Application of Machine Learning in Agriculture: Future Scope

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Abstract- Recently many machine learning model wares introduced by many researchers in tackling problem is different fields including business, management, engineering, and agriculture etc. Since efficient public entities or private businesses, large or small, need to improve profitability with cost reduction, it can be the right option to find suitable ways to utilize data that is continuously collected and made available to achieve this objective. The agricultural field is only apparently refactory to digital technology and the "smart farm" model is increasingly widespread by applying the internet of things (IOT) framework adapted to environmental and historical information through time series [1]. This paper aims at proofing the concept of applying deep learning (DL) algorithms in the agriculture field. In this paper, a broad introduction of the above topic is given in chapter 2.0. In chapter 3.0, related works are reviewed while in chapter 4, ML algorithms used in the application area are discussed. Chapter five provides an experimental simulation using a Convolutional Neural Network for early detection of disease in maize plants by analyzing imagery data.

Keywords: Machine Learning (ML); Deep Learning (DL); Internet of Things (IOT); Convolutional Neural Network (CNN)

1. Introduction

According to wiki page, Machine Learning is a scientific study of algorithms and statistical models used by machines to perform different tasks accurately without explicit instructions, focusing instead on observations and conclusions. It is seen as an artificial intelligence sub-set. Machine learning algorithms construct statistical models based on available data, defined as "training data," to render decisions and predictions without being specifically programmed. [2] Deep learning is a branch of machine learning algorithms that use several structures to progressively obtain higher-level information from raw data. For example, lower layers may identify edges in the image processing, while higher layers may identify human-meaning features like digits / letters or faces, etc. Most deep learning models are based on artificial Neural Networks (ANN) specifically Convolutional Neural Networks. [3].

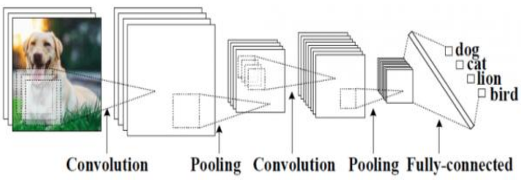


Figure of a deep learning algorithm (Convolutional Neural Network) and its layers that predict the presence of a dog in an image. Note that the layers can be more than the above.

2. Brief History

Many of the mathematical under pinnings in modern machine learning predate computers and stem from statistics. Major breakthrough include the work of Thomas Bayes in the 18th century, which led Pierre-Laplace to define Bayes theorem in 1812. Adrien-Marie Legendre also developed the Least Squares method for data fitting in 1805. And Andre markov described analysis technique later called Markov chains. These techniques are all fundamental to modern machine learning. In 1940, stored program computers where created that would hold instructions (programs) in the same memory for data. A decade later, There was a broader understanding of computers and Alan Turing published a paper entitled "Machinery and intelligence «in 1950 in which he posed the question can "can machines think", a question we still wrestle with. This paper was one of the first attempts to describe how an artificial intelligence can be developed. Marvin Minsky and Dean Edmond developed the first Artificial Neural Network- A computer based simulation of how human brains work. The Stoichatic Neural analog Reinforcement computer (SNARC), Learned from experience and was used to search a maze. During the 1950s and 60s, there was enormous enthusiasm for AI research but people became disillusioned when breakthroughs didn't occur known as the "AI winter". Things changed in the 1980s with new approaches, emergence of expert systems and rediscovering of old ideas and application to new fields. Public awareness of AI increased when an IBM computer beat the world chess champion Garry Kasparov in the first game of a match. It worked by searching 6-20 moves ahead at every position, having learnt by evaluating thousands of chess games to determine the best path to checkmate. One of the core techniques used in machine learning is back propagation, used to train deep neural networks. It was first described in the 1960s but fell out of favor until Geoff Hinton and others using fast modern processors demonstrated its effectiveness. Deep Learning nets are now mainstay of machine Learning.

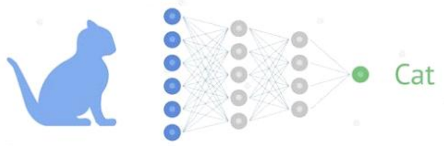


Figure 2. Neural network image recognition using backpagation.

A British company acquired by Google in 2014 called DeepMind gained prominence when it developed a neural network that could learn to play video games just by analyzing pixels on a screen. It also built a neural network that can access external memory. If deep blue's chess expertise was the was the big AI success story of the last century, then AlphaGo replaced it when it beat both the world number 1 Kie jie in 2017 and worlds number 2 Lee Sedol in 2016 in Go, an Asian board game which is more complex than chess.

Some computers scientists believe that once we develop a generalized AI, it can then be able to develop advanced versions of itself. This process has been termed singularity, a term first used by SF author Vernor Vinge. If this happens then the resulting exponential growth in AI capability will rapidly transcend human intelligence and we might find ourselves subservient to the machines. [4]

3. Related Work

In a paper entitled "Deep neural network-based recognition of plant diseases by leaf classification" Srdjan Sladojevic and his fellow researchers develop a new approach to implementing a plant disease recognition model using deep neural networks. The model was able to distinguish plant leaves from their surrounding and also predict disease of particular plants from field. The deep neural network was trained using caffe, a deep learning framework developed by Berkley vision and learning center [8].

Yang Lu and his colleagues published a paper entitled "Identification of rice diseases using deep neural networks" where they developed a rice pathology system using a Convolutional Neural Network from images of leaves and stems of diseased and healthy rice plants captured from experimental field. The CNN was trained with a dataset of over 500 images in order to identify 10 common rice diseases. Under 10-fold cross validation, the proposed CNN achieved 95.48% accuracy which was much higher than that of conventional machine learning model, as shown in their experimental simulations [9].

In a paper entitled "Deep learning-based approach for banana leaf classification" Jihen Amara and his fellow researchers proposed a deep learning-based approach that automated the process of classifying banana leaves disease. The LeNet architecture as a CNN was used in the classification of image datasets. Preliminary findings illustrated the validity of the proposed approach even under challenging conditions such as lighting, complex context, different resolution, scale, positioning and orientation of real-world images [10].

In a Journal entitled "Hyper spectral Imaging: A review on UAV-Based sensors, Data Processing and Applications for Agriculture and Forestry", Telmo. A and his fellow researchers acknowledge that traditional imagery provided by RGB and NIR sensors has proven useful but add that the methodology lacks the spectral range and precision to profile materials and organisms that only hyper spectral sensors can provide. They present a survey including hyper spectral sensors, inherent data processing and applications focusing on both agriculture and forestry [12].

Allesandro Dos Santos Ferreira and his fellow researchers, in a journal entitled "weed detection in soy bean crops " propose the use of convolutional neural network for detection of weeds in soy bean crops whereby a drone vehicle is deployed to collect a large amount of imagery data in a field with 15000 images of soil, soy bean crop, broad leaf and grass weeds and then trained with the caffeNet architecture. With the use of additional software tools superpixel segmentation algorithm was used to build robust image dataset and images were classified using the model trained by caffe software. Support Vector Machines, Adaboost and Random Forest were used in conjunction with collection of shape color and texture feature extraction techniques. The model achieved above 98% accuracy [13].

3.1 Type of Machine Learning

3.1.1 Supervised learning

This algorithm is composed of an outcome variable or a predictor variable to be predicted from a set of predictor variables (independent variables). To use this set of variables, we construct a function that maps to the actual value. The learning process is repeated until the model reaches the required level of accuracy from the training data set. Examples of supervised learning: Regression, decision trees, Random Forest, KNN, Logistic Regression etc. [5]

For simpler understanding, let us say you have a basket filled with different t fruits and your task is to arrange them into groups. The fruits in the basket are apples, Green bananas, grapes and cherries. You already know the previous work about the physical characters of fruits so arranging the same type of fruits now becomes an easy ask. In ML terminology, this is called training data.

Suppose now you take a new fruit out of the basket then you will see the size, color and shape of the particular fruit, if size is big, color is red, the shape is rounded with depression on top, you will confirm the fruit name is apple and you will put it in the apples group and then do the same for the other fruits. If you learn something before from training data and then apply this knowledge to the test data (new fruit picked), this is called supervised learning. [6]

3.1.2 Unsupervised learning

In this model, there is really no target or outcome variable to estimate the prediction. It is used for clustering community in different groups, which is generally used for categorizing clients in various groups for intervention. Examples of unsupervised learning: Apriori, K-means [5].

Suppose we still have this basket of fruits. But this time round we do not know any of their characteristics, you have honestly not seen them before, so how do we arrange them. First you will Take a fruit and base it on its color

Color: red: apples, cherries
Color: green: Bananas, grapes
So now you will take another physical character size.
Red color and big size: apple
Red color and small size: cherries
Green color and big size: banana
Green color and small size: grapes.
And now it's done. This kind of learning is called unsupervised learning [6].

3.1.3 Reinforced learning

Using this algorithm, the machine is trained to make specific decisions. The machine is exposed to an environment where it trains itself continually using trial and error. This machine learns from past training and seeks to extract the highest suitable insight to effectively make strategic decisions. Examples include: markov chain [5].

4. Machine Learning Algorithms

4.1 Convolutional neural networks

Convolutional neural networks (ConvNets or CNNs) are branches of artificial neural networks which have shown to be very successful in domain of image segmentation and classification. ConvNets has also been successful in locating faces, objects and road signs apart from power vision in robots and self-driving cars. [15]

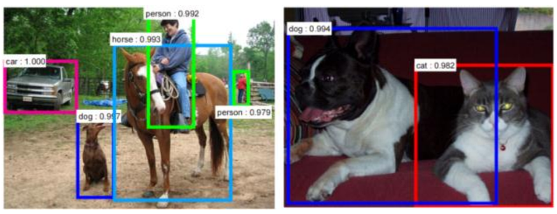


Figure 3. Showing A Convolutional Neural Network in Action Identifying Everyday Objects Like Human and Animals

In the 1990s, Yann LeChun's groundbreaking work named LeNet5 helped to propel the field of deep learning. It was primarily used for character recognition at that time, e.g. reading ZIP codes and digits. Many new architectures have been developed in recent years, but they strengthen the architecture of LeNet and use the principles of LeNet.

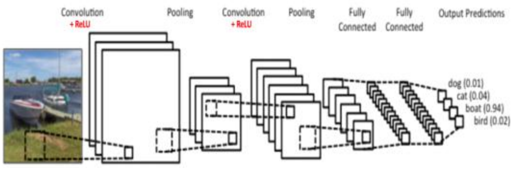


Figure 4. Depicts a similar architecture to that of the original LeNet and classifies an image into 4 groups: dog, cat, boat or bird. The Network assigns the highest probability (0.94) of the training images to Boat producing an accurate prediction.

There are 4 main operations stated in above ConvNet. Which is, or fully connected, convolution, nonlinearity (ReLU), pooling or sub sampling and classification.

In the case of ConvNets, the main aim of convolution is to extract features of an image. Convolution reserves the spatial relations between pixels by using tiny squares of input data to learn image features.

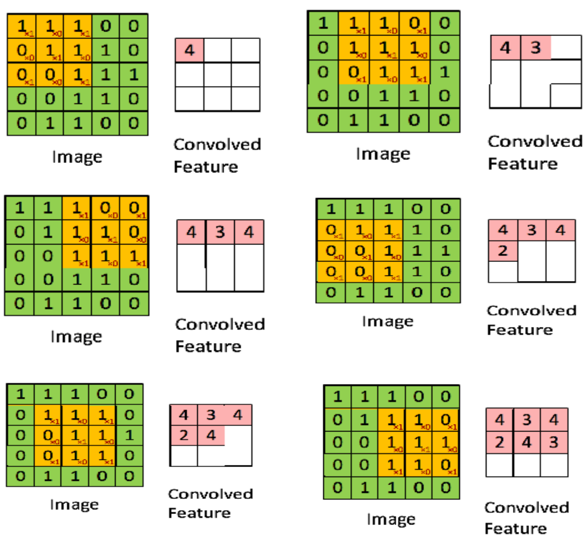
We can view each image as pixel matrix. Consider this 5x5 image whose pixel values are only 0 and 1 (pixel values vary from 0 for black and 255 for white but an activation function such as SoftMax can be used to squash these values from 0 to 1)

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

Also consider another 3x3 matrix

1	0	1
0	1	0
1	0	1

Then the convolution of 5x5 and the 3x3 is as follows



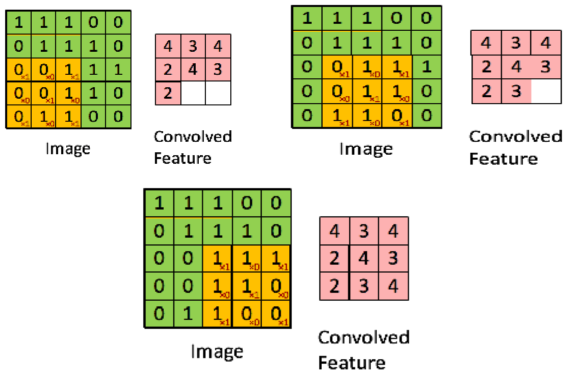


Figure 1. Visualization of A Convolution Operation

The orange matrix slides by 1 pixel or stride over the input images (green) and, for each location, an element wise multiplication is completed, and then multiplication outputs are applied to get the ultimate integer that provides a single element of the output matrix (pink). In CNN terminology, the orange matrix is called a filter or kernel or feature detector and the matrix formed after sliding filter over the image is consider the convolved feature or activation map or feature map. From the above images, it's evident to deduce that different values of filter can produce different feature maps. Considering below image of the sample.

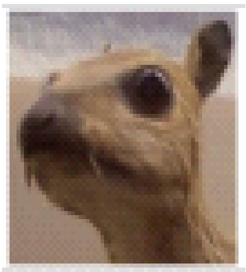


Figure 2. Sample Image

In the table below we can see the effects of different filters on the above image. It is possible to perform operations such as Edge Detection, Sharpen and blur just by changing the numeric value of the filter matrix before the convolution operation. So, this means different filters can detect different features from image, for example edges, curves etc.

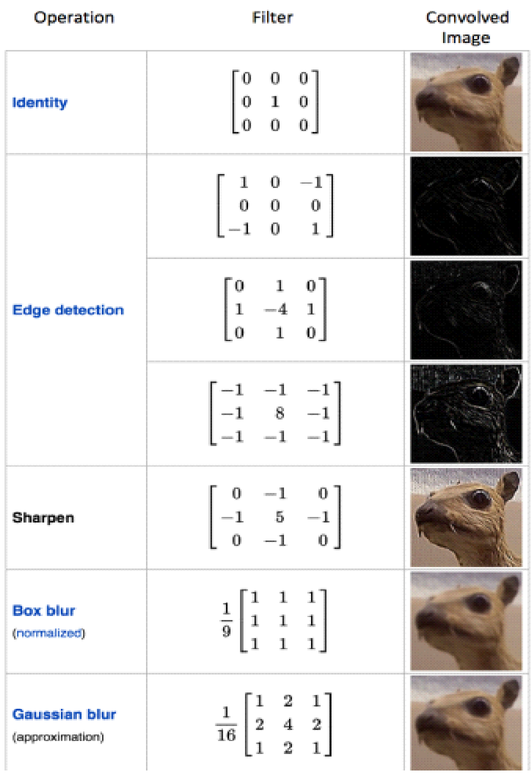


Figure 3. Depiction of capability of different filters to detect different features from input image

In practice a CNN learns the values of these filers by itself during training although we have to specify the number of filters, size of filter and architecture of network. The more the number of filters the more features are extracted from the image and the better the system becomes at recognizing patterns from unseen images.

Non-Linearity (ReLU)

An additional operation called ReLU was added after the convolutional step in figure 4. ReLU is a nonlinear operation and stands for Rectified Linear Units. ReLU is an element wise operation (applied to every pixel) performed by replacing all negative pixel values in the feature map by zero. Convolution is a linear operation i.e. element wise multiplication and addition so non linearity is accounted for by the introduction of the ReLU function, since most of the real-world data a convnet learns is basically non-linear.

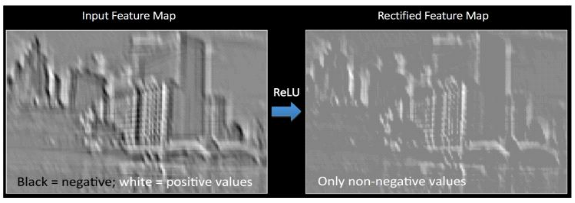


Figure 4. ReLU operation.

Other nonlinear functions such as tanh or sigmoid can be used but ReLU has proved to work better in most situations

4.2 Pooling

Spatial pooling also known as subsampling or down streaming) reduces the dimensionality of each feature map but retains the most important information. Spatial pooling can be of different types: Max, Average, Sum etc.
In case of Max Pooling, we define a spatial neighborhood (for example a 2x 2 windows) and take the largest element from the rectified feature map within that window. Instead of taking largest element one could also take the average (average pooling) or sum all of the elements in that window. In practice, Max pooling has been proven to work better.

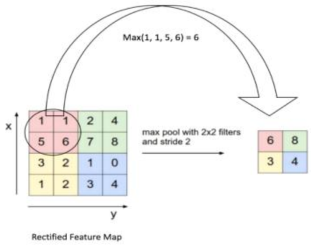


Figure 5. an example of max pooling on a rectified feature map (conv + ReLU) with 2x2 filter and a 2 stride

After sliding the filter by 2 pixels or 2 strides, we take the maximum value of the window in order to reduce dimensionality of the feature map.

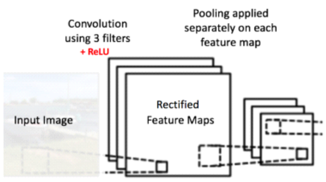


Figure 6. pooling operation applied separately on each feature map

Functions of pooling

- Makes the input representation (feature dimensions) smaller and manageable.
- Reduces number of parameters and computations in the network, therefore, controlling over fitting.
- Makes the network invariant to small transformations, distortions and translations in the input image (a small distortion in input will not change the output, since it's the max/average values which are considered)
- Helps arrive at an almost scale invariant representation of our image. This important so that an object can be detected no matter where it's located in an image.

4.3 Fully connected layer

This Layer is a traditional multi-layer perceptron that uses an activation function for example softmax in the output layer. The term fully connected implies that every neuron in the previous layer is connected to every neuron in the next layer. The output from conv + ReLU and pooling layers represent high-level features of input image, so the fully connected layer takes this as input and classifies input image into various classes based on training dataset.

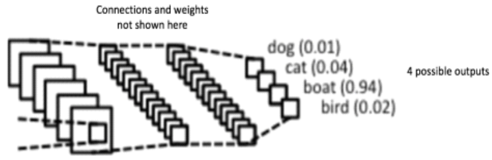


Figure 7. depiction of the fully connected layer

The sum of output probabilities from fully connected layer is 1. This is achieved by using the softmax as an activation function in the output layer of the fully connected layer. The softmax function takes a vector of arbitrary real-valued scores and squashes it to a vector of values between zero and one that sum to one [16].

4.4 Linear Regression

Linear Regression is a machine learning approach based on supervised learning. It performs a regression task. Regression Models a Target prediction value using the independent variables. It is mostly used for finding relationships between variables and forecasting. Different regression models differ based on, the kind of relationship between dependent and independent variables they are considering and the number of independent variables involved [17]

Other approaches include decision trees and state vector machines to name but a few.

5. Proof of Concept

Plant disease diagnosis through optical observation of the symptoms on plant leaves, incorporates significantly high degree of complexity. Due to this complexity and to large number of cultivated plants and their existing psychopathological problems, even experienced agronomists and plant pathologists often fail to successfully diagnose specific disease, and are consequentially led to mistaken conclusions and treatment. The existence of an automated computational system for the detection and diagnosis of plant diseases would offer a valuable assistance to the agronomist who is asked to perform such a task [7].

The system is implemented using a basic CNN architecture and created using Google colaboratory. Colaboratory is a free Jupyter environment that runs entirely in the cloud and requires no setup. With this platform, you can write and execute code, save and share your analysis, and access powerful computer resources like Graphical Processing Units (GPU) [11]. Not only is a great tool for improving coding skills, Google collab also allows absolutely anyone to develop deep learning applications using popular libraries such as PyTorch, TensorFlow, Keras and OpenCV [14]

A B

Figure 8. A) Cercospora leaf-spot disease leaf example of maize plant leaf. B) Common rust disease leaf example maize plant leaf

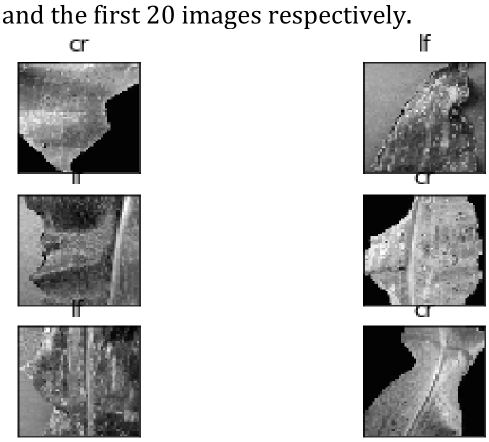
A database containing 1000 images of leaves of two different diseases (cercospora leaf spot and common rust disease) corresponding to their particular maize plant leaves was used for training and testing the CNN model. The data set is split into two, the training set, and the validity testing set by randomly splitting the 1000 images so that 920 of the images were used for training and 80 of the images were used for testing the validity of the training session of the model. The images are preprocessed so that they are 50x50 in dimension and the single channel rescale is used so that the images can make more sense to the neural network. Since a computer cannot understand raw image input, the images and their corresponding labels are then converted into numpy(python library that handles manipulation of arrays) arrays and one-hot encoded arrays respectively .The training dataset is then read into the Google collab notebook and the neural network is then implemented with the corresponding parameters and other hyper parameters(convolution, number of filters and filter size, ReLU, Maxpooling and fully connected(SoftMax)) and is then trained with a goal of reaching an acceptable amount of accuracy. The neural network is trained with six convolutional layers and five epochs. A test dataset is also established which contains images labeled with only numbers and no other descriptive label, the goal of the entire neural network is to predict which disease the test dataset images contain and label them according to the knowledge the neural network learned from the training session.

```
Training Step: 104  | total loss: 0.07146 | time: 2.293s
| Adam | epoch: 007 | loss: 0.07146 - acc: 0.9855 -- iter: 896/899
Training Step: 105  | total loss: 0.06981 | time: 3.470s
| Adam | epoch: 007 | loss: 0.06981 - acc: 0.9839 | val_loss: 0.07405 - val_acc: 0.9875 -- iter: 899/899
```

Figure 9. Real-Time Training Epoch from Notebook

As seen in figure 9 above, the neural network managed to achieve a validation accuracy of 0.9875 which is approximately 98% accuracy

The model is then tested against the unlabeled testing dataset. The neural network was tasked to predict which disease (lf-leafspot, Cr-cercaspora common rust) the images contain. First the first six are tested, then the first twelve and the first 20 images respectively.



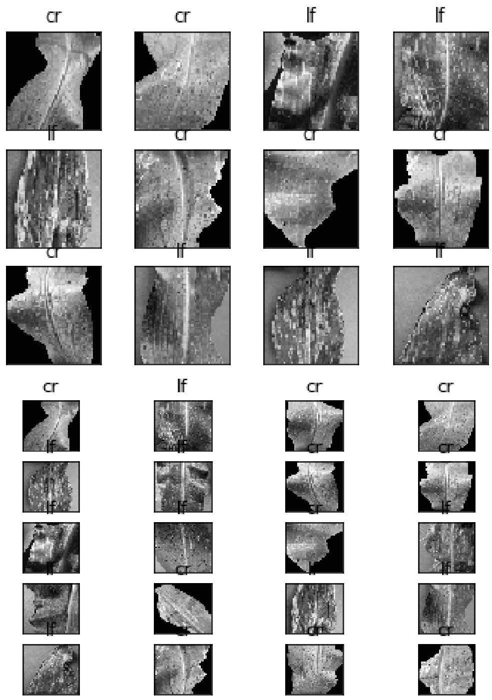


Figure 10. plant disease predictions made by the neural network

As we can see in Figure10 above, it might not be clear to the human eye but the neural network has actually managed to predict correctly which disease most off these images contain, thus proving the concept that machine learning and artificial intelligence play a very key role in the scope of smart agriculture.

6. Conclusion

In this paper, it's clear that machine learning is feasible in the scope of Agro-technology state-of-the-art. Although the paper is limited to proving the concept of machine learning in smart agriculture, there are multiple approaches to which this problem can be solved more efficiently, for example the neural network can also be trained to detect many different types of diseases and not limited to two used in this paper and can also be used to solve other problems faced in agriculture, for example detection of weeds in a farm or animal breed classification in animal farming. Neural networks also work much better when trained with bigger datasets containing tens of thousands of images and trained with numerous layers in the deep neural network. The applications of deep learning in agriculture can also be used to enhance the performance of I.O.T systems in regards to this context

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