IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

Plants Classification Using Machine Learning Techniques in Controlled Agriculture Environment

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Abstract: Considering the enormous difficulties that the globe is experiencing in providing food for an ever-increasing population, the incorporation of technology into agricultural practices has become an absolute need. Climate-controlled agricultural facilities, such as greenhouses and hydroponic systems, provide methods of food production that are both effective and environmentally friendly. It is essential to have the capacity to monitor and control plant health in order to get optimal results while optimizing these habitats. The purpose of this study is to investigate the use of machine learning techniques for the categorization of plants in controlled agricultural situations with the intention of improving precision agriculture operations. One of the most important components of a plant is water. Along these lines, the development of plants is extremely dependent on the changes that occur in the amount of water that is contained within the plant. There have been a lot of different approaches that have been developed in order to enhance plant development in times of water scarcity and dry period pressure. The purpose of this study is to organize and construct an intelligent framework that will promote plant development in a constrained water environment. This framework will be based on Support Vector Machine (SVM) and machine vision. Shading, morphological, and textural highlights were finally isolated from a large number of photographs of turf grass, wheat, and rice plants that were taken under pressure circumstances that were typical of the dry season. At that point, an SVM and an ANN were utilized in order to supervise the process of information organization by using them. When the SVM was used as the classifier, the results showed that the general arrangement exactness of ANN was 92%, and greater correctness were obtained when the SVM was used. The general precision of the SVM was 98.00% for both fresh and wilted plant conditions.

Keywords: Classification, computer vision, controlled-environment agriculture, image compression, machine learning.

I. Introduction

Plants can be found in any location, including those where we do not reside. A great number of people use substantial facts for the purpose of enhancing human civilization. The fundamental reason for this is that a great number of plant species are in jeopardy of becoming extinct. Along these same lines, it is necessary to establish a database for plant insurance. Plant components and their products, such as organic goods, leaves, stems, and blooms, among other things, are consumed by both humans and other animals in a variety of different ways. There is an extra activity in which plants play a key role; nevertheless, in general, they are utilised for the production of food items, pharmaceuticals, mustard oil preparation, the production of biofuel, and other similar activities.

Plants are viewed based on their characteristics, such as their size, shape, height, or shadow, or the portions of the plant that are next to one another. More often than not, the grouping of the plant is completed with the aid of the leaves that are located on the outside of the plant. This is determined by the characteristics of the leaves, such as their size, surface, form, and shade. Concepts related to computer vision, artificial intelligence, and image processing are mostly utilised in a variety of applications, such example acknowledgment, characterization, division, and so on.

An illustration of the flowchart of the plant distinguishing evidence may be seen in Figure 1. Over the course of the past several years, the concept of programmed perception of plants has attracted a significant number of analysts in certain areas. As long as there is life, there has been a progression of circumstances that lead to learning. The ages of living animals have increased throughout the course of time, and with that, their capacities for learning have also increased. These days, In the same way that individuals become accustomed to a path, machines discover it. Additionally, this process of learning by machines is referred to as the preparation of a machine in order to impart intelligence upon it. As a result of their ability to translate the information that is shown, various computer vision computations pave the way for the development of intelligent machines. This is accomplished by the machine via the utilisation of two primary components that are referred to as example acknowledgment and arrangement. The identification of plants is dependent on the monitoring of their morphological characteristics, such as the structure of the stem, roots, leaves, and natural products exhibited by the plant.

Due to the fact that leaves are present at a later time, they contribute a considerable amount to the overall plan for the development of programmed frameworks. In order to see a leaf, one must consider its surface, hiding, and form. The concepts of computer vision make an effort to get rid of the conventional methods and propose fresh approaches to the division of plants. In today's world, the processes and techniques that are planned for plant divisions that are computer-supported or programmed are of much greater significance.

II. Related Work

In order to measure the phenotypic of a plant, quite a few procedures need the plant to be uprooted or chopped. The cultivation conditions that these approaches claim to be highly exact [10] or that they kill plants and make it hard to trace the phenotypic change of plants over time are claimed by these techniques. In light of this, it is of the utmost importance to develop procedures that are non-destructive for automated plant phenotyping [11]. Methods such as Magnetic Resonance Imaging (MRI) [12], Computer Tomography (CT), Position Emission Tomography (PET) [13], and multispectral imaging [14] are among the most widely used non-invasive techniques for plant phenotyping. Additionally, it is challenging to deploy the tools that need expensive equipment on a widespread scale. An other method that shows promise is the utilisation of a three-dimensional camera to do volumetric reconstruction on a plant. This method is precise and offers valuable insights into the situation. On the other hand, they are tough to implement in actual situations. In the Antarctic station or on subsequent space missions, it is nearly impossible to operate gear that is both so complicated and so massive.

On the other hand, in order to effectively capture photographs of a plantation, computer vision algorithms require relatively inexpensive two-dimensional cameras. They are simple to use and do not interact with the plants in any way [15]. As a consequence of this, the algorithms that are used in our work are the primary focus of our attention.

The collection of images is possible through the use of standard cameras that are simple to set up. As a result, our approach is both simple to scale and extremely resilient.

In the past several years, there has been a rise in the amount of research effort that is being conducted in the field of noninvasive PP [16]. In order to carry out good study on PP, we often need to collect a significant amount of data.

In most cases, we make use of a variety of Internet of Things (IoT) solutions in order to automate the process of data collecting. They not only reduce the total time it takes to complete the procedure, but they also make it possible for us to gather data in a more consistent and regular manner. In addition to this, it lessens the amount of mundane duties that a skilled agronomic or biologist is required to carry out, which frees up their time for more complex activities [19].

Image Compression

Every single day, a significant quantity of photos is generated for a variety of applications, with the plant phenomics domain being the primary recipient of this data.

There is a significant quantity of valuable information included within image data, which includes spatial properties of the item that is being researched that cannot be described on any other basis. Having said that, these kind of data need a significant amount of space. In order to store and transport them in an effective manner, we require systems that are capable of compressing images. Because of this, it has been a well-liked research field for many years.

Lossless compression and lossy compression are the two categories that may be used to classify all of the image compression techniques. Lossless compression techniques are able to recover every bit of the original picture and do not shed any information during the compression process. The techniques that are used for lossy compression get rid of redundant information that cannot be retrieved back. Lossy compression is a technique that aims to minimise the size of the input image while minimising the impact of perceptual alterations that are not essential to the image. In general, we have the ability to modify the level of permitted modifications, which will also have an effect on the size of the image that has been decreased. Lossy compression is superior in terms of reducing the size of the image. Additionally, some methods for lossless compression, such as entropy coding, are capable of being utilised in conjunction with lossy compression.

For the purpose of our study, we make use of lossy compression since our data is not overly sensitive to even minute changes, and it is essential to get greater compression level constraints in the transmission channel. JPEG is now the lossy compression codec that is utilised the most frequently. The JPEG200 and WebP algorithms are two other algorithms that are gaining prominence. Another sort of compression algorithms that is fundamentally distinct from the others is one that is based on neural networks. Convolutional networks are able to learn representations and patterns from data, which enables us to leverage the knowledge that we have learnt about actual objects to achieve greater compression. Time spent compressing and decompressing the data is the price that must be paid for such performance. Although ten seconds for the compression of a single picture [9] is not adequate for use in web applications, it is acceptable for use in the transmission of data from faraway systems.

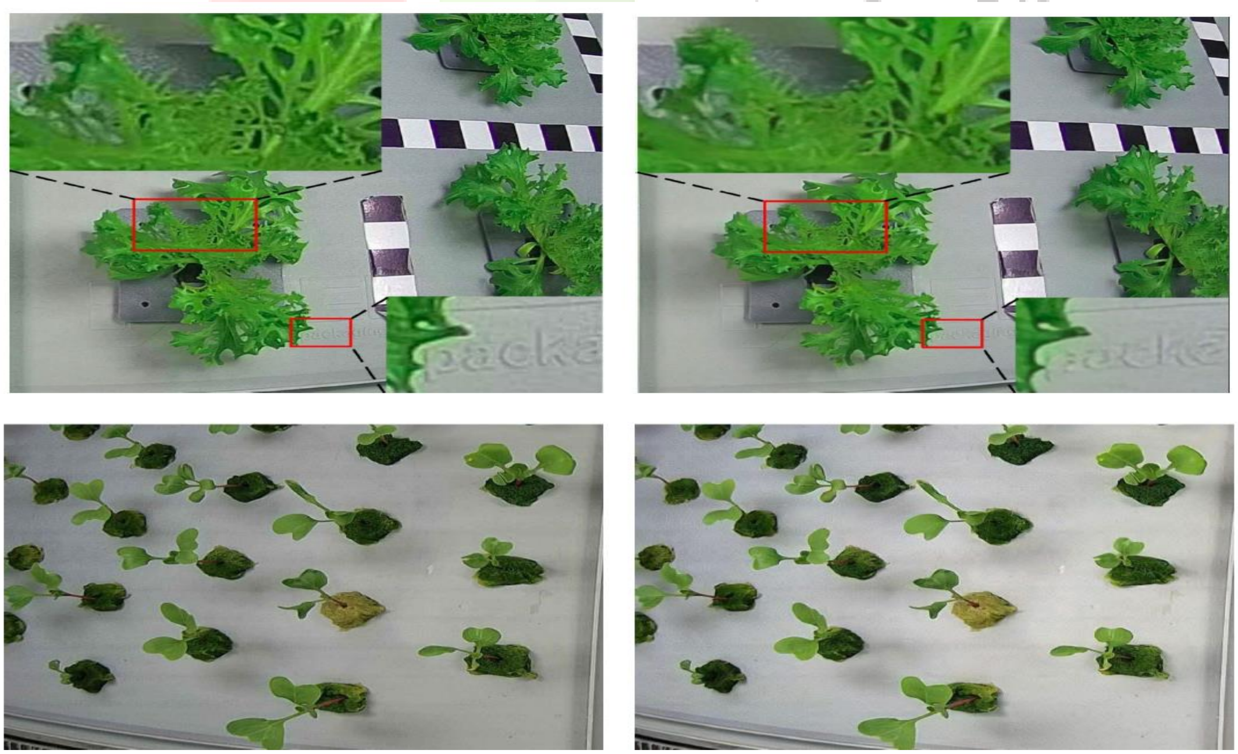


Fig. 1. Image compression examples. Original images (on the left) and reconstructed images (on the right).

There are now models that are based on Variational Autoencoders (VAEs), Recurrent Neural Networks (RNNs), and Generative Adversarial Networks (GANs). These models are effective at compressing high-resolution photographs. In order to learn partially invertible mappings from image pixels to a latent representation, VAEs are instructed to learn. The residual between the original picture and the model's outcome at the previous iteration is something that random neural networks (RNNs) are meant to lower in an iterative manner. GANs are made up of two networks that compete against one another with one another as they are being trained. In the first, a picture is produced, and in the second, an attempt is made to determine whether or not the image presented is genuine. When it comes to high-resolution photos, this specific sort of device does exceptionally well.

One linear model that may be used to solve the classification problem is called the Support Vector Machine (SVM). It is well acknowledged to be effective for a wide variety of practical issues. One of the goals of the Support Vector Machine (SVM) method is to generate a line or a hyperplane that divides the data into different groups.

In order to do this, support vector machines (SVM) locate the points that are the in closest proximity to the boundary of a class (we refer to these points as support vectors) and then search for the line that is the furthest away from the points.

IV. Literature Survey

There have been a great number of researchers that have investigated the categorization process using hierarchical systems or other procedures.

According to the following articles, they have classified the materials based on the leaves, weeds, and other features, and the characteristics that were employed for extraction are colour and texture. The features of the colour are retrieved through the use of several transformations, and an explanation is provided for each of the transformations. More than that, the classification procedure makes use of the classifiers or other neural networks that are discussed in other articles that are pertinent. Within this study, however, we made use of the SVM classifier in order to get a more accurate extraction of the function; hence, the relevant publications were incorporated.

Bakhsh Pour [1] devised a method for weed identification that makes use of surface highlights. One of the fundamental challenges that mechanical weed removal faces is the rearranging of weeds. Because there is little self-control between the cutting tine and the primary yield location, it is necessary to achieve a level of separation that is extremely exact between the weed and the primary crop. As a result of the close similarities that exist between the form characteristics of sugar beets and those of other types of weeds, it is difficult to characterise a whole component in order to have the ability to effectively recognise each and every one of the weeds with sufficient accuracy. As a result, in this inquiry, an attempt was made to combine a few shape highlights in order to provide an illustration of each and every variety of plant. The bolster vector machine and counterfeit neural networks were locked in so that the vision framework might be empowered in the dread of the weeds that were dependant on their example. Using Fourier descriptors and minute invariant highlights, you can shape highlight sets. The results showed that the general arrangement exactness of ANN was 92.92%, which means that 92.50% of the weeds were organised in a perfect manner. When the support vector machine (SVM) was used as the classifier, higher exactnesses were obtained, with a general accuracy of 95.00%, despite the fact that 93.33% of the weeds were ordered perfectly. In addition, the ANN and SVM were able to precisely classify 93.33 percent and 96.67 percent of the sugar beetroot vegetable plants, respectively.

Sue Han Lee [2] presents a half and half nonexclusive organ convolution neural system (HGOCNN), which is disseminated both organ and conventional data, linking them using another element combining conspire for species order. This system is a hybrid of the two types of neural networks. Secondly, rather of employing a CNN-constructed method to build a single image with a single organ, we broaden our technique. This is done in order to create a more comprehensive picture. Through the utilisation of the repetitious neural system-based approach, they give an additional system for plant auxiliary getting the hang of it. This story system is the foundation for arranging that is based on a different number of plants seeing one other, capturing at least one organ of a plant, and increasing the relevant circumstances between them. We also give the results that are dependant on the variables.

"Vippon" Based on the images of their leaves, Preet Kour [3] offered a fresh technique that was established for the purpose of dividing and characterising seven distinct plants. These plants were given the names Guava, Jamun, Mango, Grapes, Apple, Tomato, and Arjun. At the beginning of the procedure, continuous images as well as images taken from the crowdAI database are collected and preprocessed for the purpose of removing noise, resizing, and improving differentiation. At that point, in the subsequent step, a variety of attributes are eliminated, depending on the shading and the surface. An application of a k-means calculation is utilised in the third step, which involves the splitting of images. In the fourth step, the preparation of the assistance vector machine is carried out. Finally, in the last stage, the testing is carried out. For the purpose of selecting the most accurate and practical estimation of the instatement parameter in both the division and grouping forms, the molecular swarm enhancement computation is utilised. In the work that was proposed, greater exploratory outcomes were achieved, such as affectability = 0.9581, explicitness = 0.9676, and precision = 0.9759. Additionally, the exactness of the division and arrangement was calculated to be 95.23 when compared to other methodologies.

It was suggested by M.M.Ghazi [4] that the problem of computerising the counting operation by utilising computer vision and UAV symbolism be differentiated. An administrative location-based tallying structure is provided by them for the purpose of determining the amount of small-scale planting locations that are located on a square that has been exactly organised. The framework is created in a disconnected manner in order to take in component representations from images that are described semi-consequently afterwards. Following this, hill identification and verification are carried out on multispectral UAV images that were captured at a height of one hundred metres. The next step in our disclosure method is to make the area proposition reliant on the neighbourhood parallel examples (LBP) highlights that are separated from the near infrared (NIR) patches. After that, a convolution neural network, also known as a CNN, is utilised for the purpose of characte

rising competing districts by taking into consideration multispectral photo information.

III. Proposed Model

The plant classification model of the proposed system is given by Fig.2. The figure consists the input image module, feature extraction module, SVM classifier module.

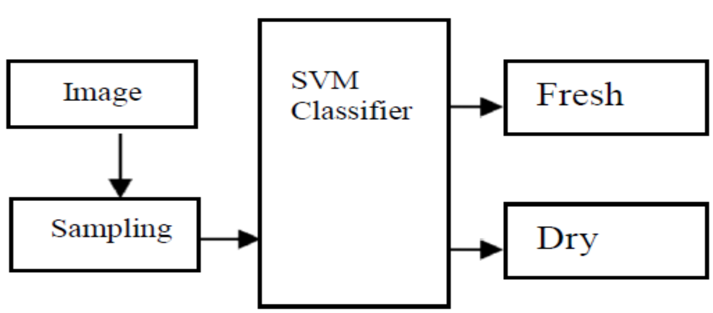


Fig .2. Plant classification model

The support vector machine (SVM) and the artificial neural network (ANN) are two examples of the software applications that may be used to do these tasks. After reviewing their presentation, which used cross-approval on a modified massive informative collection, we came to the conclusion that the assistance vector AI platform was the most suitable option. Through the use of an SVM classifier, this article regulates plant order. Bolster vector machines, often known as SVMs, are a paradigm-shifting system that allows for deduction with few parameter choices. For non-SVM professionals, this ought to become the preferred alternative to support vector machines (SVM) across a variety of application domains.

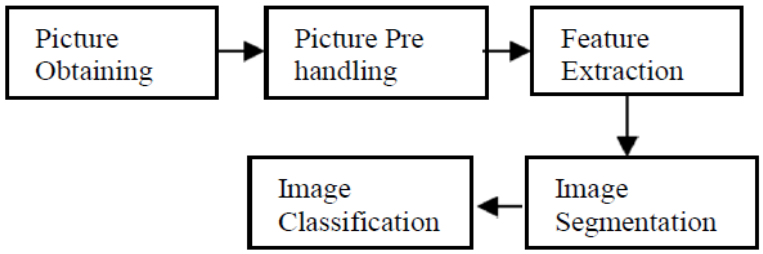


Fig.3. Plant Identification Flowchart

The well-known accomplishment of earlier strategies like neural systems, hereditary calculations, and choice trees was upgraded by the natural inspiration of these methodologies that in some sense improved the end client's capacity to create applications freely and have a feeling of trust in the outcomes. There will be around fifty photographs used to create the support vector machine (SVM), which will then be tested using a subset of the pictures. Following this, the SVM will determine the exact number of test pictures that have been ordered.

A. Image to be Input

In the field of natural sciences, the information and data contained in images are becoming increasingly crucial. It is possible to take photographs with a sophisticated camera in this manner. When we have determined that photos are essential to the completion of any further activities, we will then proceed with the pre-planning technique. While the operation is being carried out, the ruckus and various objects are being removed.

B. The Extraction of Features

The extraction of features is entirely based on the three types of highlights, which are the shading histogram, the edge histogram, and the sobel edge bearing. The shading histogram is responsible for producing the variation in shading that can be seen in the photo. The shading space models that are available include RGB, HSV, and YCbCretc, among others. Alterations in the representation of these many space models occur often.

The information image is referred to as RGB shading space photos; thus, it is possible to obtain HSV shading space by first switching from RGB shading space. Due to the fact that H is the tone, which is the actual wavelength of the shading, the HSV shading space model is used to collecting the shading histogram in an impeccable manner.

C. Texture Characteristic

Components include the surface. It is utilised to transform the images into the locations, and it will assign these kinds of locations to the appropriate categories. Surface examination procedures are utilised with distinct criteria for extraction, including quantifiable strategies and channel approaches. There are a number of surface examination processes that are utilised. The distinctions between the highlights are based on the highlights of the surrounding pictures.

D.SVM

The assistance that Regulatory learning computations are what the Support Vector Machine (SVM) is all about. For the purpose of grouping and the relapse process, SVM utilises. It makes use of a component technique in order to alter the information, and it is dependent on the modification that it will discover the ideal bounds between the yields that are the subject of comparison.

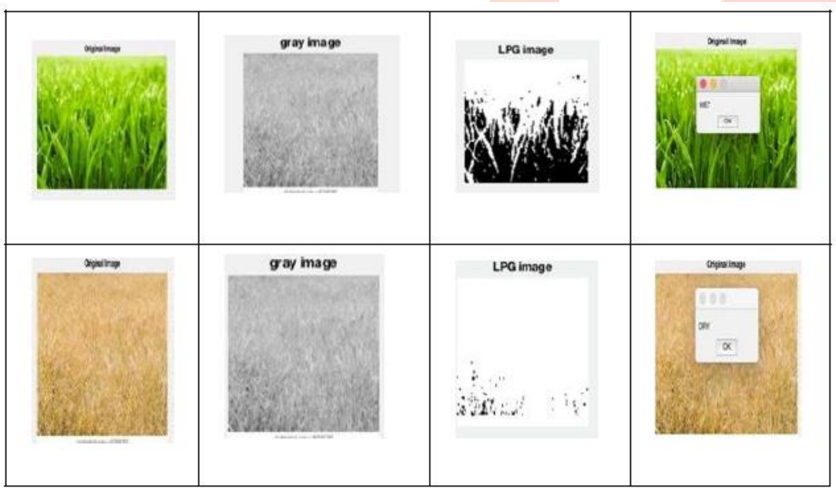
On the other hand, the assist vector machine models include a significantly larger number of elements that we are able to make use of. In the support vector machine (SVM), the radial basis function (RBF), polynomial, and sigmoid are the components that are utilised. The RBF choice is the one that is supported by the majority of people. The fact that they adhere to their beliefs and offer very minimal criticism over the whole breadth of the true x-pivot makes this an essential point.

IV. Performance Evaluaiton

Within the framework that has been presented, we are required to produce fifty input photos and compute the exactness of the characterisation based on the test pictures. The measurement of the precision of the arrangement is the extent of the number of test photos that are sorted suitably by the absolute number of photographs multiplied by 100. Relying on the Hyper plane classifier, grouping is accomplished through the use of Support Vector Machine. A product routine was built in MATLAB that would take in a.mat file discussing the preparation and test information, train the classifier by using the train documents, and then use the test record to do the arrangement task on the test information. All of these steps would be performed in order. The result of the plants categorization by MATLAB is presented as Figure 3.

$$classification\ Rate = \frac{Correctly\ classified}{Total\ no\ of\ samples} * 100$$

Linear support vector machine (SVM) is a learning approach for supervised computing devices that may be utilised for classification and regression problems. The feature sets that are developed are fed into the process. The classifier will assign the label to the image, and it will also specify which category the photograph belongs to. The classifier is predefined predominantly based on the feature, and it will assign the label to the photograph. This categorization is utilised for each and every analysis, as well as the phase of testing things out. The kernel is the mechanism that is utilised by the support vector machine (SVM).



An unstructured picture is used as the input for artificial neural networks (ANN), which then apply a computational model that works on the image and transform it into equivalent categorization output labels. It is taught to understand the necessary properties for classification intention, and it takes fewer preprocessing efforts than other training methods. A study has been conducted to evaluate the effectiveness of SVM and ANN classifiers in comparison to one another. Using the same data, two different models have been properly trained. In this study, we compare the classification accuracy of two different classifiers by utilising decreased colour, texture, and combination features. The total results are shown in Table 1, along with a comparative graph that may be seen in Figure 4.

Technique	Number of Images	Accuracy
ANN	50	93%
SVM	50	98%

Table 1. Comparison of ANN and SVM.

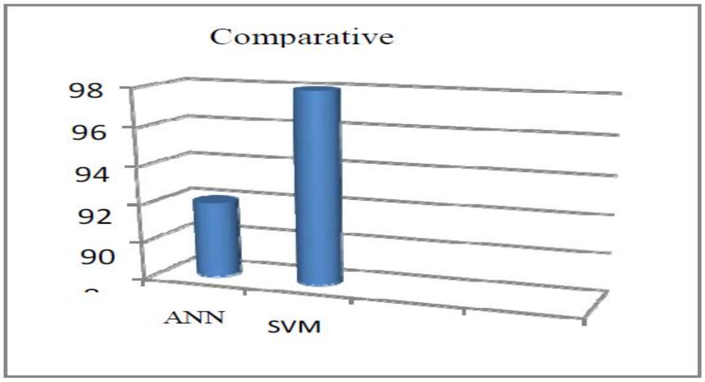


Fig .5. Comparison Graph of ANN and SVM.

V.Conclusion

Using a support vector machine (SVM) classifier, the categorization of plants is determined by a few fundamental characteristics such as colour and structure. During the course of the study that was presented, we carried out two different strategies for picture categorization. Through the use of an adequate study operation, we were able to examine that the SVM classification is superior to the ANN classification. The performance of artificial neural networks (ANN) was relatively poor in comparison to that of support vector machines (SVM). This was owing to the fact that the ANN classifier was unable to differentiate between plants, but SVM was quite efficient in categorizing plants (both fresh and wilted). Finally, it was discovered that the accuracy percentage for SVM was 98%, while the accuracy percentage for ANN was 93%. As part of your future work, you should make plans to incorporate some real-time photographs that are based on the fundamental approach of a wireless sensor network or the internet of things.

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