Deconstruction and perception theories in supervised learning

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Abstract

The images have clear-cut things such as the composition, coloring, and modification of the picture, then defining what the picture is, its pixels, dimensions, and color technology used, moreover machine learning (ML) translates this into his full knowledge of sufficient information about the image and his recognition of it, but, what if the picture was a puzzle since 1892. Specifically, the rabbit and the duck was "Kaninchen und Ente" from the 23 October 1892 publication by the magazine Fliegende Blätter under a question entitled ("Which animals resemble each other the most?") with the words "rabbit and duck" written underneath[1]. It will take - crucially - to dismantle the science of machine learning, the sub-section of artificial intelligence that is the broader gateway to the deep learning process to solve the mystery of the Rabbit-Duck Illusion [2].

Keywords: Deconstruction; Machine Learning; Supervised Learning; Deep Learning; Neural Network; Data Mining; Theory of Perception; Visual Tricks; Visual Stimulus; Cross-domain Matching Correlation Analysis.

1. Introduction

In this paper, we will present CROSS-DOMAIN MATCHING CORRELATION ANALYSIS in addition to theory of perception, alongside the difference between deconstruction theory and perception theory comparison in future thinking through the image in four steps: (1) Labeled Data & Labels. Labeled data refers to data that has been tagged with one or more labels that identify specific properties or characteristics, classifications, or contained objects. Labels make that data more useful in certain types of machine learning setups known as supervised machine learning setups. Labels. In simple linear regression, a label is the thing we're predicting—the y variable. The label could be the future price of sugar, the type of animal depicted in a photograph Duck - rabbit, the meaning of an audio clip, or anything else. (2) Model Training: Learning (determining) good values for all of the weights and the bias from labelled examples is what training a model is all about. A machine learning algorithm builds a model in supervised learning by examining many examples and attempting to find a model that minimizes loss; this process is known as empirical risk minimization. (3) Prediction: refers to the output of an algorithm after it has been trained on a historical dataset and applied to new data in order to forecast the likelihood of a specific outcome. (4) Test data: The test dataset is a subset of the training dataset that is used to evaluate a final model objectively. There are additional methods for computing an unbiased, or increasingly biased, assessment of model skill on unknown data in the context of the validation dataset.

Reconstructing deconstructing models

How to disassemble machine learning is, on the other hand, how to disassemble the image inside the learning machine, as the image is nothing but squares of pixels, alongside the squares are from the family of the diagram, and the diagram is from the family of mathematics, moreover mathematics means that there are numbers, and the numbers are data that express the matrix of the image in vector the end.

Deconstruction Theory in ML Computer Science is an unbounded body of thinking and language within data science. Certainly, the nature of language and the logic of language in a machine does not possess full awareness, but rather has an almost complete awareness as long as one remains skeptical; skepticism is a conscious assumption. As for the machine's thought, which is very limited to the logic of the nature of the language used, it is similar to the image that is formed through colors, just as the machine is formed through codes. What the machine makes in various and varied fields does not limit the language as much as it limits the machine’s use of itself. The question here is: when are the codes merged into one machine infinitely and indefinitely, then the problem will lie in the language, and if the libraries, commands, dictionaries, and functions of the language expand. Can you talk to the machine instead of just commanding it?

The totality of modern assumptions forces each machine to perform only two actions, the principle of reward and punishment, with the adaptation of the machine to the uses of the modern world, but what about the machine?

Could it be infinite? If we break down what it consists of, which is unlimited, we will know that the components of machine learning are unlimited. The limits of machine thinking are still the limits of the language used. The limits of the language used come from a deficiency in the branching of the language itself, despite its derivation from other languages. For example, Python's relationship to the machine is programmatic, though influenced by and Influenced in many languages.

The codes in the language are like screwing the machine within the limits of the machine language commands. And all of this will be formulated through a CROSS-DOMAIN MATCHING CORRELATION ANALYSIS of an image of a rabbit or a duck, in addition to we will attach it to a comprehensive analysis of the theory of machine perception to analyze every piece of information related to the features of the image from the first step of similarity until the separation between rabbits and ducks, but the dilemma is a human, psychological and philosophical as one sees a rabbit or a duck first and then decides Which one is closest to his perspective intellectual? Does this affect the biological, social, and psychological aspects? For example. In Switzerland, people, young and old, tended to see a rabbit during Easter, but when they recurred the experiment in October, they saw a duck [3]

We shall employ distinct strategies to identify the steps of machine learning in the possibility of choosing the object that the machine sees with the mirror of data, not with the eyes of human choices.

The ideas of constructivism and constructivist learning dominate modern education [4] At the heart of non-deconstruction is this approach based on the assumption that human beings actively and individually acquire knowledge and competencies through processes called construction, reconstruction, and deconstruction. [5]

Labeled Data & Labels, Model Training, Prediction, Test data. All that has just been mentioned are the tools for the deconstruction of the theory itself and at the same time they are the building blocks for the deconstruction theory.

The image as a model and the model as two images

Duck head or rabbit head? Fig.1.

The orbit of philosophical and psychological research, and it's time to be a technological research orbit.

How will you understand this picture if it is surrounded by pictures of ducks that a duck will see.

And how would you see it if there were other pictures of rabbits that you would see?

See the thing as [6].

We, as humans, do not see one side, either a rabbit or a duck. Being able to see this image as a single unit is definitely not within the capabilities of humans.

New image called Rabbit Duck. Try to change her name. Try to change your point of view.

Whatever your reaction, you are the one who changed and the image remained the same! [6]

Neither the duck, nor the hare, nor the bunny-duck, nor the duck-hare will be able to comprehensively describe the picture on a micro or macro level.

Hence the machine vision of the thing was put forward.

Fig.1. Duck or Rabbit "Kaninchen und Ente" from the 23 October 1892 publication by the magazine Fliegende Blätter.

2. How to see the image by the machine

Machine vision of an image consists of two things: training and prediction. There are two methods of training and prediction: The First. Fig.2. Attach a picture of a duck, then another picture of a rabbit,

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and then the main picture of a duck-rabbit. As for the second method Fig.3. One image includes a duck and a rabbit, and the visual intentionality in a rabbit or a duck recognizes them.

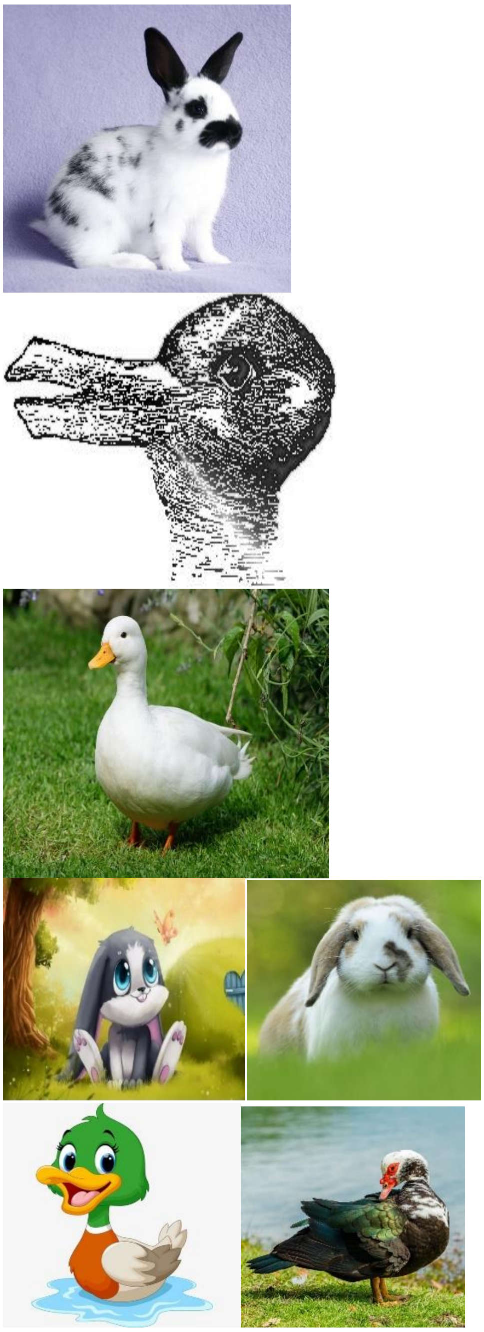

Fig.2. the first method Training and prediction on the main images, adding an animated rabbit and an animated duck, in addition to images of rabbits and ducks.

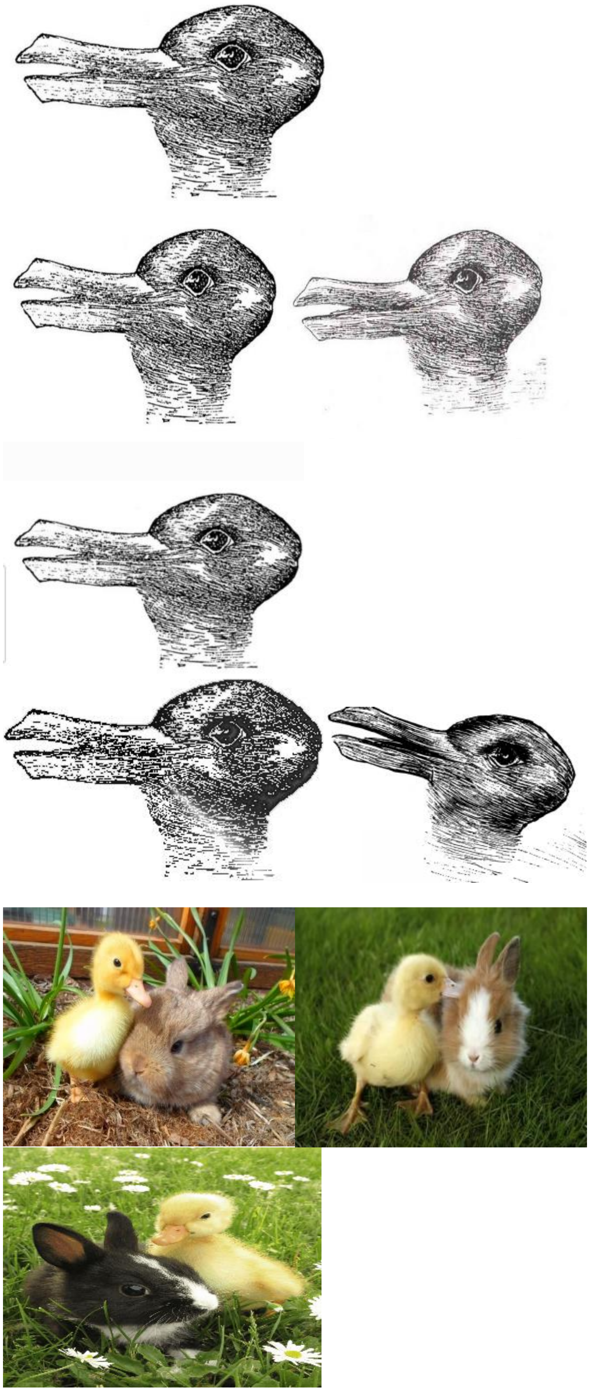

Fig.3. the second method: One picture contains a duck and a rabbit together.

Result 1 (Test and Score)

In the first method order to reach the results were used supervised learning, also known as supervised machine learning, is a machine learning and artificial

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intelligence subcategory. It is distinguished by the use of labeled datasets to train algorithms that accurately classify data or predict outcomes.

K- Nearest neighbor algorithm Steps to implement the K-NN algorithm: 1-Data Pre-processing step. 2-Fitting the K-NN algorithm to the Training set. 3-Predicting the test result. 4-Test accuracy of the result (Creation of Confusion matrix) 5-Visualizing the test set result. In addition to Trees parameters steps: 1-Induce binary tree. 2-Min.several instances in leaves. 3-Do not split subsets smaller than. 4-Limit the maximal tree depth and logistic Regression steps in Logistic Regression: To implement Logistic Regression in Python. The steps are as follows: 1-Data Pre-processing steps 2-Fitting Logistic Regression to the Training set 3-Predicting the test result. 4-Test accuracy of the result (Creation of Confusion matrix) 5-Visualizing the test set result. Table 1 showed the test and score.

Table1
Method 1

Model	AUC	CA	F1	Precision	Recall
KNN	0.966	0.872	0.869	0.888	0.872
Tree	0.801	0.769	0.760	0.765	0.769
Logistic Regression	0.951	0.923	0.922	0.922	0.923

Show average over classes (Duck- rabbit, Ducks, Rabbits)

In the confusion matrix Number of instances:

A- Logistic Regression. (L)
B- Tree. (T)
C- KNN. (K)

A. (L)

Predicted

Actual	Duck-Rabbits	Ducks	Rabbits	Σ
Duck-Rabbits	11	0	0	١١
Ducks	0	7	2	٩
Rabbits	0	1	18	١٩
Σ	١١	٨	٢٠	٣٩

B. (T)

Predicted

Actual	Duck-Rabbits	Ducks	Rabbits	Σ
Duck-Rabbits	10	0	1	١١
Ducks	0	4	5	٩
Rabbits	1	2	16	١٩
Σ	١١	٦	٢٢	٣٩

C. (K)

Predicted

Actual	Duck-Rabbits	Ducks	Rabbits	Σ
Duck-Rabbits	11	0	0	١١
Ducks	1	6	2	٩
Rabbits	2	0	17	١٩
Σ	١٤	٦	١٩	٣٩

In confusion matrix proportion of predicted:

A. (L)

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Actual \ Predicted	Duck-Rabbits	Ducks	Rabbits
Duck-Rabbits	100.0 %	0.0 %	0.0 %
Ducks	0.0 %	87.5 %	10.0 %
Rabbits	0.0 %	12.5 %	90.0 %
Σ	١١	٨	٢٠

١

B. (T)

Actual \ Predicted	Duck-Rabbits	Ducks	Rabbits
Duck-Rabbits	90.9 %	0.0 %	4.5 %
Ducks	0.0 %	66.7 %	22.7 %
Rabbits	9.1 %	33.3 %	72.7 %
Σ	١١	٦	٢٢

C. (K)

Actual \ Predicted	Duck-Rabbits	Ducks	Rabbits
Duck-Rabbits	78.6 %	0.0 %	0.0 %
Ducks	7.1 %	100.0 %	10.5 %
Rabbits	14.3 %	0.0 %	89.5 %
Σ	١٤	٦	١٩

Note: It should be noted that the results of Logistic Regression and the tree obtained a percentage of greater than 90%, whereas the result of the kNN algorithm is low for them. This was also considered in the order of the results, as shown in the preceding tables.

The best way to predict the image of a Duck-Rabbits is Logistic Regression, then KNN, then Tree. Most of the misclassified in prediction are inherent in the tree algorithm then KNN. The less misclassified it is Logistic Regression. Finally, Comprehensive display of misclassified.

Logistic regression misclassified ducks, and two images were chosen as rabbits.

Logistic regression misclassified Rabbits, and one image was chosen as Ducks.

Tree misclassified Duck-Rabbits, and one image was chosen as a Rabbit.

Tree misclassified Ducks, and five images were chosen as Rabbits.

Tree misclassified Rabbits, and one image was chosen as Duck-Rabbits.

Tree misclassified Rabbits, and two images were chosen as Ducks.

KNN misclassified Ducks, and one image was chosen as Duck-Rabbits.

KNN misclassified Ducks, and two images were chosen as Rabbits.

KNN misclassified Rabbits, and two images were chosen as Duck-Rabbits.

Note: - The most frequently misclassified image is this one, which was taken with the eyes of rabbits in the logistic regression and with the eyes of rabbits in the tree, as well as Duck- Rabbits in kNN. Fig.4.

Fig.4. Duck animation image

Receiver operating characteristic

ROC analysis investigates and employs the relationship between a binary classifier's sensitivity and specificity. The proportion of positives correctly classified is measured by sensitivity; the proportion of negatives correctly classified is measured by specificity. The true positive rate TPR is traditionally plotted against the false positive rate FPR, which is one minus the true negative rate. If a classifier produces a score proportional to its belief that an instance belongs to the positive class, lowering the decision threshold - the threshold above which an instance is deemed to belong to the positive class - increases both true and false positive rates. When the decision threshold is changed from its maximum to its minimum value, a piecewise linear curve from (0,

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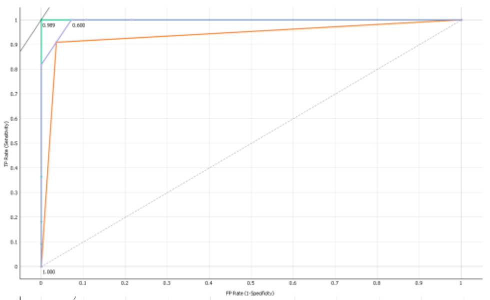
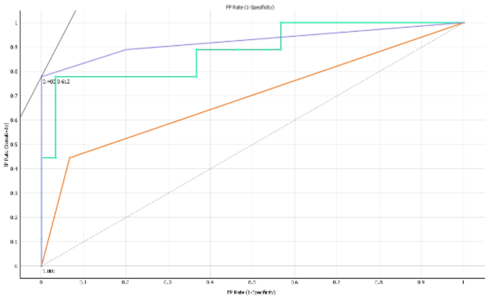
0) to (1, 1) is formed, with each segment having a non-negative slope. The ROC curve is the primary tool in ROC analysis. It can be used to solve a variety of issues.

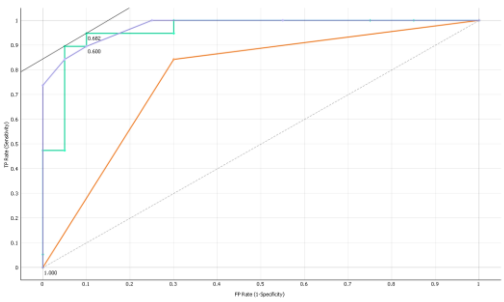
1- Logistic Regression.
2- Tree
3- KNN

Duck- Rabbit: **Ducks:**





Rabbits:



Result 2 (Test and Score)

In the second method order to reach the results were used the same way in the first method with the difference of training to memorize and predict the given images. The images were merged very sensitively. The single image contains a rabbit and a duck together, and the original image is as it is. Table 2 showed test and score.

Table 2
Method 2

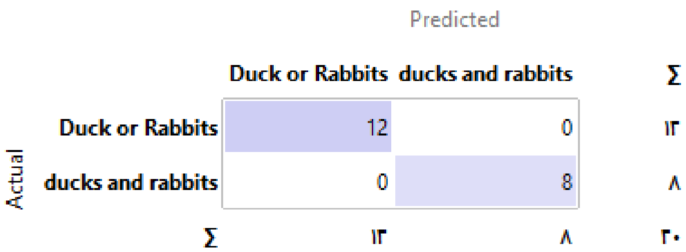
Model	AUC	CA	F1	Precision	Recall
KNN	1.000	1.000	1.000	1.000	1.000
Tree	0.917	0.900	0.901	0.920	0.900
Logistic Regression	1.000	1.000	1.000	1.000	1.000

Show average over classes (Duck or rabbits, Ducks and Rabbits)

In the confusion matrix Number of instances:

A- Logistic Regression. (L)
B- Tree. (T)
C- KNN. (K)

A. (L)



B. (T)

Predicted

Actual

	Duck or Rabbits	ducks and rabbits
Duck or Rabbits	10	2
ducks and rabbits	0	8
Σ	١٠	١٠

C. (K)

Predicted

Actual

	Duck or Rabbits	ducks and rabbits
Duck or Rabbits	12	0
ducks and rabbits	0	8
Σ	١٢	٨

In confusion matrix proportion of predicted:

A. (L)

Predicted

Actual

	Duck or Rabbits	ducks and rabbits	Σ
Duck or Rabbits	100.0 %	0.0 %	١٢
ducks and rabbits	0.0 %	100.0 %	٨
Σ	١٢	٨	٢٠

B. (T)

Predicted

Actual

	Duck or Rabbits	ducks and rabbits	Σ
Duck or Rabbits	100.0 %	20.0 %	١٢
ducks and rabbits	0.0 %	80.0 %	٨
Σ	١٠	١٠	٢٠

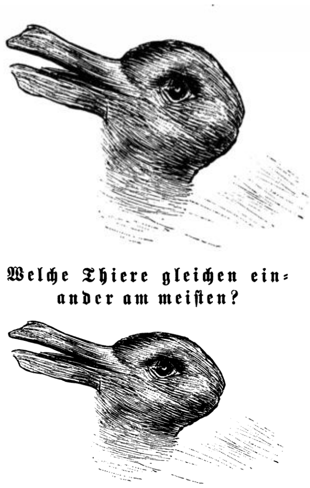
C. (K)

Predicted

Actual

	Duck or Rabbits	ducks and rabbits	Σ
Duck or Rabbits	100.0 %	0.0 %	١٢
ducks and rabbits	0.0 %	100.0 %	٨
Σ	١٢	٨	٢٠

Note: Logistic Regression equals KNN, Furthermore, they have the same percentage and are error-free. Concerning tree errors, we will attach two images in which the machine failed to predict what is expected and what is not expected.



Kaninchen und Ente.

Tree misclassified Duck or Rabbits, and two images were chosen as Ducks and rabbits.

Note: The duck in the previous two images has its beak to the left, and the difference between them is the writing in German on one of them.

Receiver operating characteristic

ROC analysis. Following Logistic Regression = KNN, we place each ROC on its own.

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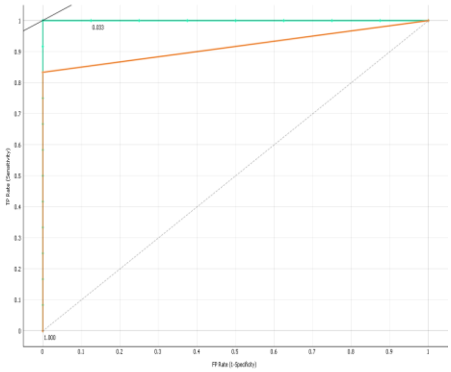
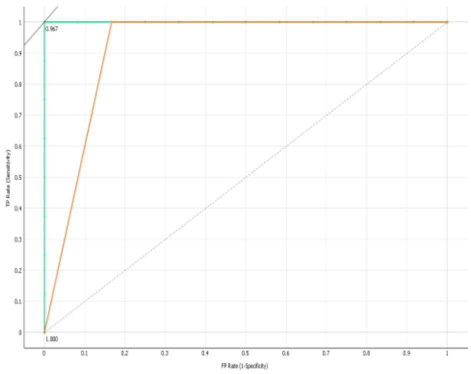
1- Logistic Regression.
2- Tree
3- KNN

Without KNN.

Duck or Rabbits

Ducks and Rabbits

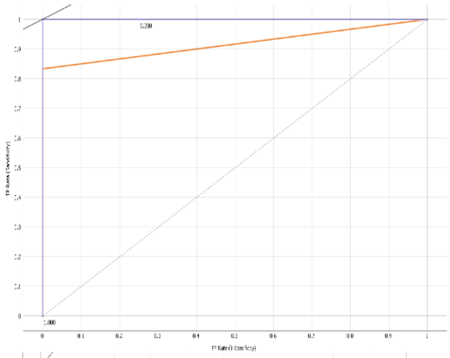


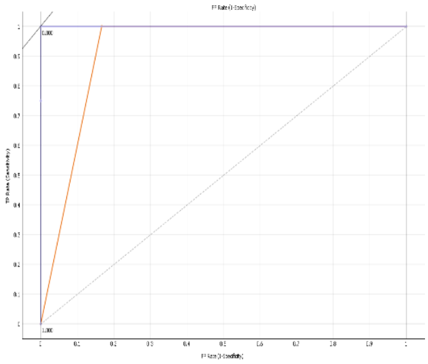


Without Logistic Regression.

Duck or Rabbits

Ducks and Rabbits





Deconstruction theory

Predictability (Predictions) is defined as the ability to anticipate, analyses, deconstruct, and build. After that 4 Machine learning analysis steps into topics: 1- Labeled Data & Labels. 2- Model Training. 3- Prediction. 4- Test data. Then Disassembly building. Fig.5.

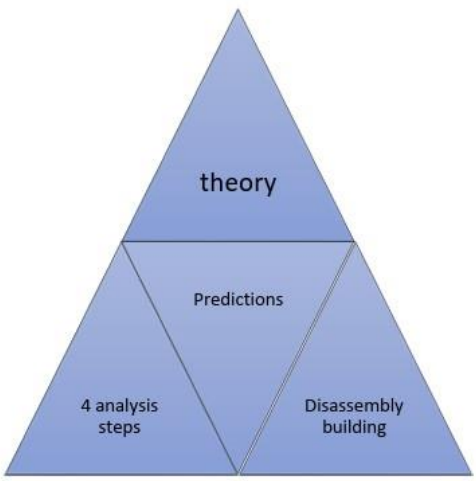


Fig.5. The pyramid shape illustrates the deconstruction theory.

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Predictions in the first method:

Tree	KNN	Logistic Regression
Rabbits	Rabbits	Rabbits
Rabbits	Rabbits	Ducks
Rabbits	Rabbits	Rabbits

Predictions in the second method:

KNN	Tree	Logistic Regression
Duck or Rabbits	Duck or Rabbits	Duck or Rabbits
Duck or Rabbits	Duck or Rabbits	Duck or Rabbits
Duck or Rabbits	Duck or Rabbits	Duck or Rabbits
Duck or Rabbits	Duck or Rabbits	Duck or Rabbits
Duck or Rabbits	Duck or Rabbits	Duck or Rabbits
Duck or Rabbits	Duck or Rabbits	Duck or Rabbits
Duck or Rabbits	Duck or Rabbits	Duck or Rabbits

In The First Method:

In anticipation, prediction, analysis, disassembly and construction were done. The First predict the required data in the form of a rabbit or a duck distributed by the algorithm. The Second: Analysis Each row was analyzed on the basis of the best method of the algorithm itself and how to read the prediction of a duck or a rabbit analysis. Except for logistic Regression in the First method the prediction appeared as a duck. The Third Disassembly: In the first method, the image of a rabbit or a duck is decomposed into a rabbit alone and a duck alone. Finally, Construction: Based on the required training data in the single image, which is an expression of two separate images, the rabbit was built alone and the duck alone, despite the presence of a rabbit or duck image.

In The Second Method:

Prediction=analysis=disassembly=construction=Duck or Rabbits

The predictions are any data in algorithm = same data in the other algorithm.

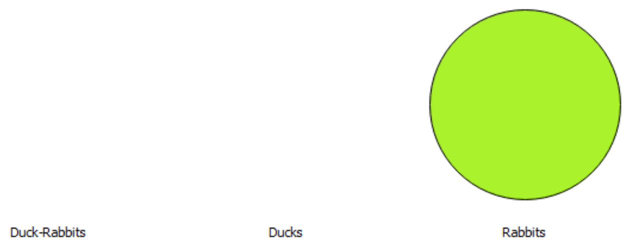
Examples: KNN/ Rabbits = Tree /Rabbits.

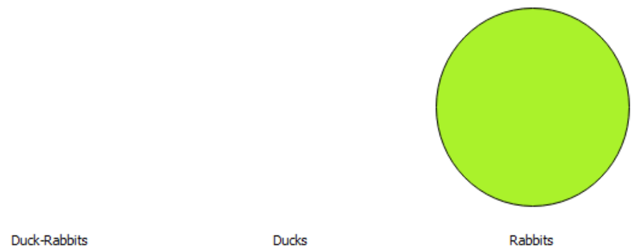
Logistic Regression / Duck or Rabbits = KNN / Duck or Rabbits.

KNN / Rabbits = Tree / Rabbits = Logistic Regression / Rabbits.

The First Method's prediction pie chart:

A. Duck-Rabbits
B. Ducks
C. Rabbits





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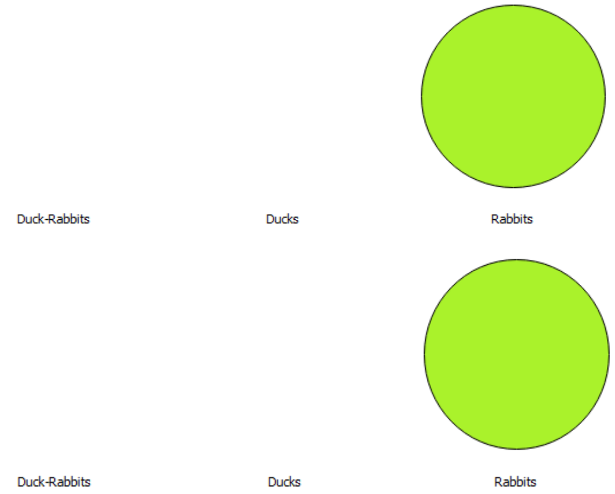
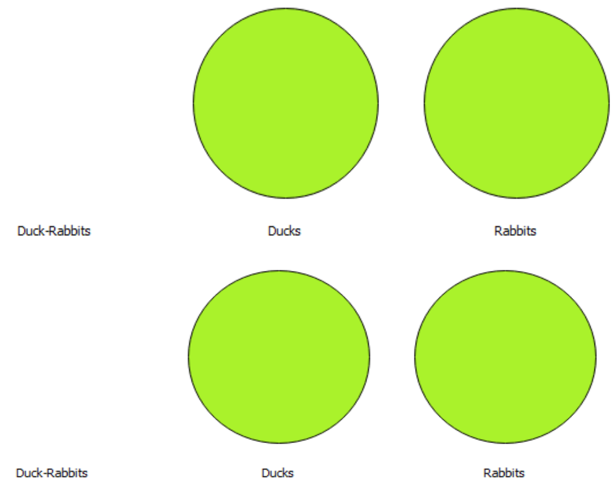
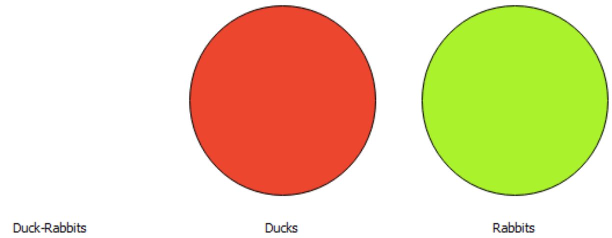


KNN = Split by tree = Tree = Split by KNN = Rabbits

KNN = Split by KNN = Tree = Split by Tree = Rabbits



KNN = Split by Logistic Regression = Tree = Split by Logistic Regression = Ducks = Rabbits



Logistic Regression ≠ Split by Logistic Regression

Ducks ≠ Rabbits

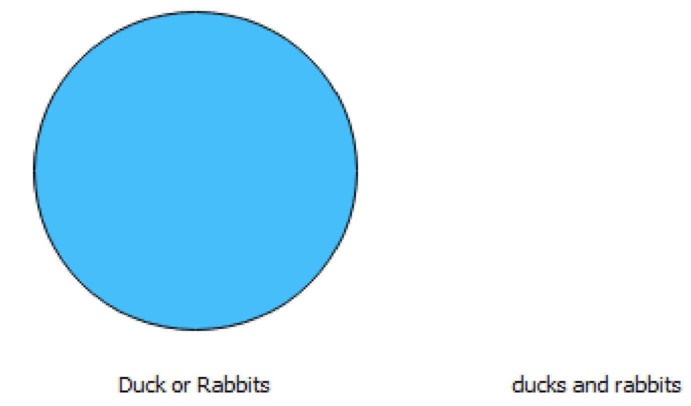
Logistic Regression = Split by Logistic Regression

Logistic Regression = Split by Tree

The Second Method's prediction pie chart:

A. Duck or Rabbits
B. Ducks and Rabbits

KNN = Tree = Logistic Regression = split by three algorithm



Four Supervised Steps:

1- Labeled Data & Labels:

The optical illusion is a rabbit or a duck: it is named after both rabbits and ducks, despite the fact that the original image, as well as copies of the original image, are saved in the journal. In the first method, image training was only possible by separating the rabbits and ducks, whereas the second method combined the images of each rabbit and duck in the same visual frame. Except for separating the rabbits from the ducks, classifying the image as a rabbit or a duck was successful in more than one algorithm. So the only difference between the classification and the label was the method of prediction. They have a directly proportional relationship. The higher the label, the higher the rating. As well as vice versa

2- Model Training:

Changes in the image itself have been affected by uncertainty after a training paradigm, as described in detail in Technological Theory of Perception (page 25 in this paper), but there is an attempt to find the best ways as well. So if it was just a duck, then there would be no rabbit, or if it was just a rabbit, then there would be no duck. Instead, both in the duck-Rabbit field. Likewise, since the situation was a duck or rabbits/ducks and rabbits, the specific results were different and the images were fewer in the second method. As a result, two animals image training is accelerated by just one frame.

3- Prediction:

The expectations of the three algorithms are the broadest and most comprehensive search orbit throughout the previous pages based on unexpected and expected results together. Whether in algorithms or data analysis trained to make the best possible prediction by predicting the incoming probabilities.

4- Test data:

The test dataset of a rabbit or duck is a subset of the training dataset that is used to objectively evaluate the final model. An additional method was to calculate a very incrementally biased assessment of model skill on unknown data in the context of the validation dataset. The table is on page 18. As well as testing rabbits... ducks... each separately, ignoring the rabbits and ducks in method one. As for the second method, it ignored ducks and rabbits, predicting a duck or rabbits.

Disassembly building Fig.6.

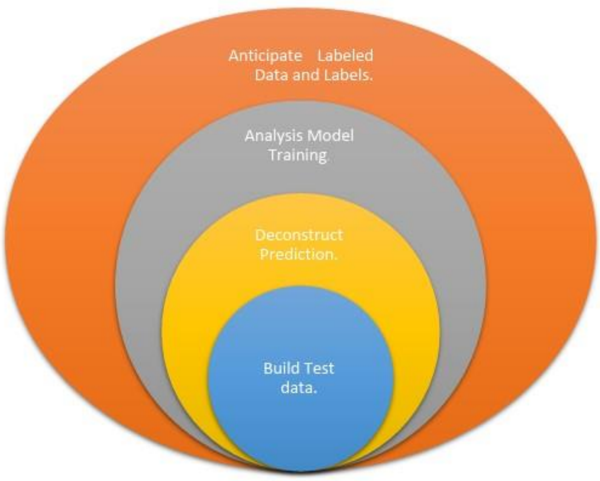


Fig.6.Analysis Steps:

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Anticipate Labeled Data and Labels: - Selection.

Analysis Model Training: - Expected results.

Deconstruct Prediction: - Build the right choice.

Build Test data: - Access to parse the data.

Deconstruction theory consists of four supervised analysis steps that are integrated into predictions for the construction of a Disassembly building.

3. CROSS-DOMAIN MATCHING CORRELATION ANALYSIS

Shimodaira's notation [7] is used to describe CDMCA here. Let D represent the number of domains (or views). When $D = 2$, CDMCA is reduced to CVGE. Assume we have sets of data vectors from multiple domains $d\,(= 1, \ldots, D)$ of varying dimensionality p_d, and that each domain has n_d data vectors $x_i^d \in R^{pd}, (i = 1, \ldots, n_d$. Furthermore, we are given the strength of relevance, which we refer to as the matching weight $w_{ij}^{de} \in R \geq o$ between two data vectors x_i^d, x_j^e from different d-th and e-th domains. For ex ample, in Flickr, if a certain tag has been added to a photo by some user, the photo will be tagged with that tag. If this tag and the photo match, the matching weight will be set to 1, otherwise it will be set to 0.

Linear projections are now available. By minimizing the objective function, $A^d \in R^{k \times p_d}, (\, d = 1, \ldots, D)$from each domain d to K-dimensional common space can be obtained.

$$\frac{1}{2}\sum_{\mathrm{d}=1}^{\mathrm{D}}\sum_{\mathrm{e}=1}^{\mathrm{D}}\sum_{\mathrm{i}=1}^{\mathrm{n_d}}\sum_{\mathrm{j}=1}^{\mathrm{n_e}} w_{ij}^{de}\left\|A^d x_i^d - A^e x_j^e\right\|_2^2 \quad (1)$$

Subject to the restriction described later in (2). We can estimate optimal projection matrices using CDMCA. $\hat{A}, \ldots, \hat{A}^D$ By solving an eigenvalue problem. We explain CDMA in detail in a simplified setting.
$D = 3,\ w_{ij}^{11} = w_{kl}^{22} = w_{mn}^{33} = 0, (\forall_i, j, k, l, m, n)$, This is also the case with our proposed method. In this case, the objective function (1) becomes

$$\sum_{i=1}^{n1}\sum_{j=1}^{n2} w_{ij}^{12}\left\|A^1 x_i^1 - A^2 x_j^2\right\|_2^2 + \sum_{j=1}^{n2}\sum_{k=1}^{n3} w_{jk}^{23}\left\|A^2 x_j^2 - A^3 x_k^3\right\|_2^2 + \sum_{i=1}^{n1}\sum_{k=1}^{n3} w_{ik}^{13}\left\|A^1 x_i^1 - A^3 x_k^3\right\|_2^2$$

for avoiding the trivial solution $\hat{A}^d = 0$ the optimization problem is solved with the constraint.

$$\sum_{d=1}^{a} A^d (X^d)^\top M^d x^d (A^d)^\top = I_k, \quad (2)$$

Where $x^d = (x_1^d \,.\,.\,. x_{n_d}^d)^\top \in R^{nd \times pd}(\, d = (1,2,3)$ are domain data matrices, and $M^d = \sum_{e \neq d} diag\,(W^{de} 1_{n_e})$ with $W^{de} = (W^{ed})^\top = (W_{ij}^{de}) \in R^{nd \times ne}(d, e = 1,2,3)$ are weighted matrices that match. Let us define two matrices, G and H, as follows:

$$G = \begin{pmatrix} G^1 & o & o \\ o & G^2 & o \\ o & o & G^3 \end{pmatrix}, H = \begin{pmatrix} o & H^{12} & H^{13} \\ H^{21} & o & H^{23} \\ H^{31} & H^{32} & o \end{pmatrix},$$

Where $G^d = (X^d)^\top M^d X^d$ and $H^{de} = (X^d)^\top W^{de} X^e$are submatrices for $d, e = 1,2,3.$ we will compute eigenvectors $u_1 \ldots, u_k$ of $(G^{-1/2})^\top HG^{-1/2}$ for the largest K eigenvalues. The optimal projections $\hat{A}^1, \hat{A}^2, \hat{A}^3$ are then obtained as

$$(\hat{A}^1\ \hat{A}^2\ \hat{A}^3)^\top = G^{-1/2}(u_1, \ldots, u_2)$$

3.1. PROJECTING IMAGES, TAGS AND GROUPS INTO A COMMON SPACE FOR BIDIRECTIONAL RETRIEVAL

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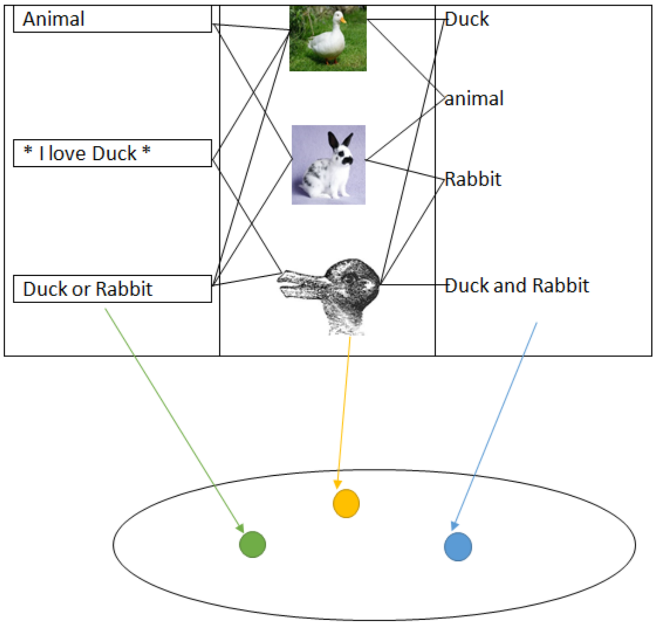
In this section, we describe our CDMA-based method for image retrieval and tag retrieval. The vectors of images, tags, and groups are projected into a common space in our proposed method by leveraging the information of image-tag and image-group relationships, as shown in Fig.7.

The image domain and the tag domain are denoted by I and T respectively. Data vectors for image-features are $x_i^1 \in R^{pi}(i = 1, \dots, n_1)$, and those for tag-features are as follows:$x_j^T \in R^{pT}(j = 1, \dots, n_T)$, Our goal here is to learn projection matrices$A^{\wedge I}, A^{\wedge T}$ which map x_i^I and x_j^T respectively, into a K-dimensional common space by$\hat{y}_i^I \coloneqq \hat{A}^I \hat{x}_i^T, \hat{y}_j^T \coloneqq \hat{A}^T \hat{x}_j^T \in R^K$.

In addition to the image and tag domains, Flickr offers a group domain for images, which is denoted by the letter G. Because photos from the same groups are likely to have similar labels [8], we anticipate that this additional domain for groups will improve retrieval performance. While existing cross-modal approaches based on the ordinary CCA can only deal with one-to-one relationships between images and tags$n_I = n_T, w_{ij} = o(i \neq j))$ when learning projections, our proposed method based on CDMCA can deal with many-to-many relationships between data vectors from multiple domains. Once we've learned the projection matrices, we can use them to project new data vectors into the common space where the relevant pairs of images and tags are close.



Group **Image**
Tag

Low- Dimensional Common Space

Fig.7. Been used CDM to project image, tag, and group data vectors into a low-dimensional common space, where related data vectors get closer together.

We ran some experiments with Flickr photos and tags. In our experimental setting, if an i-th image has a j-th tag, we set the matching weight $w_{ij}^{IT} = W_{ji}^{TI} =$ 1 and 0 if the i-th image lacks the j-th tag. Similarly, the matching weightw_{ik}^{IG} is 1 if an i-th image belongs to a k-th group, otherwise it is 0. It is important to note that our method does not take into account relationships between tags and groups, which means $w^{TG} = o$.

Finally, relevant image-tag pairs can be discovered by measuring the Euclidean distance between images and tags projected into the common space.

4. Theory of perception

The theory of perception in the deep learning specific neural network consists of a hierarchy that begins with the image of perception, then the image

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of feeling the image, and finally awareness of this image. Fig.8.

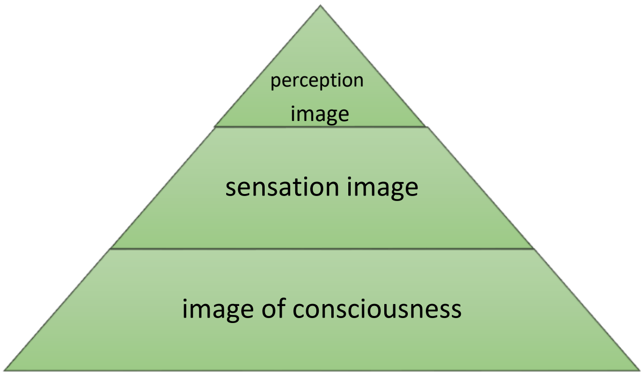

Fig.8. Perception theory through pyramid drawing

The process of technological perception is a process in machine learning that determines what the image is, what the image's borders are, and whether the image consists of more than one image, such as optical illusions, or not. This process is called perceptual validation.

Based on that, the following process of sensing the image takes place, such as the image of a rabbit or a duck. Was the image sensed in the prediction results as a rabbit-duck, or as a duck, or as a rabbit, or as a duck or Rabbits? Thus, perception is achieved by feeling the perception itself. This process is called prediction by the sense that perceives the possibilities of the image discussed by the scientific research.

This is followed by the digestive awareness of classifying the image in different places from the final choice of the fact of detailed depiction of the object in the image, for example: who is more deserving of the rabbit or the duck in the image. Therefore this process is the most comprehensive of the expected results.

Guessing steps:

Perception image: - recognition material.

Sensation image: - Feeling predictable.

Image of consciousness: - Likelihood of expected results.

A First Method:-

Table1

Model	AUC	CA	F1	Precision	Recall
Neural Network	0.960	0.872	0.873	0.879	0.872

Show average over classes (Duck- rabbit, Ducks, Rabbits)

A Second Method:-

Table2

Model	AUC	CA	F1	Precision	Recall
Neural Network	1.000	1.000	1.000	1.000	1.000

Show average over classes (Duck or rabbits, Ducks and Rabbits)

In the confusion matrix Number of instances:

D- Neural Network (N)

d. (N)

The First Method

Predicted

Actual	Duck-Rabbits	Ducks	Rabbits	Σ
Duck-Rabbits	11	0	0	١١
Ducks	1	7	1	٩
Rabbits	0	3	16	١٩
Σ	١٢	١٠	١٧	٣٩

In confusion matrix proportion of predicted:

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Predicted

		Duck-Rabbits	Ducks	Rabbits	Σ
Actual	Duck-Rabbits	91.7 %	0.0 %	0.0 %	١١
	Ducks	8.3 %	70.0 %	5.9 %	٩
	Rabbits	0.0 %	30.0 %	94.1 %	١٩
	Σ	١٣	١٠	١٧	٣٩

The Second Method:

Predicted

		Duck or Rabbits	ducks and rabbits	Σ
Actual	Duck or Rabbits	12	0	١٢
	ducks and rabbits	0	8	٨
	Σ	١٢	٨	٢٠

In confusion matrix proportion of predicted:

Predicted

		Duck or Rabbits	ducks and rabbits	Σ
Actual	Duck or Rabbits	100.0 %	0.0 %	١٢
	ducks and rabbits	0.0 %	100.0 %	٨
	Σ	١٢	٨	٢٠

Neural network misclassified ducks as Duck-Rabbits, another image were chosen as rabbits.

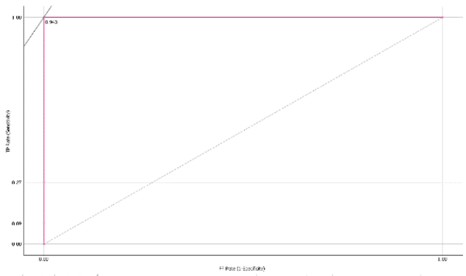
Note1: in the first method neural network misclassified nearest logistic regression misclassified.

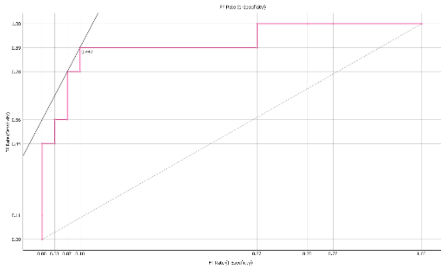
Note2: neural network method2 = logistic Regression method 2 = KNN method 2 = the best possible prediction

ROC analysis investigates in the first method

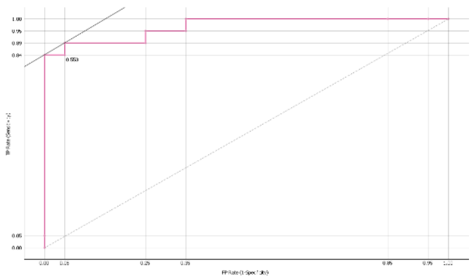
Duck- Rabbit:

Ducks:





Rabbits:



In the Second Method:

Duck or Rabbits **Ducks and Rabbits**

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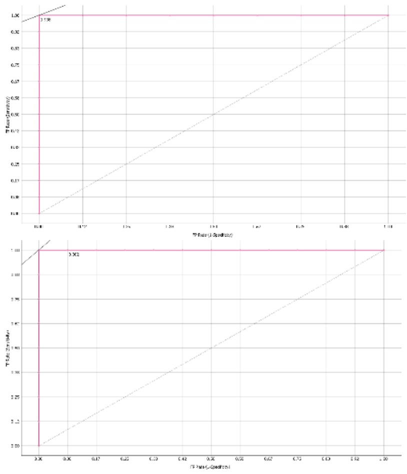

Theory of perception consists of Recognize the feeling of expecting results by Neural Network.

5. Discussion on two theories

Comparison of deconstruction theory and perception theory

Name	Deconstruction Theory.	Theory of perception.
Type	Mechanism theory.	Technological theory.
Properties	Analysis.	Guessing.
Reasons	1- Anticipate Labeled Data and Labels. 2- Analysis Model Training. 3- Deconstruct Prediction. 4- Build Test data.	1- Perception image. 2- Sensation image. 3- Image of consciousness.
Results	1- Selection. 2- Expected results. 3- Build the right choice. 4- Access to parse the data.	1- Recognition material. 2- Feeling predictable. 3- Likelihood of expected results.
Number of steps	Four.	Three.
Advantage	Used in machine learning.	Used in deep learning.
Disadvantage	Does not recognize the perceptual contents of the image.	Does not recognize the deconstructive contents of the image.

6. Conclusions

In this paper, theoretical foundations were laid based on two theories: deconstruction and perception. The first analyzes the machine learning and the second guesses the image that was placed in the deep learning. ALL OF THIS IS APPENDIX TO CROSS-DOMAIN MATCHING CORRELATION ANALYSIS AND PROJECTING IMAGES, TAGS AND GROUPS INTO A COMMON SPACE FOR BIDIRECTIONAL RETRIEVAL.

Through experience, the two theories were confirmed in the results and special tests through the pictures presented by a duck or rabbits, duck, rabbit, duck-rabbit. Using three algorithms: Tree, KNN, and Logistic Regression. In addition to neural network.

Probabilities, results, and linear algebra were also considered to communicate the idea of merging between machine learning and the application of deconstruction theory, which built the perception theory by neural network.

A comparison was made between the two perspectives, from a theoretical and practical point of view, to recover the difference in tasks, despite the unification of the original image, a duck or a rabbit. The technological vision did not unify the image in a psychological, philosophical, and historical way, but rather it was able to dismantle the image and realize it in terms of taking the possibilities.

The second method is the infinite basis for perception until the results of the machine learning algorithms are equal to deep learning (neural network), but it does not mean image deconstruction as the first method.

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Author contributions

Conceptualization [M.S.]; methodology [M.S.]; software [M.S.]; validation [M.S.]; formal analysis [M.S.]; investigation [M.S.]; resources [M.S.]; data curation [M.S.]; writing—original draft preparation [M.S.]; writing—review and editing [M.S.]; visualization [M.S.]; supervision (K.H, O.E]; project administration [M.S.]; funding acquisition [M.S.]

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Conflict of interest

The authors declares no conflict of interest

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