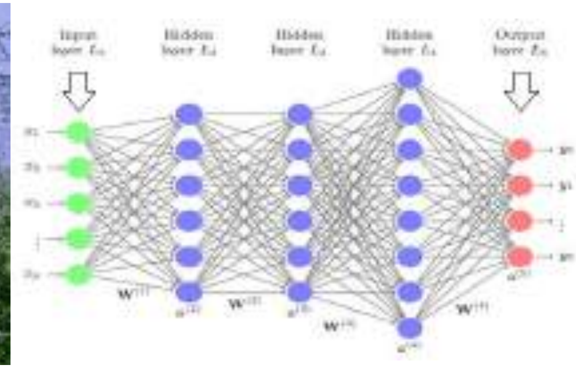
Machine Learning & Deep Learning in Precision Agriculture



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Some of Our Recent Studies

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Computers and Electronics in Agriculture

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Crop yield prediction using machine learning: A systematic literature review

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ARTICLE INFO

Keywords:
Crop yield prediction
Decision support system
Systematic literature review
Machine learning
Deep learning

ABSTRACT

Machine learning is an important decision support tool for crop yield prediction, including supporting decisions on what crops to grow and what to do during the growing season of the crops. Several machine learning algorithms have been applied to support crop yield prediction research. In this study, we performed a Systematic Literature Review (SLR) to extract and synthesize the algorithms and features that have been used in crop yield prediction studies. Based on our search criteria, we retrieved 567 relevant studies from six electronic databases, of which we have selected 50 studies for further analysis using inclusion and exclusion criteria. We investigated these selected studies carefully, analyzed the methods and features used, and provided suggestions for further research. According to our analysis, the most used features are temperature, rainfall, and soil type, and the most applied algorithm is Artificial Neural Networks in these models. After this observation based on the analysis of machine learning-based 50 papers, we performed an additional search in electronic databases to identify deep learning-based studies, reached 30 deep learning-based papers, and extracted the applied deep learning algorithms. According to this additional analysis, Convolutional Neural Networks (CNN) is the most widely used deep learning algorithm in these studies, and the other widely used deep learning algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN).

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Development of a recurrent neural networks-based calving prediction model using activity and behavioral data

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ARTICLE INFO

Keywords:
Calving prediction
Recurrent neural networks
Machine learning
Precision dairy farming

ABSTRACT

Accurate prediction of calving time in dairy cattle is crucial for dairy herd management to reduce risks like dystocia and pain. Prediction of calving using traditional, manual observation such as observing breeding records and visual cues, however, is a complicated and error-prone task whereby even experts can fail to provide a proper prediction. Moreover, manual prediction does not scale for larger farms and becomes very soon time-consuming, inefficient, and costly. In this context, automated solutions are considered to be promising to provide both better and more efficient predictions, thereby supporting the health of the dairy cows and reducing the unnecessary overhead for farmers. Although the first automated solutions appear to have mainly focused on statistical solutions, currently, machine learning approaches are now increasingly being considered as a feasible and promising approach for accurate prediction of calving. In this context, the objective of this study is to develop machine learning based prediction models that provide higher performance compared to the existing tools, methods, and techniques. This study shows that the calving of the cattle can be predicted by applying several behaviors of cattle, behavioral monitoring sensors, and machine learning models. Bi-directional Long Short-Term Memory (Bi-LSTM) method has been applied for the prediction of the calving day, and the RusBoosted Tree classifier has been used to predict the remaining 8 h before calving. The experimental results demonstrated that Bi-LSTM provides better performance compared to the LSTM algorithm in terms of classification accuracy, while the RusBoosted Tree algorithm predicts the remaining 8 h accurately before calving. Furthermore, Recurrent Neural Networks provide high performance for the prediction of calving day.

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Original papers

Analysis of transfer learning for deep neural network based plant classification models

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ARTICLE INFO

Keywords:
Plant classification
Transfer learning
Deep neural networks
Fine-tuning
Convolutional neural networks

ABSTRACT

Plant species classification is crucial for biodiversity protection and conservation. Manual classification is time-consuming, expensive, and requires experienced experts who are often limited available. To cope with these issues, various machine learning algorithms have been proposed to support the automated classification of plant species. Among these machine learning algorithms, Deep Neural Networks (DNNs) have been applied to different data sets. DNNs have been however often applied in isolation and no effort has been made to reuse and transfer the knowledge of different applications of DNNs. Transfer learning in the context of machine learning implies the usage of the results of multiple applications of DNNs. In this article, the results of the effect of four different transfer learning models for deep neural network-based plant classification is investigated on four public datasets. Our experimental study demonstrates that transfer learning can provide important benefits for automated plant identification and can improve low-performance plant classification models.

sensors

MDPI

Article

Sensor Failure Tolerable Machine Learning-Based Food Quality Prediction Model

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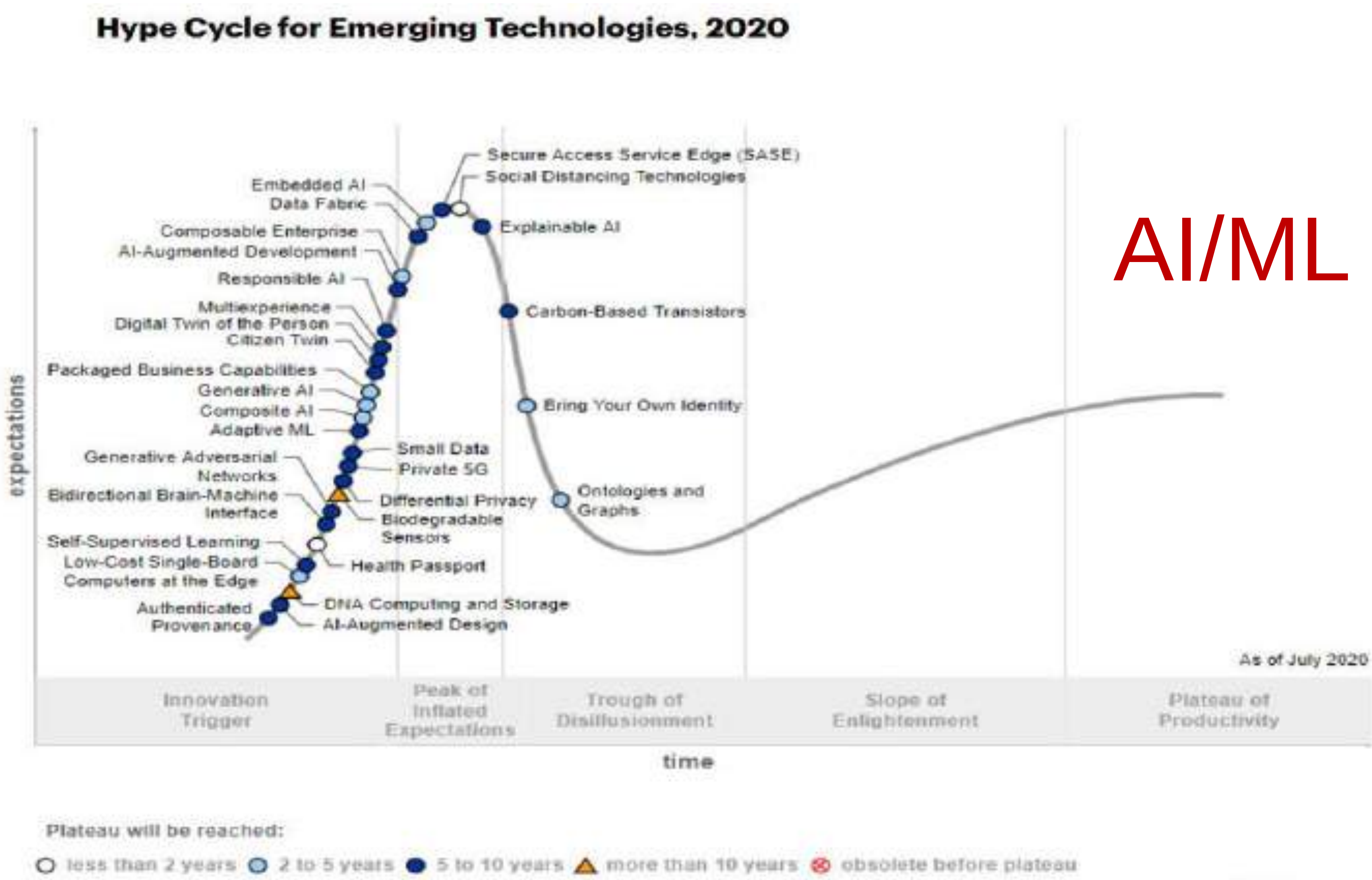
Abstract: For the agricultural food production sector, the control and assessment of food quality is an essential issue, which has a direct impact on both human health and the economic value of the product. One of the fundamental properties from which the quality of the food can be derived is the smell of the product. A significant trend in this context is machine olfaction or the automated simulation of the sense of smell using a so-called electronic nose or e-nose. Hereby, many sensors are used to detect compounds, which define the odors and herewith the quality of the product. The proper assessment of the food quality is based on the correct functioning of the adopted sensors. Unfortunately, sensors may fail to provide the correct measures due to, for example, physical aging or environmental factors. To tolerate this problem, various approaches have been applied, often focusing on correcting the input data from the failed sensor. In this study, we adopt an alternative approach and propose machine learning-based failure tolerance that ignores failed sensors. To tolerate for the failed sensor and to keep the overall prediction accuracy acceptable, a Single Plurality Voting System (SPVS) classification approach is used. Hereby, single classifiers are trained by each feature and based on the outcome of these classifiers, and a composed classifier is built. To build our SPVS-based technique, K-Nearest Neighbor (kNN), Decision Tree, and Linear Discriminant Analysis (LDA) classifiers are applied as the base classifiers. Our proposed approach has a clear advantage over traditional machine learning models since it can tolerate the sensor failure or other types of failures by ignoring and thus enhance the assessment of food quality. To illustrate our approach, we use the case study of beef cut quality assessment. The experiments showed promising results for beef cut quality prediction in particular, and food quality assessment in general.

Keywords: classifier; single plurality voting system; ensemble classifier; machine learning; beef cut quality prediction

Gartner Hype Cycle



AI/ML

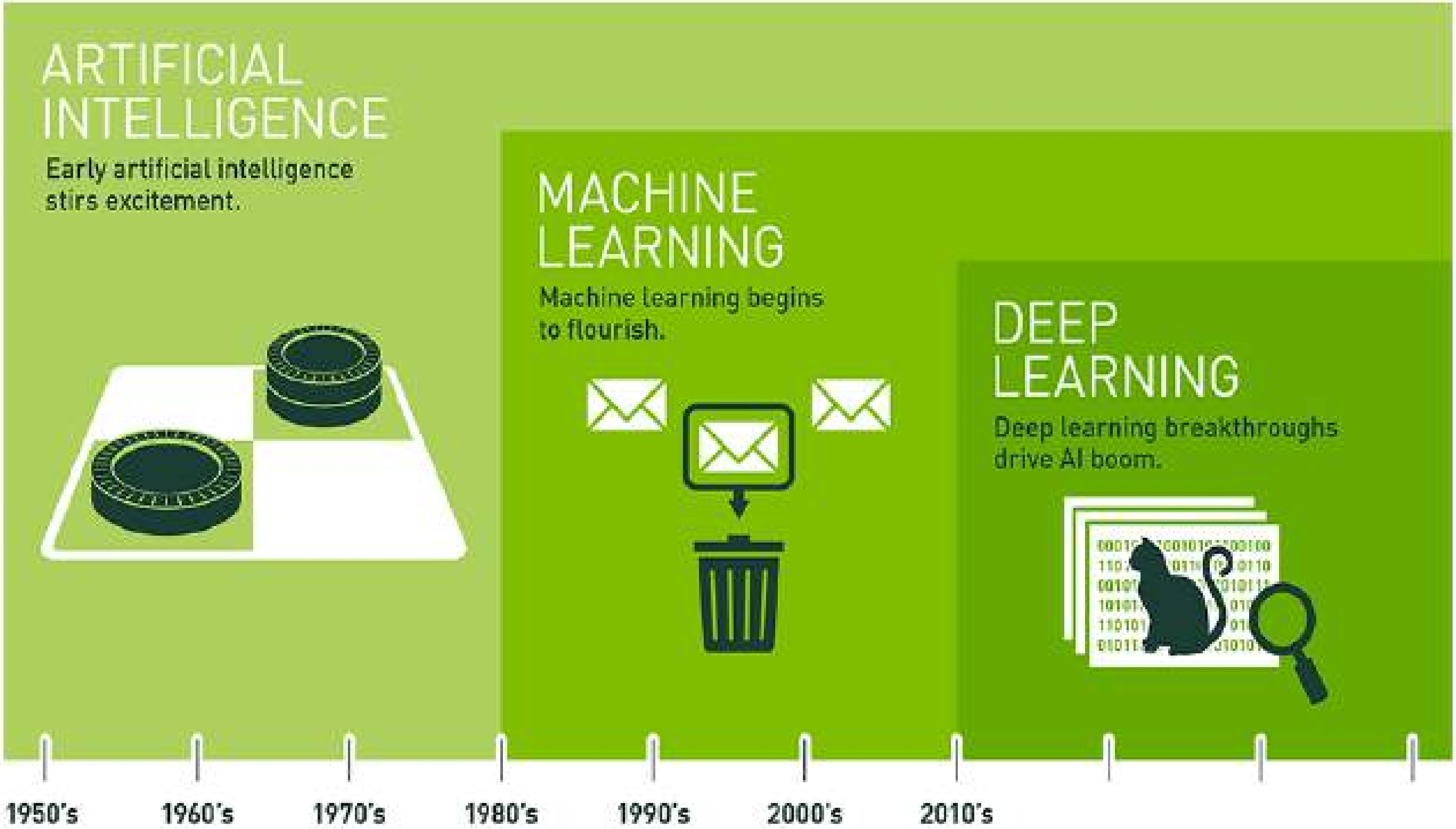
https://www.forbes.com/sites/louiscolumbus/2020/08/23/whats-new-in-gartners-hype-cycle-for-emerging-technologies-2020/#79f3d106a46a

What is Artificial Intelligence?

- English Oxford Living Dictionary
  - *The theory and development of* ***computer systems*** *able to* ***perform tasks*** *normally* ***requiring human intelligence****, such as visual perception, speech recognition, decision-making, and translation between languages*
- The Encyclopedia Britannica
  - *The ability of a digital computer or computer-controlled robot to perform* ***tasks commonly associated with intelligent beings***
- Webster
  - *A branch of computer science dealing with the* ***simulation of intelligent behavior in computers****. The capability of a machine to imitate intelligent human behavior.*

1. Robotics
2. Computer Vision
3. Natural Language Processing
4. **Machine Learning**
5. Planning, Scheduling, Search Methodologies
6. Multi-Agent systems
7. Knowledge Representation and Reasoning
8. Philosophical Aspects

AI



Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

What is Machine Learning?

- Machine Learning
  - A field of computer science that aims to teach computers how to learn and act **without being explicitly programmed**
- The Encyclopedia Britannica
  - ***Machine learning****, in artificial intelligence, discipline concerned with the implementation of computer software that can learn autonomously*

Machine Learning Tasks

1. Classification
2. Regression
3. Clustering
4. Anomaly Detection
5. Data Reduction

Machine Learning Tasks

1. **Classification (Binary or Multi-Class Classification)**
   - Predict which of a set of classes this individual belongs to
   - Ex: Among all the customers of Vodafone, which are likely to **respond** to a given offer?
     - **Will respond**
     - **Will not**

Edible or Poisonous ?

Sample Dataset-1 (Classification Task)

Independent Variables (features)

Dependent Variable (class label)

Fisher's *Iris* Data

Sepal length	Sepal width	Petal length	Petal width	Species
5.1	3.5	1.4	0.2	*I.* setosa
4.9	3.0	1.4	0.2	*I.* setosa
4.7	3.2	1.3	0.2	*I.* setosa
4.6	3.1	1.5	0.2	*I.* setosa
5.0	3.6	1.4	0.2	*I.* setosa
5.4	3.9	1.7	0.4	*I.* setosa
4.6	3.4	1.4	0.3	*I.* setosa
5.0	3.4	1.5	0.2	*I.* setosa
4.4	2.9	1.4	0.2	*I.* setosa
4.9	3.1	1.5	0.1	*I.* setosa
5.4	3.7	1.5	0.2	*I.* setosa
4.8	3.4	1.6	0.2	*I.* setosa
4.8	3.0	1.4	0.1	*I.* setosa

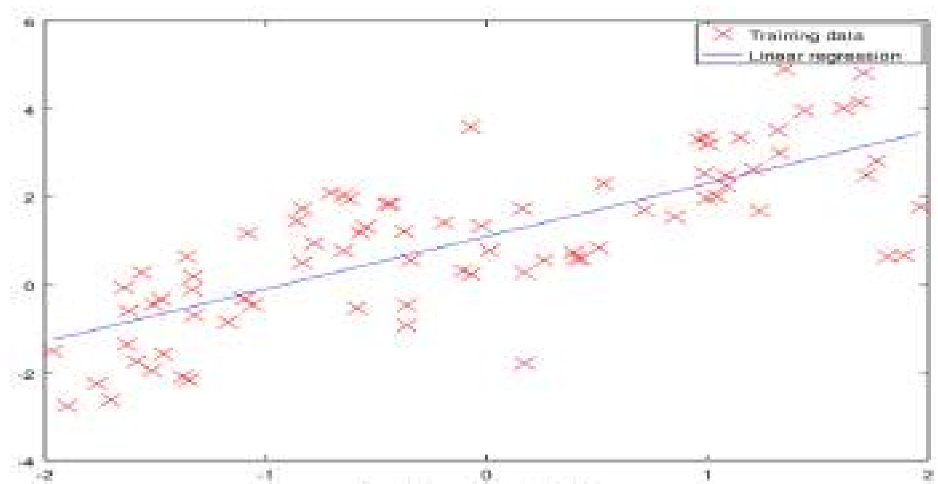
Iris Classification

CLASSIFICATION ALGORITHMS

2. Regression ("value estimation")

- Predict the numerical value of some variable for that individual

- Ex: **How much** will a given customer use the service? (service usage)
  - 4GB data usage



Sample Dataset-2 (Regression Task)

Output value

FEATURES

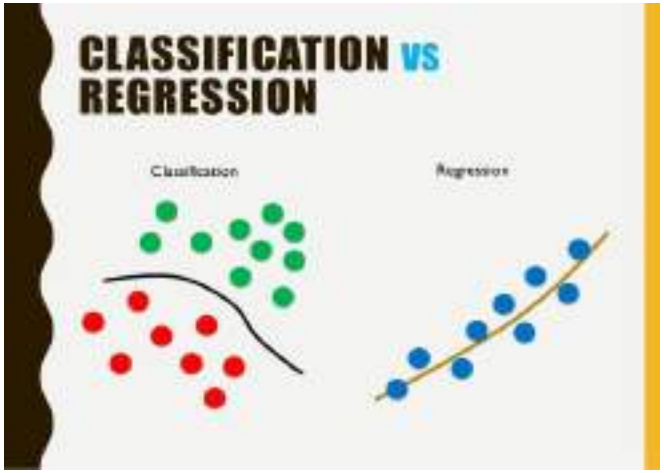
	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

Wine Quality dataset

REGRESSION ALGORITHMS

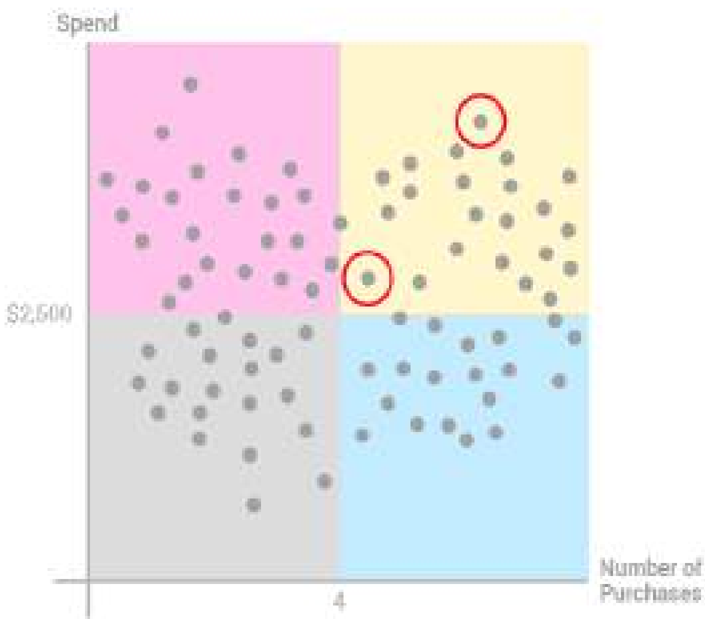
Classification vs. Regression

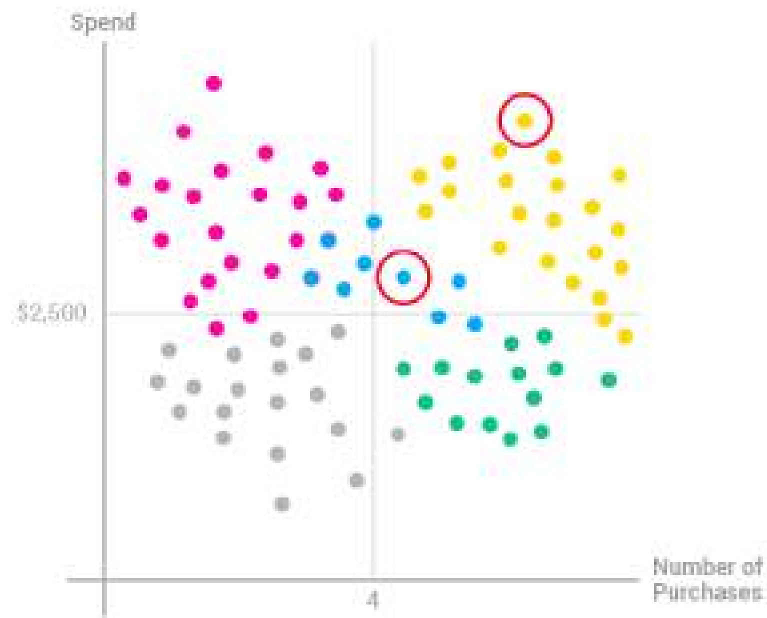
- **Classification**
  - predicts <u>whether</u> something will happen
- **Regression**
  - predicts <u>how much</u> something will happen



3. Clustering

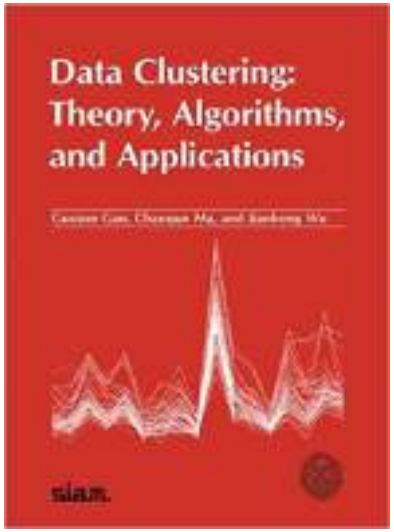
- **Group individuals** in a population together by **their similarity**
  - Ex: What kind of customer groups/segments do we have?
  - Ex: What products should we offer or develop?

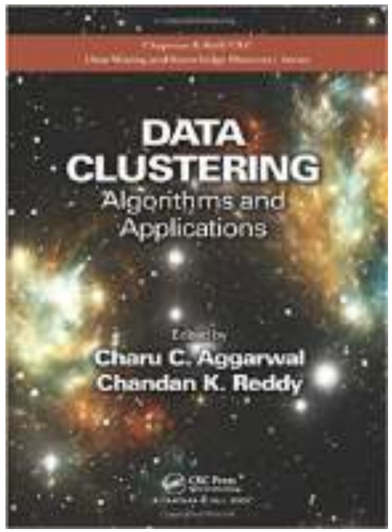




Clustering

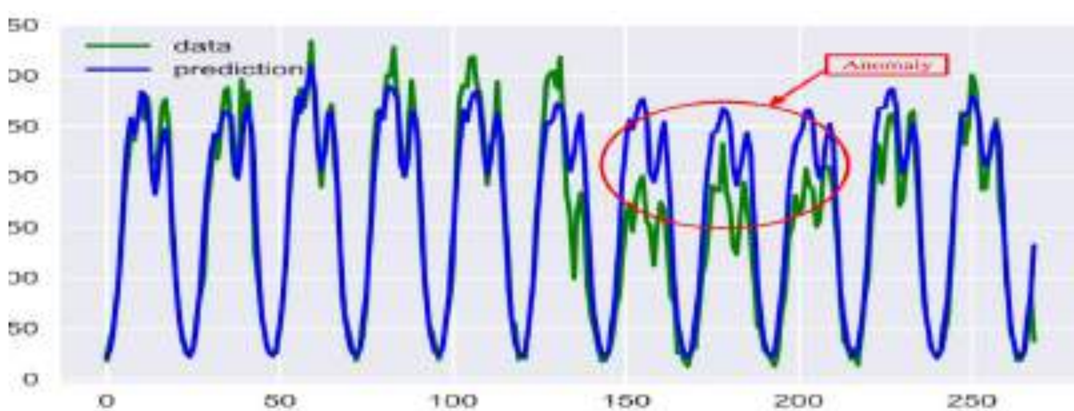
- Dozens of approaches (K-means clustering, X-means clustering, …)





4. Anomaly detection

- Attempts to characterize the **typical behaviour** of an individual, group, population
- **Ex:** What is the **typical cell phone usage** of this customer segment?
- **Ex:** Fraud detection applications
  - Someone breaking into your iTunes account

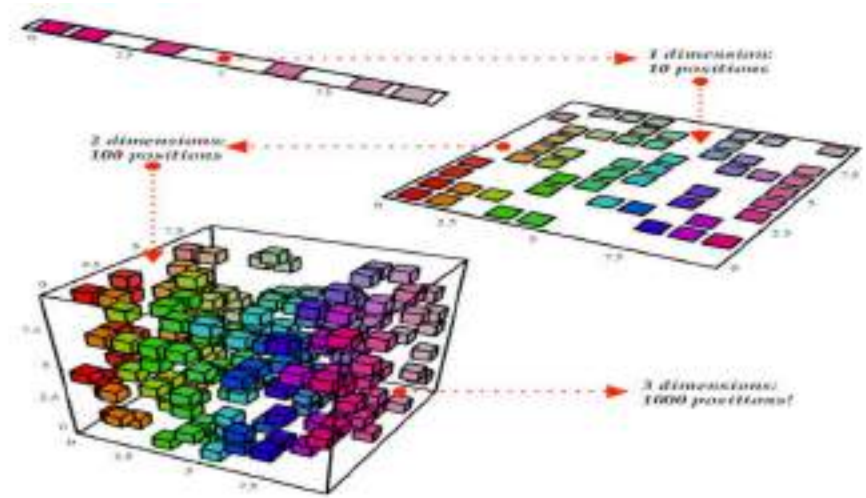


5. Data Reduction

- Attempts to take a large dataset and replace it with a smaller one that contains much of the important information

- Involves loss of information

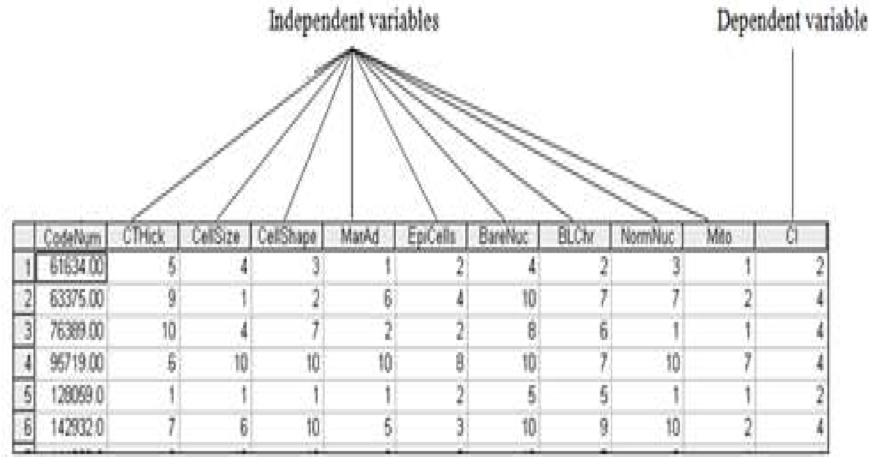
- **<u>Ex:</u>** Which features are most important?



Machine Learning Types

A. Supervised learning
B. Unsupervised learning
C. Semi-supervised learning
D. Reinforcement learning

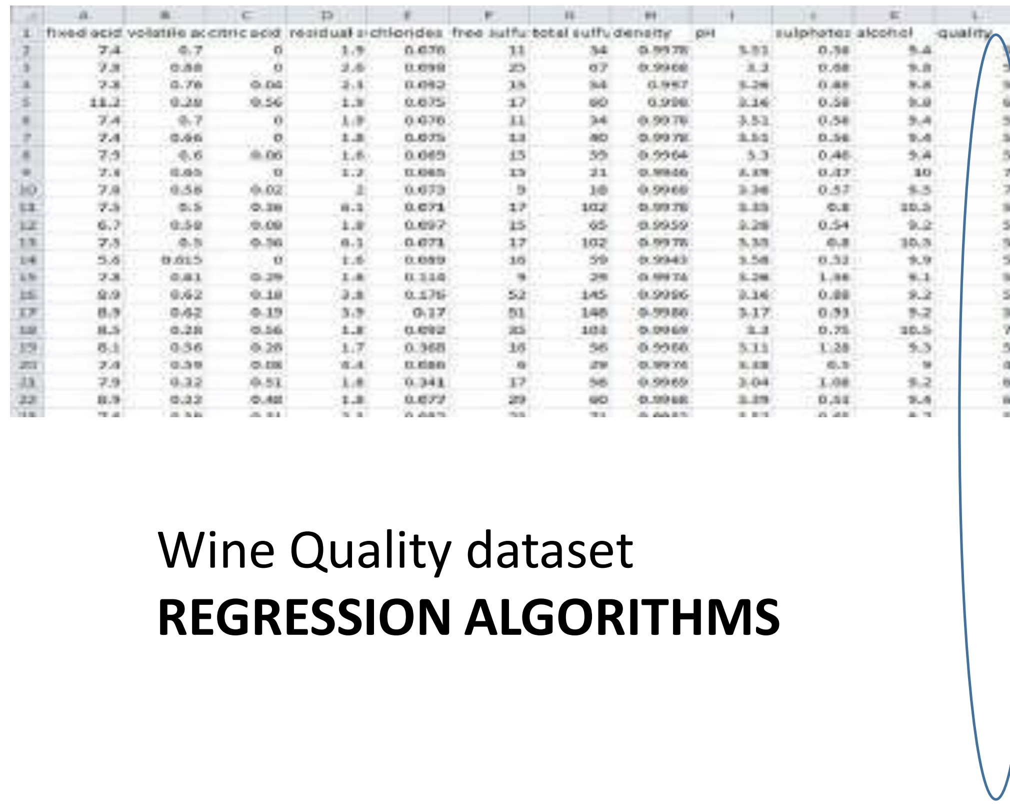
A. Supervised



	CodeNum	CThick	CellSize	CellShape	MarAd	EpiCells	BareNuc	BLChr	NormNuc	Mito	Cl
1	61634.00	5	4	3	1	2	4	2	3	1	2
2	63375.00	9	1	2	6	4	10	7	7	2	4
3	76389.00	10	4	7	2	2	8	6	1	1	4
4	95719.00	6	10	10	10	8	10	7	10	7	4
5	128059.0	1	1	1	1	2	5	5	1	1	2
6	142932.0	7	6	10	5	3	10	9	10	2	4

Breast Cancer dataset

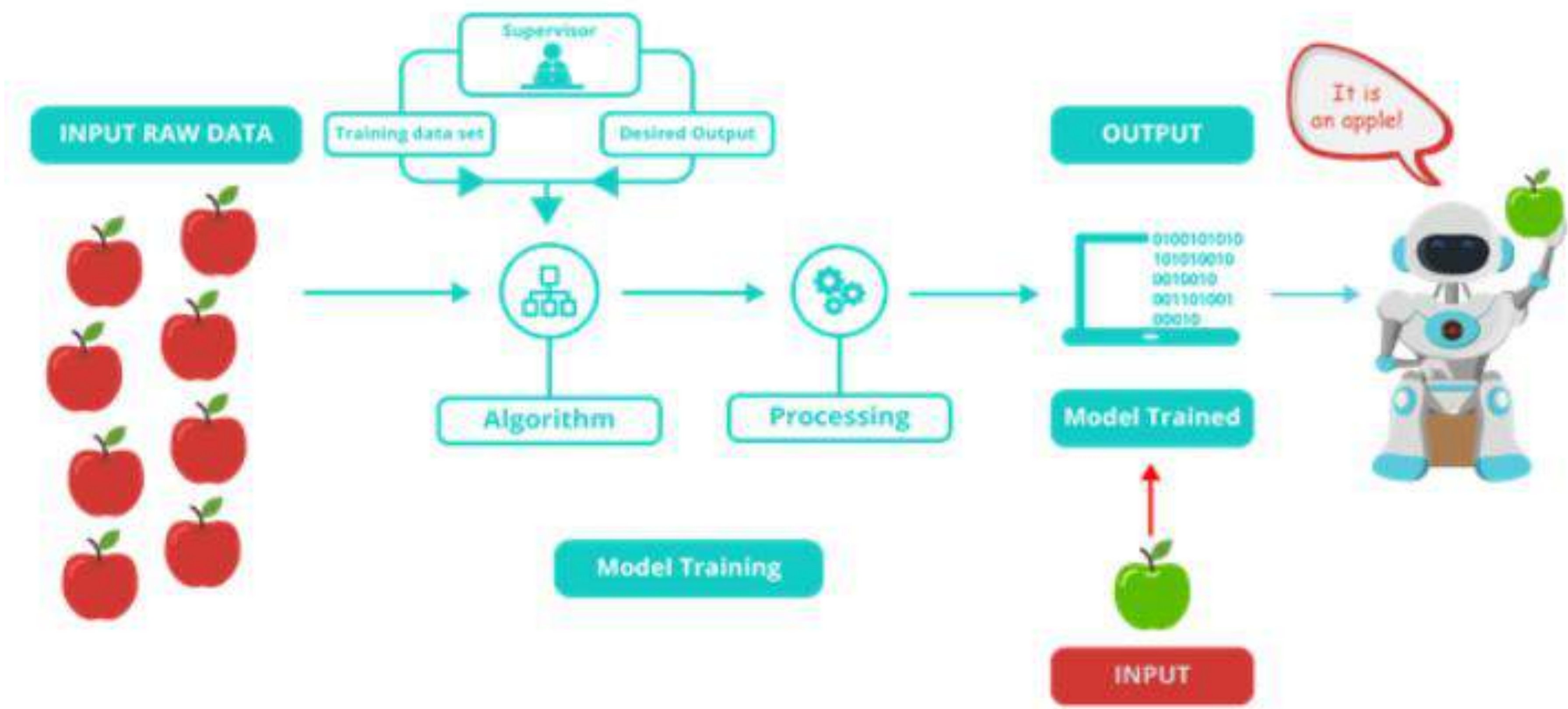
CLASSIFICATION ALGORITHMS



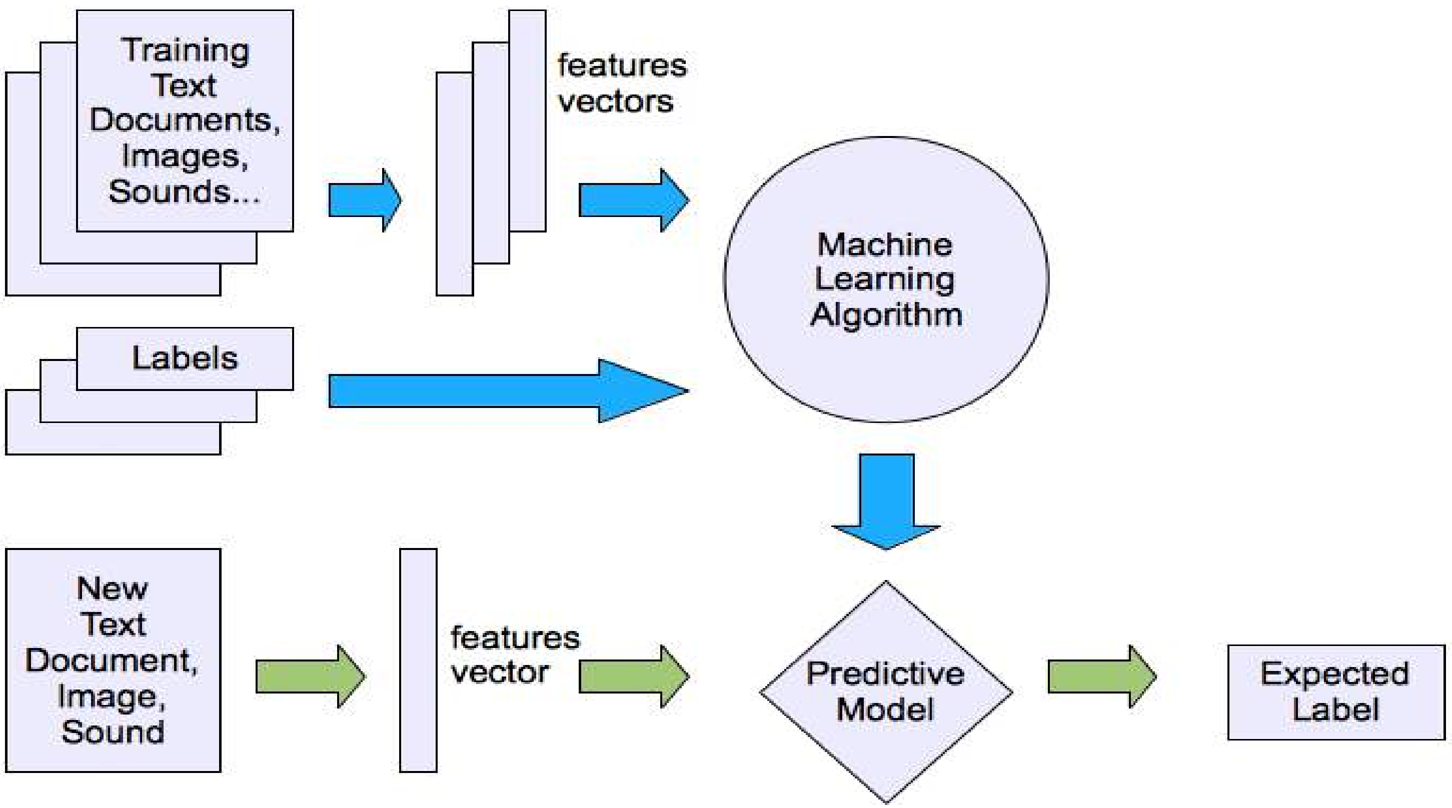
Wine Quality dataset

REGRESSION ALGORITHMS

A. Supervised



A. Supervised Learning

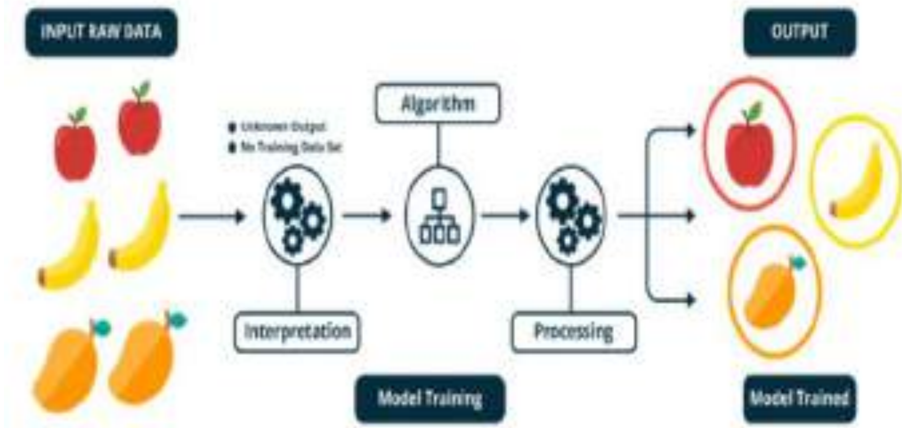


B. Unsupervised

case ID

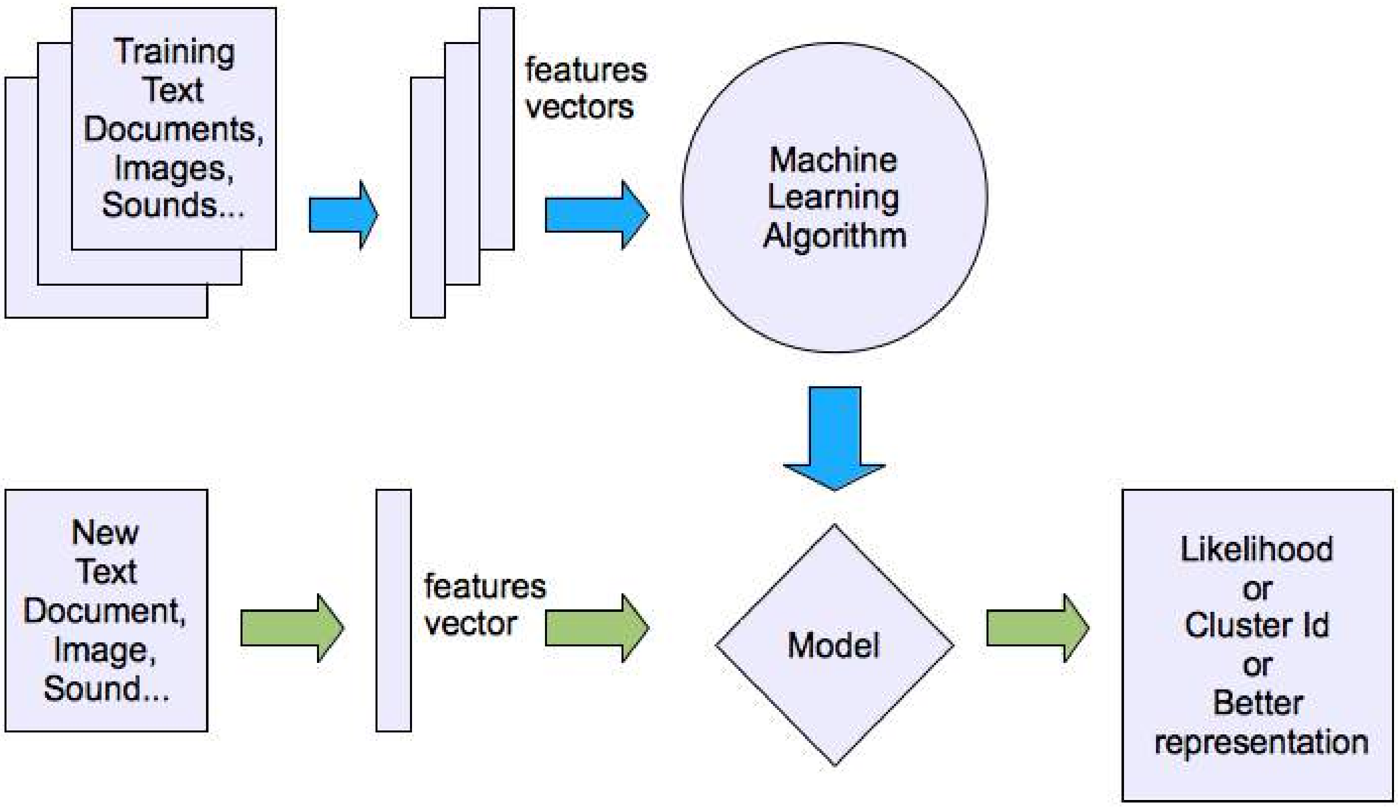
attributes

CUST_ID	CUST_GENDER	AGE	CUST_MARITAL_STATUS	EDUCATION	OCCUPATION
101501	F	41	NeverM	Masters	Prof.
101502	M	27	NeverM	Bach.	Sales
101503	F	20	NeverM	HS-grad	Cleric.
101504	M	45	Married	Bach.	Exec.
101505	M	34	NeverM	Masters	Sales
101506	M	38	Married	HS-grad	Other
101507	M	28	Married	< Bach.	Sales
101508	M	19	NeverM	HS-grad	Sales
101509	M	52	Married	Bach.	Other
101510	M	27	NeverM	Bach.	Sales

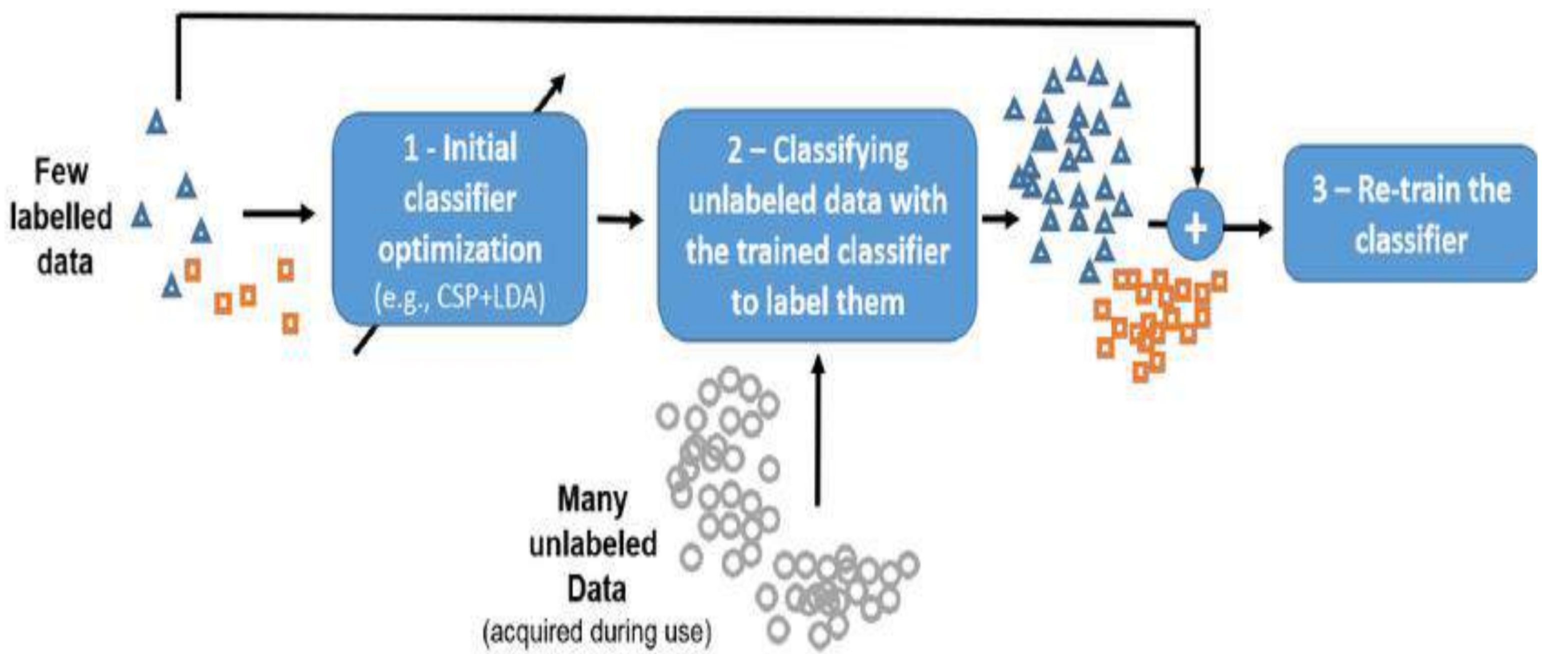


No output label !

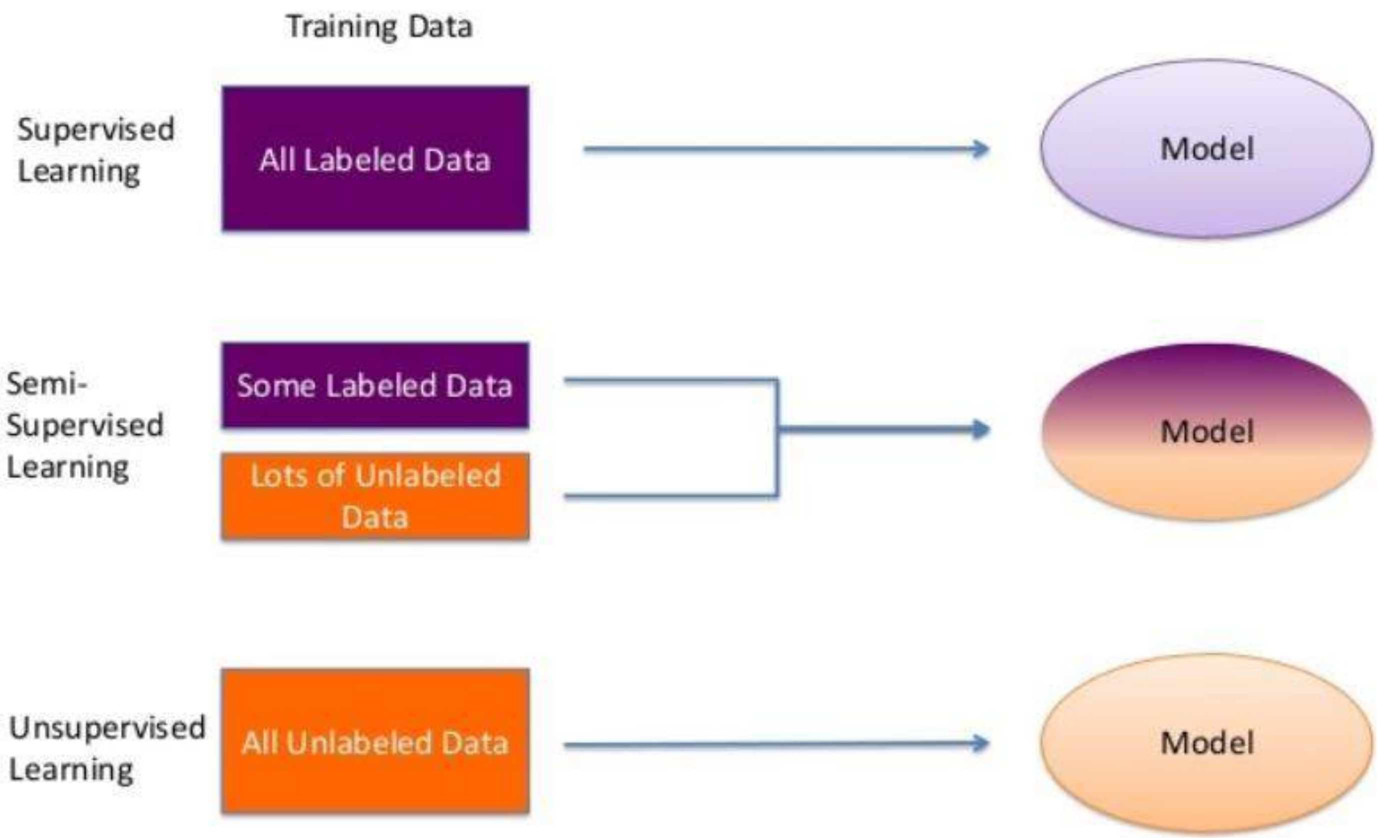
B. Unsupervised Learning



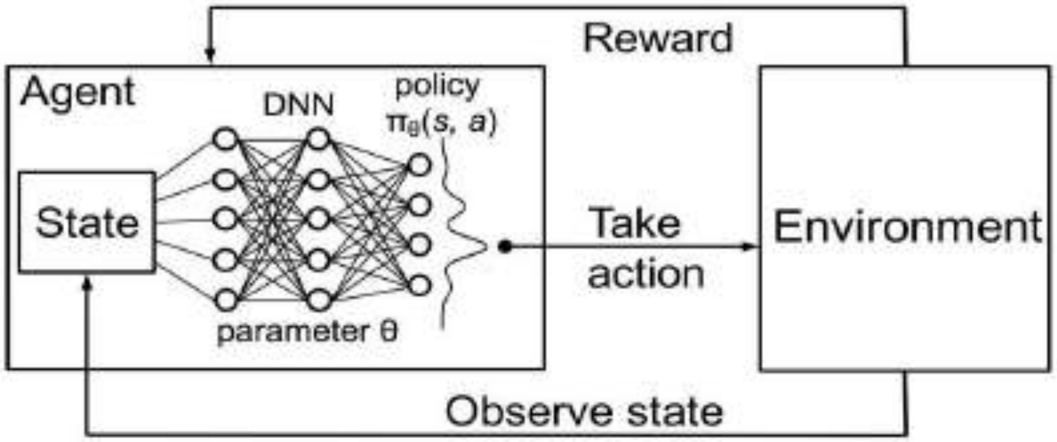
C. Semi-supervised

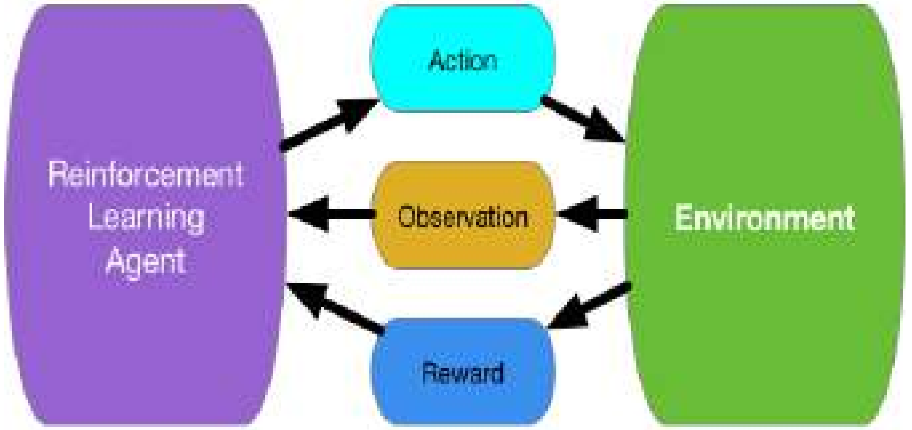


Supervised/Unsupervised/Semi-supervised

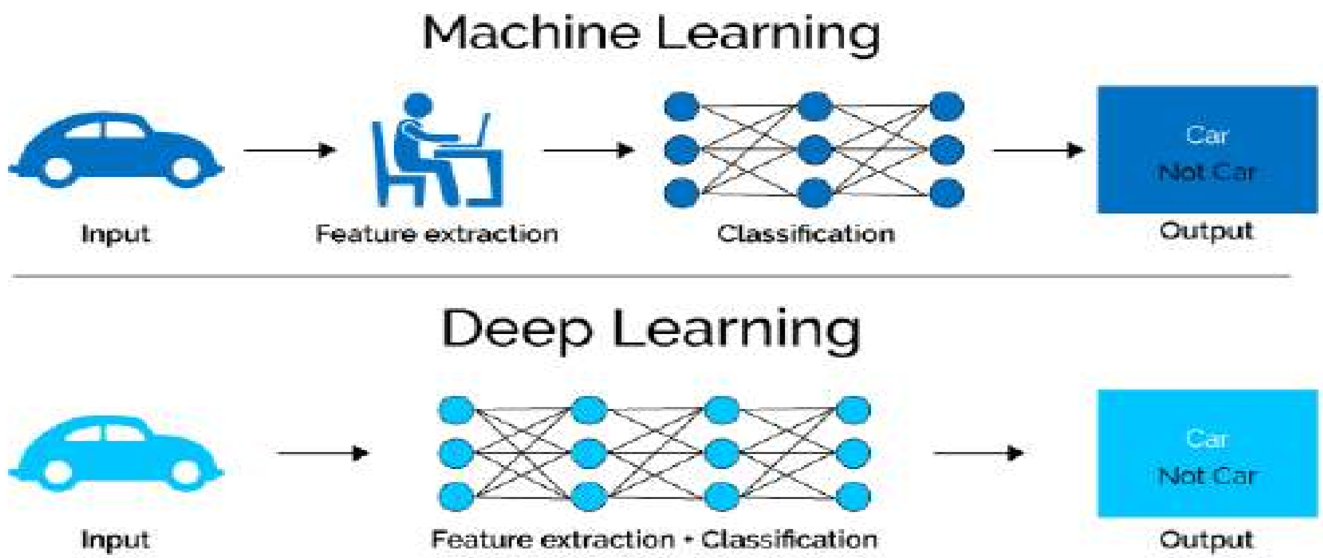


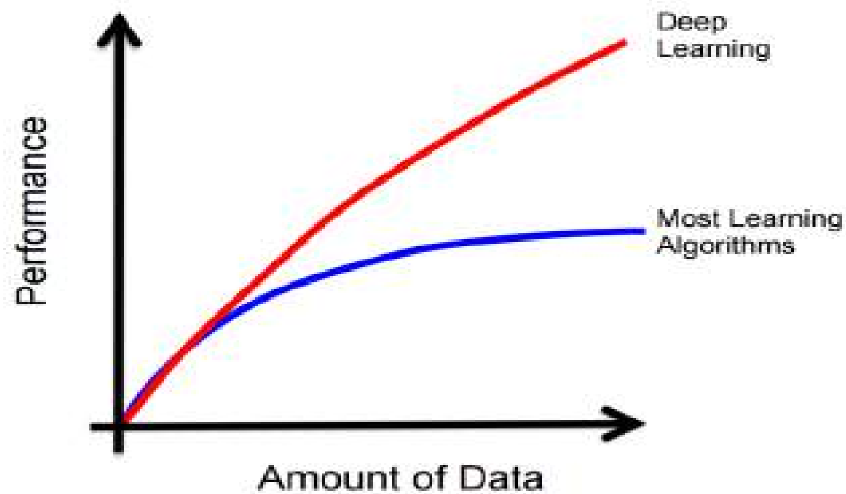
D. Reinforcement





Why Deep Learning? Scalable Machine Learning

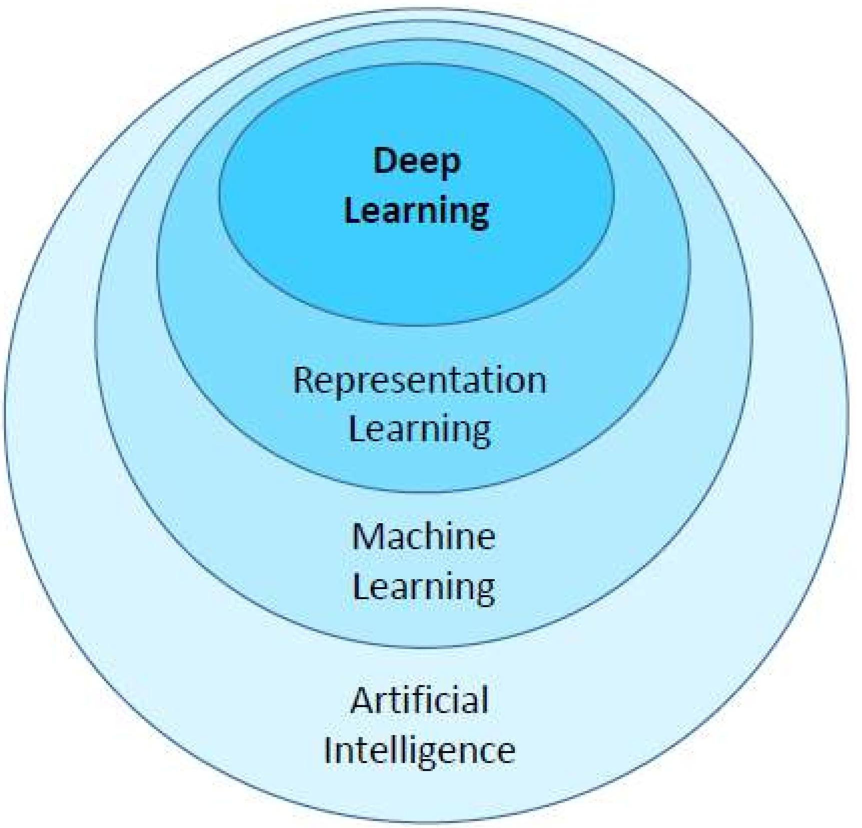


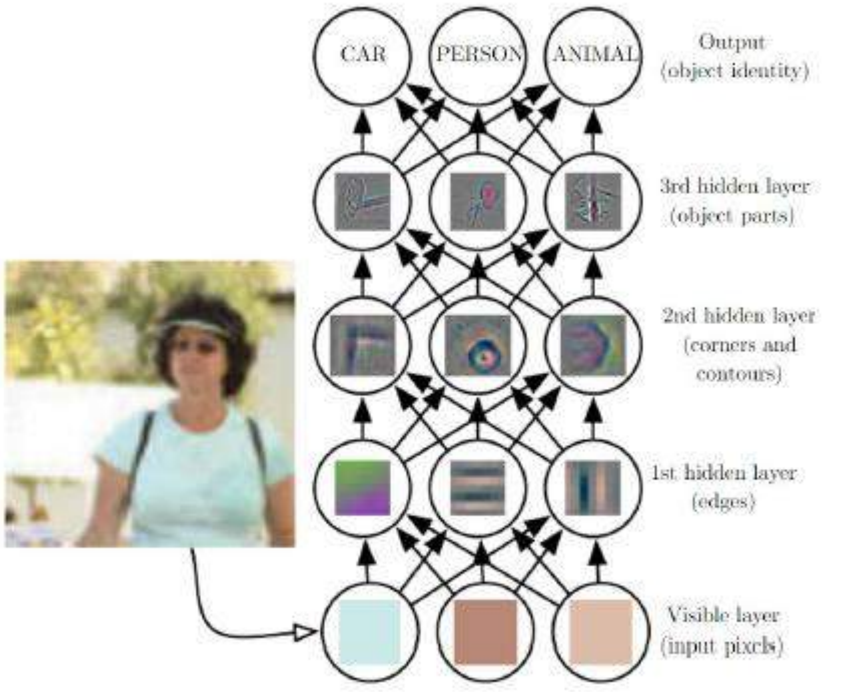


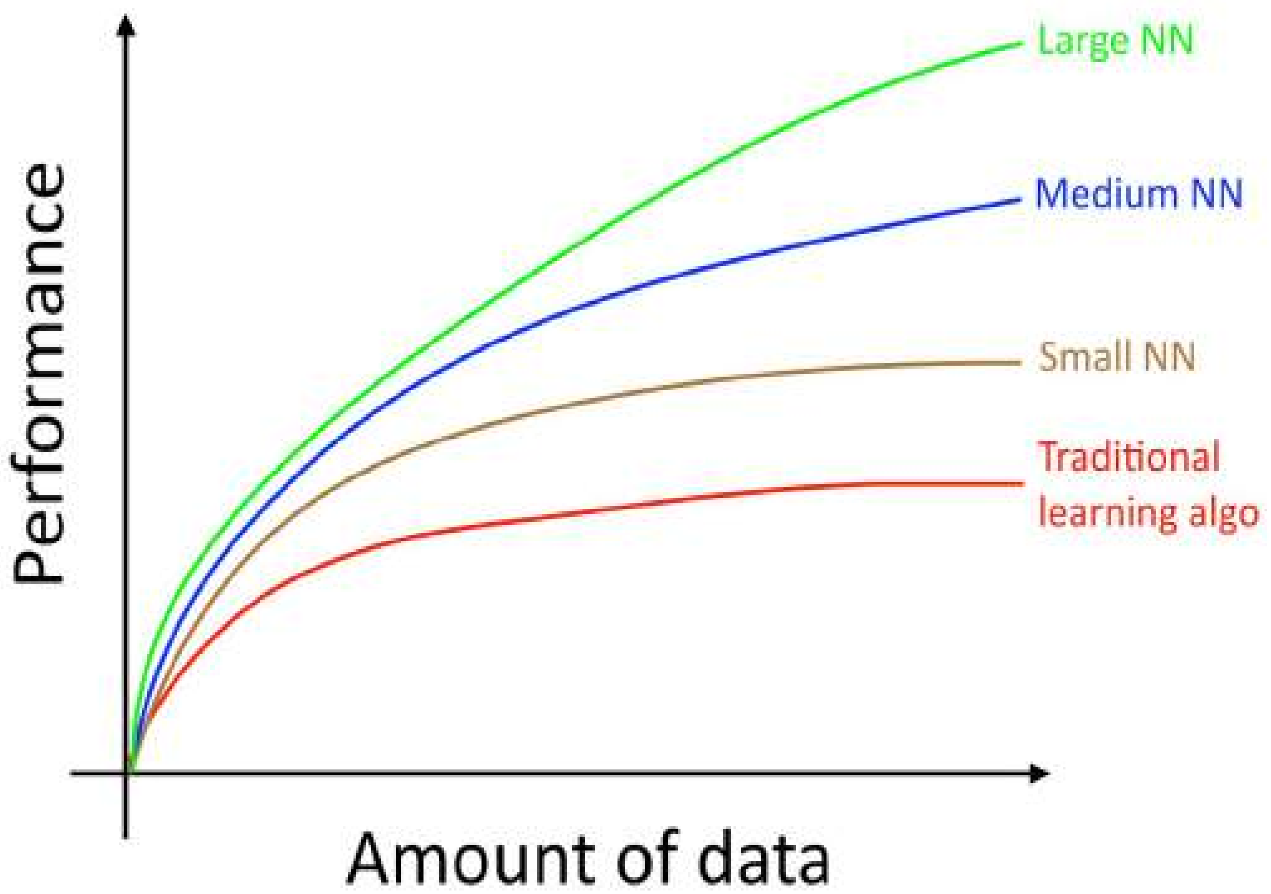
https://deeplearning.mit.edu

Deep Learning is **Representation Learning**

- (aka Feature Learning)

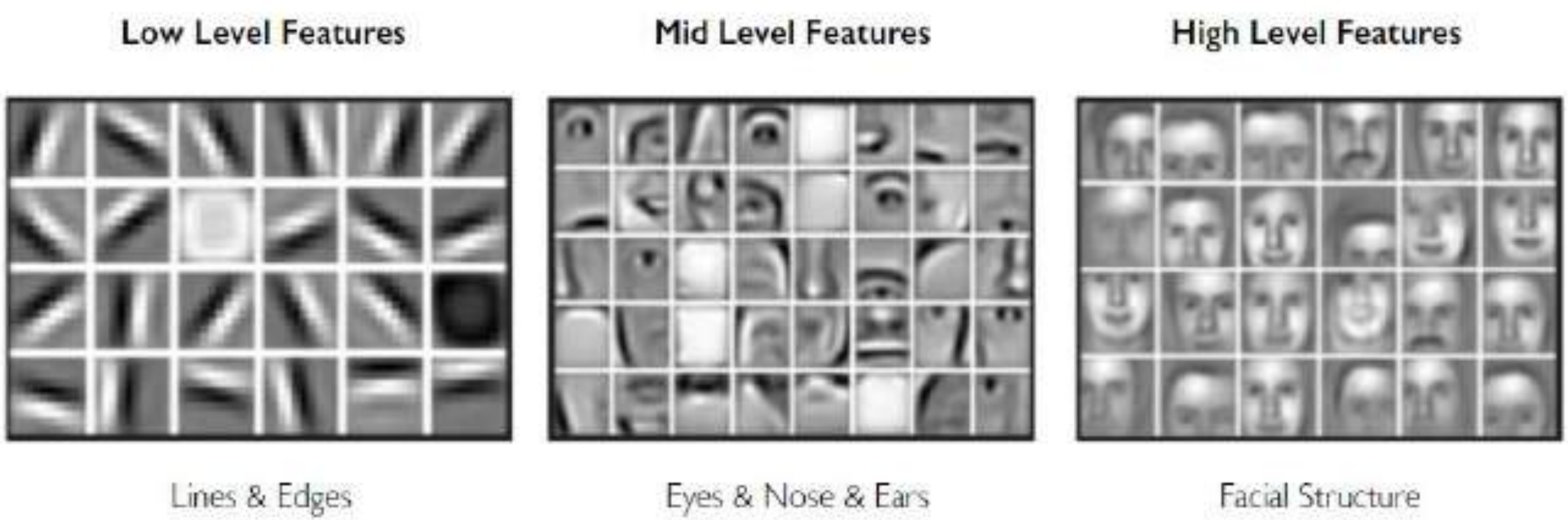




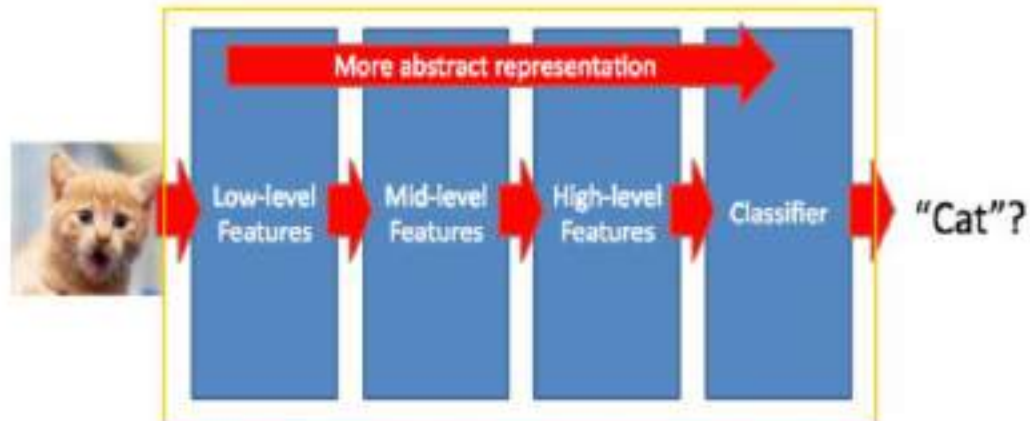

Large NN
Medium NN
Small NN
Traditional
learning algo
Performance
Amount of data

Why Deep Learning?

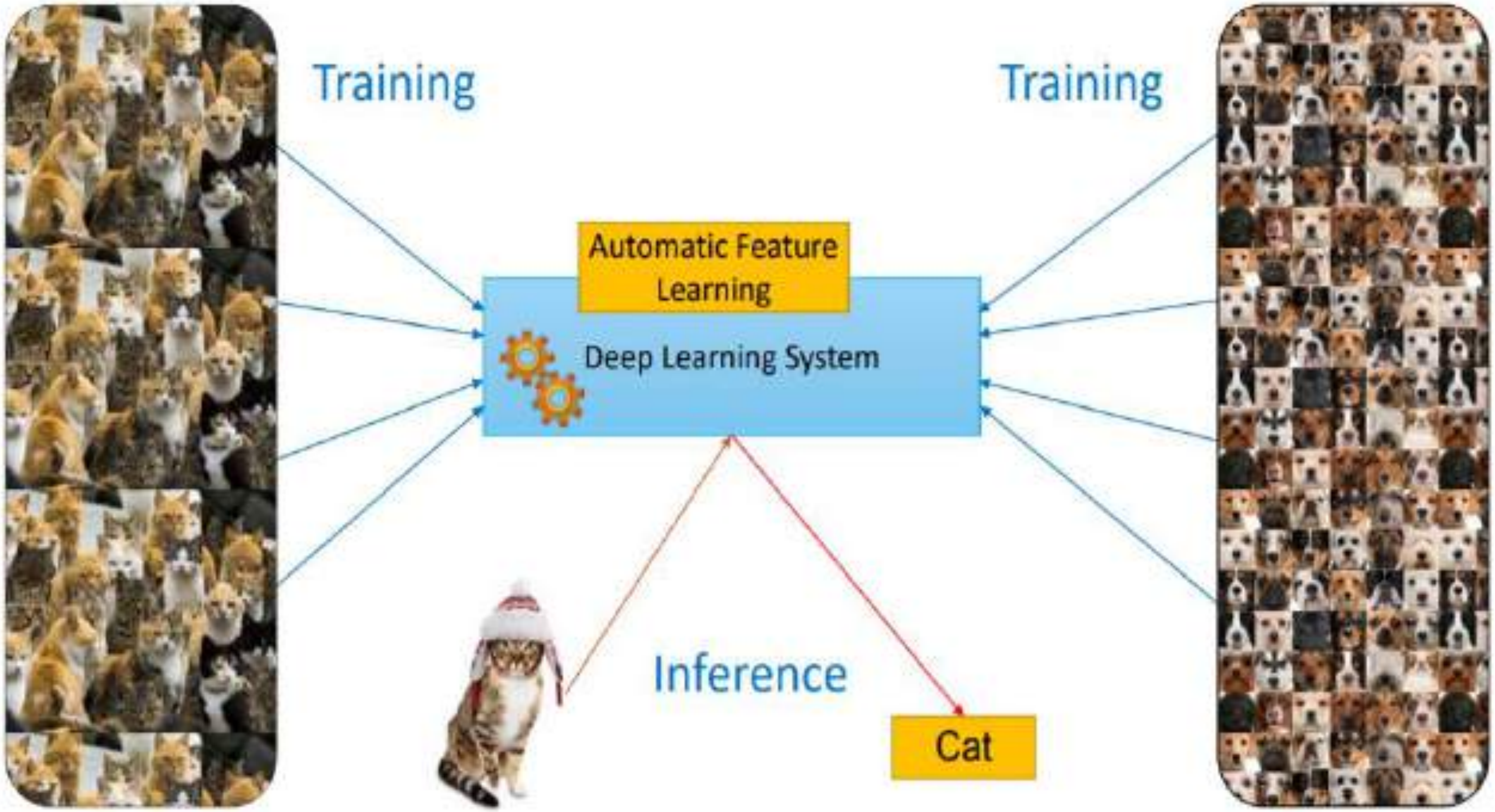
- Hand engineered features
  - time consuming, brittle, and not scalable in practice
- Can we learn the **underlying features** directly from data?



Typical ML Flow



Deep Learning: train layers of features so that classifier works well.


Training
Training
Automatic Feature Learning
Deep Learning System
Inference
Cat

The Rise of Deep Learning

https://www.youtube.com/watch?v=gLoI9hAX9dw&t=92s

https://www.youtube.com/watch?v=fa5QGremQf8

https://www.youtube.com/watch?v=_sBBaNYex3E

https://www.youtube.com/watch?v=SsWm0m7K30U

Why Now?

- Neural Networks date back decades, so why the resurgence?

1952 Stochastic Gradient Descent

1958 Perceptron
- Learnable Weights

⋮

1986 Backpropagation
- Multi-Layer Perceptron

1995 Deep Convolutional NN
- Digit Recognition

⋮

1. Big Data

- Larger Datasets
- Easier Collection & Storage

IMAGENET

WIKIPEDIA
The Free Encyclopedia

2. Hardware

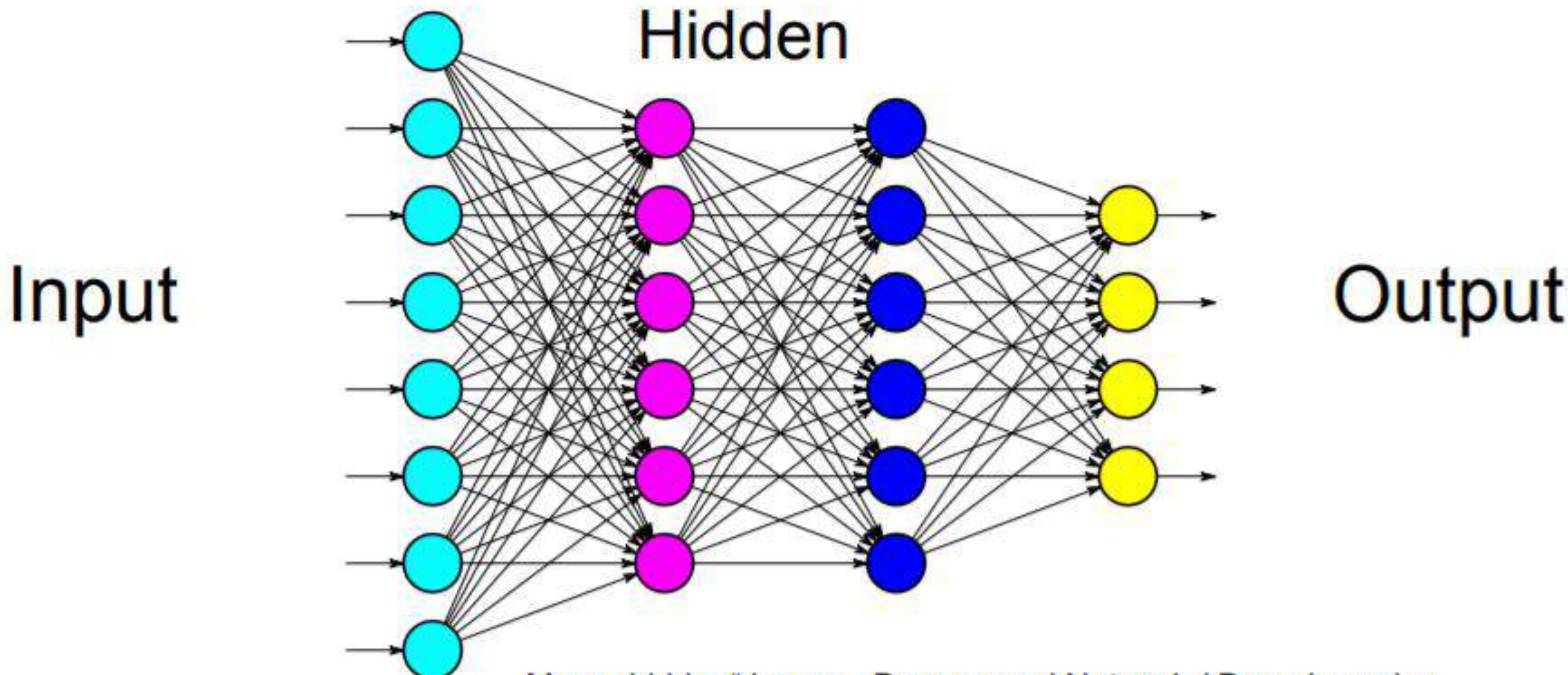
- Graphics Processing Units (GPUs)
- Massively Parallelizable

3. Software

- Improved Techniques
- New Models
- Toolboxes

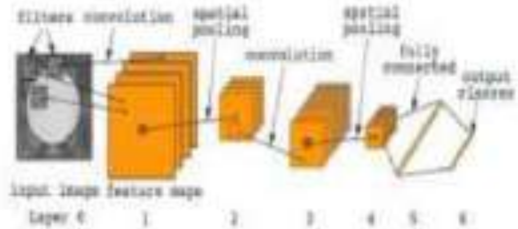
TensorFlow

Neural Network



Many „hidden“ Layer = Deep neural Network / Deep Learning

LeNet : Tensorflow vs. Keras



```
# The model
stride = 1  # output is 28x28
Y1 = tf.nn.relu(tf.nn.conv2d(X, W1, strides=[1, stride, stride, 1], padding='SAME') + B1)
stride = 2  # output is 14x14
Y2 = tf.nn.relu(tf.nn.conv2d(Y1, W2, strides=[1, stride, stride, 1], padding='SAME') + B2)
stride = 2  # output is 7x7
Y3 = tf.nn.relu(tf.nn.conv2d(Y2, W3, strides=[1, stride, stride, 1], padding='SAME') + B3)

# reshape the output from the third convolution for the fully connected layer
YY = tf.reshape(Y3, shape=[-1, 7 * 7 * M])

Y4 = tf.nn.relu(tf.matmul(YY, W4) + B4)
YY4 = tf.nn.dropout(Y4, pkeep)
Ylogits = tf.matmul(YY4, W5) + B5
Y = tf.nn.softmax(Ylogits)

# cross-entropy loss function (= -sum(Y_i * log(Yi)) ), normalised for batches of 100  images
# TensorFlow provides the softmax_cross_entropy_with_logits function to avoid numerical stability
# problems with log(0) which is NaN
cross_entropy = tf.nn.softmax_cross_entropy_with_logits(logits=Ylogits, labels=Y_)
cross_entropy = tf.reduce_mean(cross_entropy)*100

# accuracy of the trained model, between 0 (worst) and 1 (best)
correct_prediction = tf.equal(tf.argmax(Y, 1), tf.argmax(Y_, 1))
accuracy = tf.reduce_mean(tf.cast(correct_prediction, tf.float32))

# training step, the learning rate is a placeholder
train_step = tf.train.AdamOptimizer(lr).minimize(cross_entropy)

# init
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init)
```

Tensorflow

```
model = Sequential()
model.add(Conv2D(32, kernel_size=(3, 3),
                 activation='relu',
                 input_shape=input_shape))
model.add(Conv2D(64, (3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.25))
model.add(Flatten())
model.add(Dense(128, activation='relu'))
model.add(Dropout(0.5))
model.add(Dense(num_classes, activation='softmax'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

model.fit(x_train, y_train,
          batch_size=batch_size,
          epochs=epochs,
          verbose=1,
          validation_data=(x_test, y_test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

Keras

Keras Model Life-Cycle

1. Define Network
2. Compile Network
3. Fit Network
4. Evaluate Network
5. Make Predictions

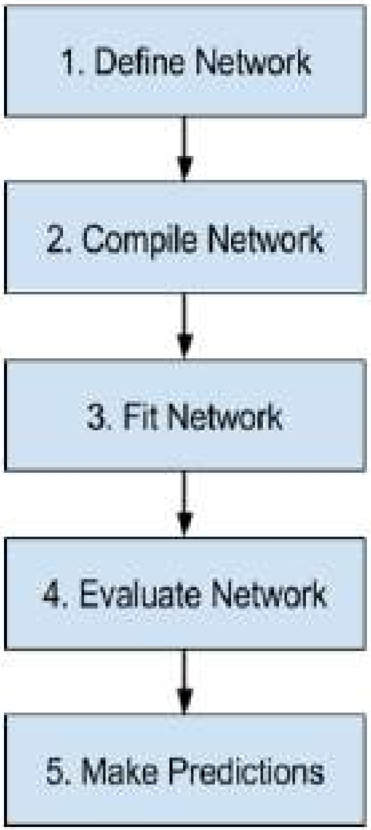
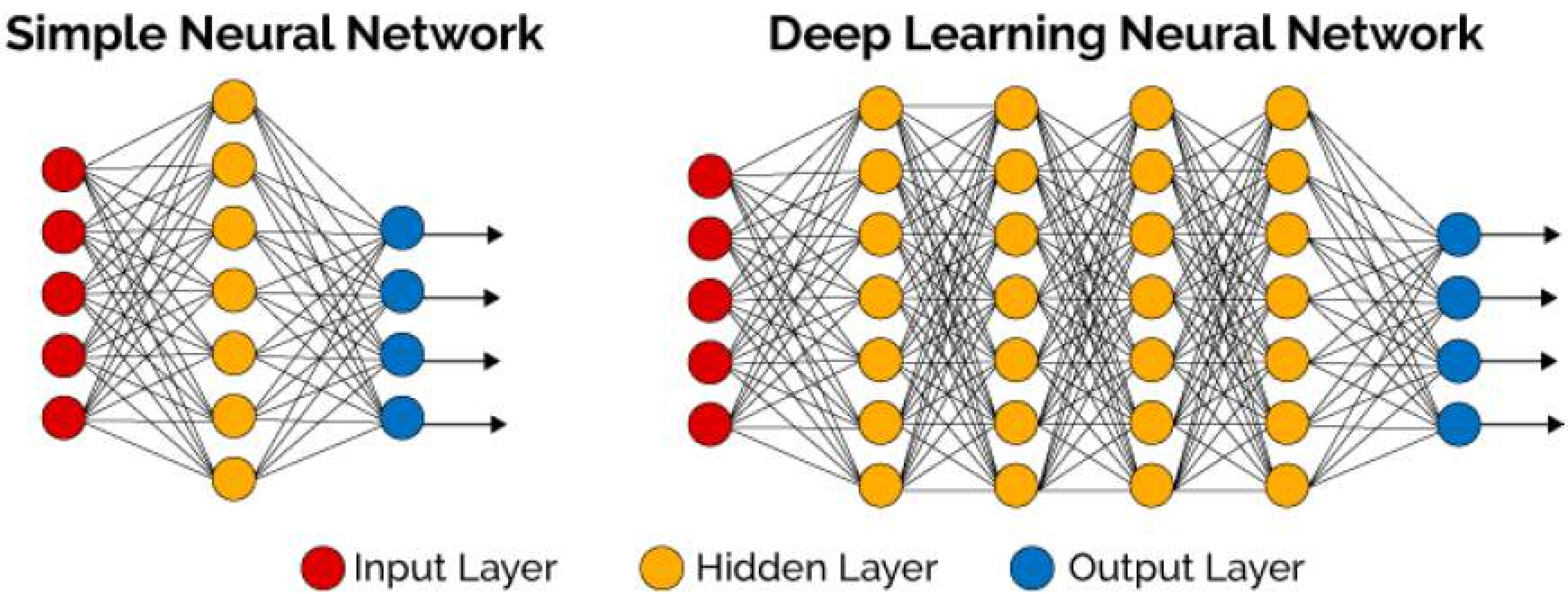


Figure 4.1: 5 Step Life-Cycle for Neural Network Models in Keras.

Combing Neurons in Hidden Layers:
The "Emergent" Power to Approximate



ML in Agriculture

sensors

MDPI

Review

Machine Learning in Agriculture: A Review

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Abstract: Machine learning has emerged with big data technologies and high-performance computing to create new opportunities for data intensive science in the multi-disciplinary agri-technologies domain. In this paper, we present a comprehensive review of research dedicated to applications of machine learning in agricultural production systems. The works analyzed were categorized in (a) crop management, including applications on yield prediction, disease detection, weed detection crop quality, and species recognition; (b) livestock management, including applications on animal welfare and livestock production; (c) water management; and (d) soil management. The filtering and classification of the presented articles demonstrate how agriculture will benefit from machine learning technologies. By applying machine learning to sensor data, farm management systems are evolving into real time artificial intelligence enabled programs that provide rich recommendations and insights for farmer decision support and action.

Keywords: crop management; water management; soil management; livestock management; artificial intelligence; planning; precision agriculture

ML in Agriculture

1. **Crop management**
   a. Crop Yield Prediction
   b. Disease detection
   c. Weed detection
   d. Crop quality
   e. Species recognition
2. **Livestock management**
   a. Animal welfare
   b. Livestock production
3. **Water management**
4. **Soil management**

Application of ML for Crop Yield Prediction

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Crop yield prediction using machine learning: A systematic literature review

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A R T I C L E I N F O

Keywords:
Crop yield prediction
Decision support system
Systematic literature review
Machine learning
Deep learning

A B S T R A C T

Machine learning is an important decision support tool for crop yield prediction, including supporting decisions on what crops to grow and what to do during the growing season of the crops. Several machine learning algorithms have been applied to support crop yield prediction research. In this study, we performed a Systematic Literature Review (SLR) to extract and synthesize the algorithms and features that have been used in crop yield prediction studies. Based on our search criteria, we retrieved 567 relevant studies from six electronic databases, of which we have selected 50 studies for further analysis using inclusion and exclusion criteria. We investigated these selected studies carefully, analyzed the methods and features used, and provided suggestions for further research. According to our analysis, the most used features are temperature, rainfall, and soil type, and the most applied algorithm is Artificial Neural Networks in these models. After this observation based on the analysis of machine learning-based 50 papers, we performed an additional search in electronic databases to identify deep learning-based studies, reached 30 deep learning-based papers, and extracted the applied deep learning algorithms. According to this additional analysis, Convolutional Neural Networks (CNN) is the most widely used deep learning algorithm in these studies, and the other widely used deep learning algorithms are Long-Short Term Memory (LSTM) and Deep Neural Networks (DNN).

Application of DL in Agriculture

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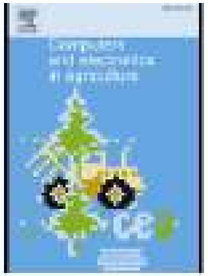

Review

Deep learning in agriculture: A survey

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ABSTRACT

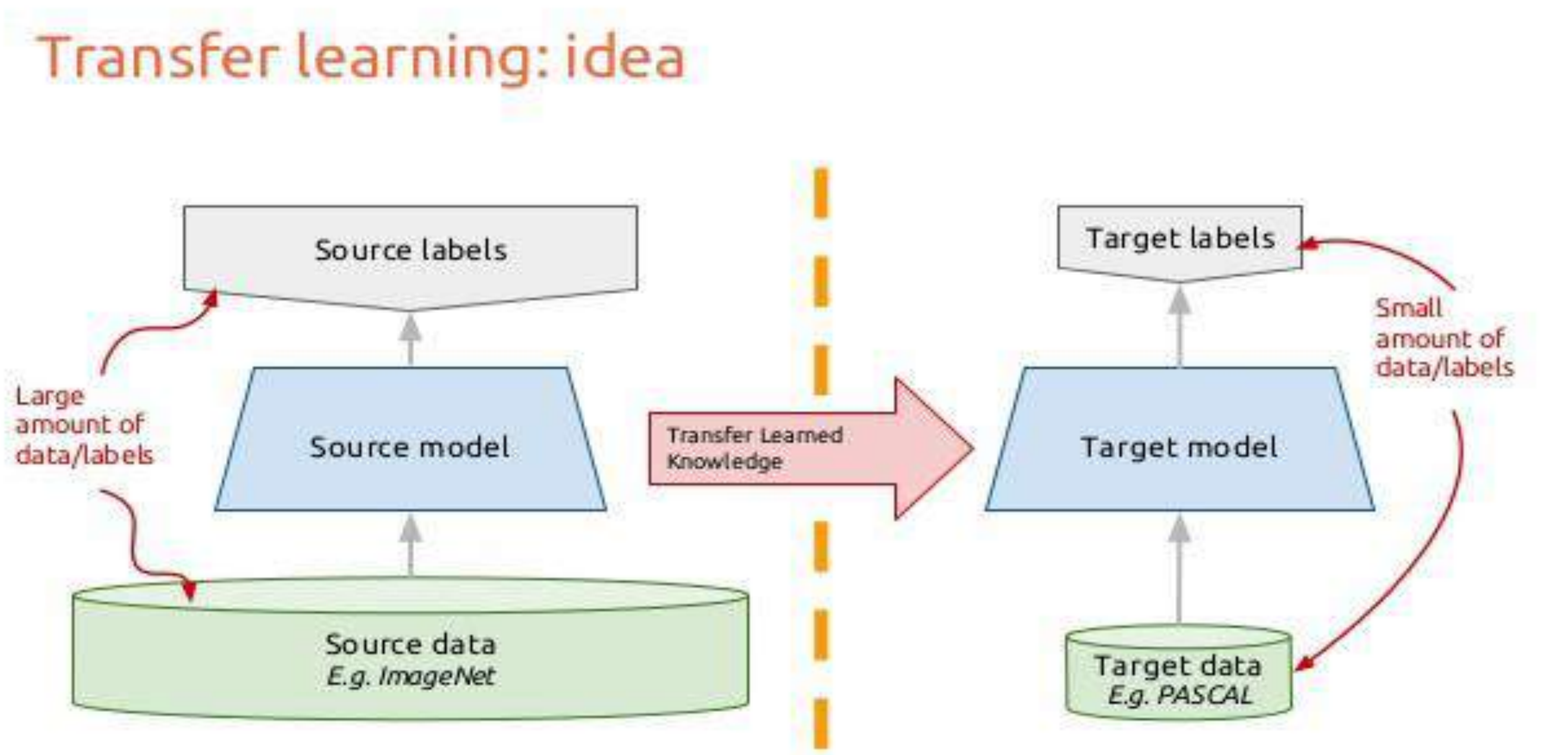
Deep learning constitutes a recent, modern technique for image processing and data analysis, with promising results and large potential. As deep learning has been successfully applied in various domains, it has recently entered also the domain of agriculture. In this paper, we perform a survey of 40 research efforts that employ deep learning techniques, applied to various agricultural and food production challenges. We examine the particular agricultural problems under study, the specific models and frameworks employed, the sources, nature and pre-processing of data used, and the overall performance achieved according to the metrics used at each work under study. Moreover, we study comparisons of deep learning with other existing popular techniques, in respect to differences in classification or regression performance. Our findings indicate that deep learning provides high accuracy, outperforming existing commonly used image processing techniques.

Application of DL in Agriculture

1. Leaf classification
2. Leaf disease detection
3. Plant disease detection
4. Land cover classification
5. Crop type classification
6. Plant recognition
7. Plant phenology recognition
8. Segmentation of root and soil
9. Crop yield estimation
10. Fruit counting
11. Obstacle detection
12. Identification of weeds
13. Crop/weed detection and classification
14. Prediction of soil moisture content
15. Animal research
16. Weather prediction

How to Create and Train Deep Learning Models

1. Training from Scratch
2. **Transfer Learning**
3. Feature Extraction



Deep Learning Architectures

1. Deep Feed-Forward Neural Networks
2. Convolutional Neural Networks (CNN)
3. Recurrent Neural Networks (RNN)
   - LSTM
   - Bi-LSTM
4. Generative Adversarial Networks (GAN)
5. Autoencoders
6. Deep Belief Networks (DBN)
7. Restricted Boltzmann Machines

https://arxiv.org/pdf/1905.13294.pdf