - https://papers.nips.cc/paper/2017/file/3f5ee243547dee91fbd053c1c4a845aa-Paper.pdf

How Attention works in Deep Learning: understanding the attention mechanism in sequence models -https://theaisummer.com/attention/

"Visual Transformers: Token-based Image Representation and Processing for Computer Vision", 2020; [http://arxiv.org/abs/2006.03677 arXiv:2006.03677]

Questions?


ARE THERE ANY QUESTIONS? FEEL FREE TO ASK ANY-THING AT ALL.
DilbertCartoonist@gmail.com
Dilbert.com
WHY DO GHOSTS HAVE CLOTHES?
9-22-11 ©2011 Scott Adams, Inc./Dist. by Universal Uclick
IF SOMEONE GIVES YOU A WEDGIE AT THE MOMENT YOU DIE, WILL YOU HAVE IT FOR ETERNITY?

Torchvision models

All pretrained on the 1000-class Imagenet dataset.

Training

- Model
- Dictionary of dataloaders
- Loss function
- Optimizer
- Epoch number
- Inception flag

CNN Transfer Learning Hyperparameters

Finetuning - update all parameters

Feature extraction - only update final layer(s)

Resnet - 2015

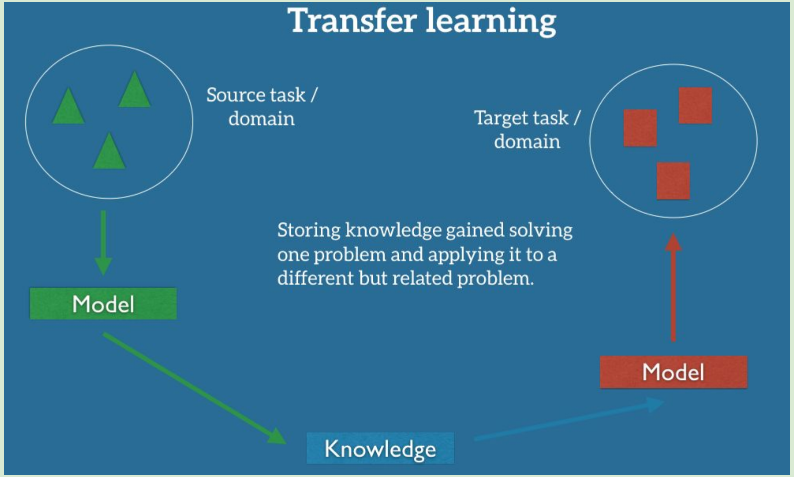
Alexnet -

VGG - 2015

Squeeznet - 2016

Densenet - 2016

Inception v3 - 2015



https://ruder.io/transfer-learning/