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Design of deep learning system for agricultural purpose

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Abstract
Agriculture and its requirements are, at the time, quite challenging to handle. The bulk of the country's residents are dependent on agriculture for their income. Food production should also be increased to keep up with the World's population growth. Agriculture has benefited significantly from recent technological advancements. Agricultural experts are becoming excited by current technology advances such as the Internet of Things (IoT), Machine Learning (ML), and Deep Learning (DL). IoT agriculture and farming are a whole new area of IoT application. We all know how to use IoT-based analytics like sensing soil temperature, nutrients, and humidity and regulating and monitoring water consumption for plant growth. The Internet of Things collects and produces vast volumes of data across several sectors and applications. Many challenges facing the agriculture business may be dealt with using deep learning and IoT technologies.

Keywords: IoT, Machine learning, Deep learning, Artificial neural networks

1. Introduction
World production is expected to climb by 70% by the year 2050. Our work focuses on addressing three main food-security challenges: overcoming hunger, supporting smallholder farmers, and developing resilient agriculture. Farmers in India confront various obstacles, including soil that farmers may not understand, unexpected rain that may wreak havoc on crops, and diseases and problems related to water management that impairs agricultural production. We see an increasing focus on food, which brings forth newer agricultural techniques. The United Nations Food and Agriculture Organization (FAO) estimates that by 2025, there will be around 8 billion people on Earth, and by 2050, this figure will be close to 9 billion. According to FAO [1-3], as a consequence, forecasting is straightforward.
The Internet of Things (IoT) dates back to 1999. Study, as seen in [5]. To boost the quality of agricultural production, agriculture is using the Internet of Things (IoT). Intelligent cities, transportation, traffic control, security, and supply chain management are among other sectors in which IoT works effectively. By their very nature, surveillance devices generate a large volume of organized and unstructured and semi-structured data at an unending rate. To anticipate the future and find the knowledge available now, analytics must be applied to this data. An in-depth analysis of vast volumes of information is no easy feat. Data is only helpful if it results in action, and this requires a sophisticated learning system. The primary challenge is determining how to examine massive amounts of data derived from sophisticated IoT data. Recent years have seen a surge in interest in Deep Learning (DL) technology. It is used in a variety of IoT applications because of its ability to provide rapid results. It's well known that when we use IoT devices, we're already using connected gadgets. When coupled with deep learning, the related intelligence notion is created. Using deep learning, issues that are exceedingly difficult to solve in the actual World would be made much more straightforward [6-8]. A significant percentage of remote sensing data is derived from images depicting agricultural landscapes and serving as an effective remedy for various challenges. The most active area of agricultural research in this field is image analysis, which utilizes intelligent data analytics to uncover abnormalities in crop photographs, a range of farming applications. This chapter will evaluate how these ideas apply in agriculture and how the Internet of Things (IoT) and its sensor-based applications might help advance the use of sensors. A range of new advances, including machine learning (ML) and artificial intelligence (AI), have influenced precision farming, agricultural growth, and environmental forecasting analytics.

1.1. Agriculture's IoT

IoT is becoming engaged in a variety of real-world applications. For example, the Internet of Things has a significant impact on agriculture output efficiency. We provide a framework for intelligent agriculture by leveraging sensors such as soil moisture sensors, water level sensors, and temperature sensors to monitor agricultural activities such as crop and plant monitoring, irrigation monitoring, etc. Similarly, farmers may watch agricultural fields continually from any location. There is far more to be gained via IoT-based smart farming than conventional agricultural procedures such as planting, manual tilling, and harvesting [9]. In Figure 1, you can see several ways that IoT-based agriculture is being put to use. One of the Internet of Things' emergent uses smart agriculture. Large volumes of structured, unstructured, and semi-structured data are produced continuously by sensors. [21] As it's referred to, big data is a collection of large amounts of data, such as data obtained from commercial, sensor, and social networking sources. For the most part, IoT has three fundamental issues: data collecting, data storage, and data analysis and search. The data analysis procedure is shown in Figure 2.

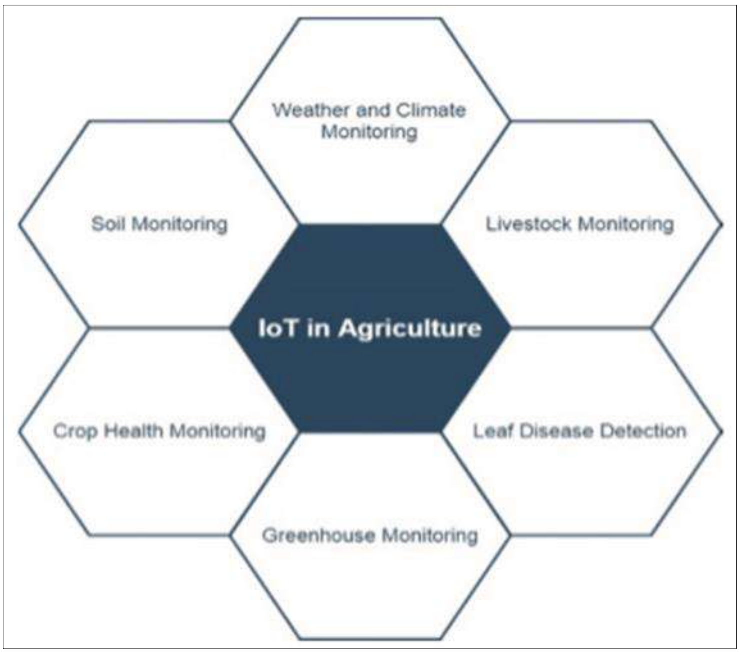

Fig 1: Connecting agriculture's Internet of things [10]

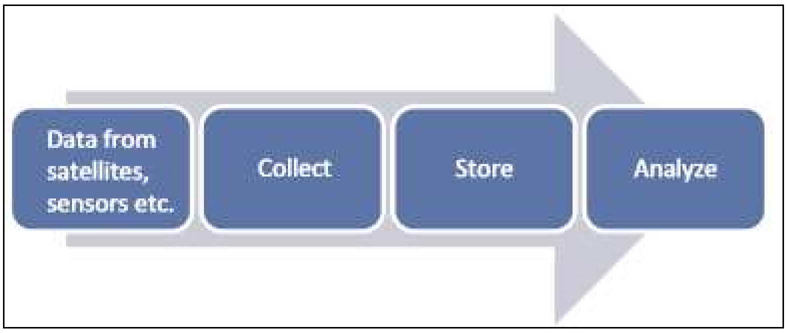

Fig 2: Process of data analysis [11]

Problem	Description
Water Irrigation problems	Of the freshwater available on the planet, 70% is used for agriculture (Projectguru n.d.) To successfully use a water management system that is intelligent, a brilliant system is required [12]
Lack of information about dirt	Crop soil is altered every day by weather conditions, and farmers must always consider which soil is best for their crops [13-14]
Identifying diseases the plant-related issue	Addressing the latent danger of leaf disease may lurk in plants until it is too late to do anything about it [15]. is a vital feature, but if it isn't done in time, there may be a delay in the diagnosis of plant disease, which makes the use of automated detection important [15-16]
Sourcing and procurement Management Problem	The supply chain might be aided by sensors that rely on location information, indicating a drop in privacy concerns and an increase in comprehension by customers [17-19]
An inadequate nutrient supply accommodation of soil and plant concerning nutrient needs Detection	Intelligent objects should be handled effectively [20]
The concentration of Nitrate was found	As with other application areas; smart farming generates massive amounts of complex data. Additionally, the data emanates from a variety of sensor systems.

As with other application areas, smart farming generates massive amounts of complex data. It is a heterogeneous information resource due to the different sensor systems. Therefore, the critical question is how to measure this real-world IoT data to discover valuable information. Several analysis methodologies are available for IoT big data to get critical insights from the tremendous volumes of data created by IoT devices. Based on the Internet of Things, So-called smart farming, which maximizes water and fertilizer use, might be advantageous to farmers.

The resulting knowledge bits are provided to IoT frameworks for developing management strategies

Table 1: Agricultural Word on Deep Learning

No.	Agriculture is an application area	Instructive problem description	Structure used	Utilized dataset	Reference
1.	Plant recognition	See various plants from seven different views whole-plant, flower, branch, fruit, Leaf, stem, and all-natural, pesticide-free harvesting	Caffe	the Plants life-clef 2015 data collection has 91759 images	[2-3]
2.	Crop categorization (variety/classification):	Some crop types, such as sugar beets, maize, wheat, soybeans, and sunflowers, are described in this passage.	Brought to fruition by the writers,	the data collected by two European satellites (Landsat-8 and Sentinel-1A RS) revealed the existence of 19 multi-temporal scenes."	[6-7]
3.	the detection of illnesses that affect leaves	Other than healthy leaves, there are 13 types of plant illnesses.	Caffe	The authors created a self-created database of 4483 photos.	[5]
4.	Counting fruit	Number of tomatoes predicted by image processing	TensorFlow	24,000 artificially-created photos produced by the authors	[9-12]
5.	The estimated moisture content of the soil	Prediction of the soil moisture content across a maize field that has received watering.	Authors who developed the idea.	Information on soil collected from an irrigated cornfield in China's northwest was provided	[15]
6.	Disease detection in plants	An easier way is to identify 14 crop species and 26 illnesses.	Caffe	The data collection contains 54306 photos of damaged and healthy plant specimens, created using Plant Village's public information.	[20]

By applying Deep Learning's unsupervised learning methods, a framework becomes increasingly intelligent on its own. Deep Learning can identify the most critical qualities that contribute to the delivery of accurate and dependable results. Since deep learning can generate non-human qualities without human involvement, IoT big data might save data scientists enormous amounts of time. Whereas traditional machine learning algorithms employ just a few characteristics, deep learning (DL) uses many complex traits. IoT sensor systems must be easy to use to get the advantages. Deep Learning algorithms may be used in real-time analysis of data obtained from IoT sensors to develop and remodel IoT applications in the future.

2. Material and Methods

Artificial neural networks (ANNs) or computer frameworks that mimic the operation of the human brain are behind deep learning. The areas in which deep learning is now being used include natural language processing, autonomous gameplay, voice control in tablets, phones, hands-free speakers, and autonomous autos (DL). In this scenario, a computer model uses speech, text, or photos to categorize objects directly. Deep Learning models (DLM) are taught using many labelled data and neural network topologies with several hidden layers. Neural network design is used for several deep learning approaches. Deep learning models are often known as Deep Neural Networks because of this reason (DNN). Deep learning is a method that trains artificial neural networks (ANNs), which consist of several layers that grow in number and complexity over time.

Having analyzed the data, it is clear that process productivity is connected to the depth of the network. NNs collect data and enhance training methods via the use of learning algorithms. Processing will be more effective if the dataset is more extensive. Deep learning aims to emulate the way our brains process information. Self-driving cars, along with voice and image recognition, are part of this business. Machine learning algorithms cannot manage highly dimensional and intricate data with considerable input and output volumes. When you have enormous volumes of complex data like image processing, image translation, and natural language processing, use cases like these are pretty valuable. To deal with such complex issues, the development of deep learning was used. Deep learning helps create depth in the model by revealing relevant information sequentially, automatically predicting and recognizing agricultural activities. Perhaps the fascinating part of deep learning focuses on relevant traits or qualities from raw data. Feature extraction is used when you want to turn the information into characteristics that may define the input. Feature extraction utilizes a few automated ways to provide crucial data attributes to users, students, teachers, or scholars. In Deep Learning, there is no need to extract photo properties manually. When training is finished, the network can identify features. To represent the network and proven dataset's framework, all you have to do is type in the pixel or image. Figure 3 shows how Deep Learning works (DL).

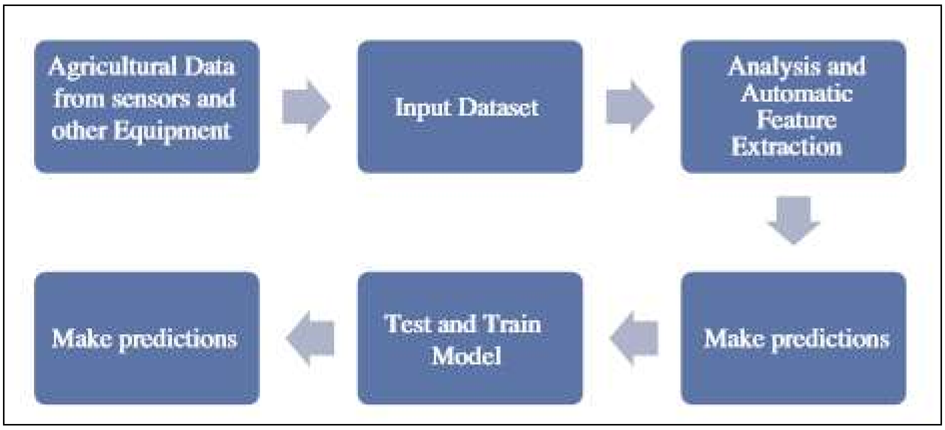

Fig 3: Deep learning, Source: Authors Field Work, 2021

Data scientists and learning specialists use deep learning and machine learning to increase analytics and learn in IoT applications. The data created by IoT devices is enormous, and Deep Learning is used to go through all the information and find the most important pieces. For example, image categorization is used in many IoT applications, including plant disease identification, traffic sign identification, and human posture identification. In addition, images and videos are the sources of input data for ML and DL algorithms in many IoT applications. Intelligent video cameras are also employed in various applications, including smart homes, smart agriculture, and smart cities.

2.1. Deep Learning: Content, Algorithms, Frameworks, And Applications

Predictive analytics automation is a tool for using deep learning. DL is used in various industries, such as agriculture, where it is employed for several objectives, including fruit identification, crop classifications, plant classifications, and fruit weight estimation in hydroponic agriculture. To have a sustainable farm, you must grow healthy crops. Complex issues such as Image identification, object identification, natural language processing, Image classification, and Image segmentation have proved to be solved via deep learning. while dealing with vast volumes of data, deep learning's classification accuracy generates exceptional results.

As a consequence, you will need a considerable number of training datasets. Automatic agricultural forecasting and detection are also powered by deep learning. The current growth in intelligent agriculture is covered, including deep learning and machine learning.

The irrigation system, which incorporates the Internet of Things, is described in this article. For data collection, sensors and k-nearest neighbour classification were utilized. An algorithm was used to anticipate soil water irrigation using sensor data. This watering system has several components working together, and the irrigation was programmed to be intelligent. This setup uses a Raspberry Pi 3 and an Arduino Uno to power the system. The data sets created on the cloud server, and the expected data were kept in the cloud so that farmers could access the information using their mobile phones. Deep neural networks (DNNs) were utilized to build an intelligent hydroponic system based on the Internet of Things (IoT) (DNN). It can monitor several environmental variables while ensuring the control system is responsive to environmental changes such as temperature, pH, illumination, and moisture. Learning these parameters using Deep Neural Networks is commonplace now. The simulation process included collecting all of the characteristics in real-time over weeks, and the team then trained them 10,000 times with an accuracy of 88%. This system was built using Arduino and the Raspberry Pi 3. In the cloud, the data was constantly updated to keep pace with projections.

We used deep convolutional networks to develop a model for classifying leaf photos and identifying plant illness. They studied the deep learning technique to categorize and identify plant illness, as shown in the image above. The model can accurately identify thirteen plant diseases. Approximately 3000 initial photographs were acquired from the Internet and used to build the database. CNNs learned to learn by training on Caffe, a DL framework. The model's accuracy was 96.3 percent. WSN (Wireless Sensor Network) and IoT were also employed for smart farming. Using the technique, the ideal amount of production will be estimated, and the farm irrigation framework will be optimized for the following crop rotation. This was done by routine monitoring of the field. For field surveillance reasons, soil characteristics such as temperature, moisture, and others were obtained. They constructed a WSN to access sensor data, then analyzed uploading cloud data.

2.2. Many well-known deep learning algorithms

This section provides an overview of the most frequently used Deep Learning algorithms:

2.2.1 Convoluted neural network (CNN)

CNN's are made up of a complex artificial neural network (ANN) called a deep feedforward ANN (DFANN), which analyzes visual images. These networks are constructed from neurons with programmable weights and biases. Neurons receive inputs and then perform a dot product on those inputs. For example, a CNN converts two-dimensional information into three-dimensional output, such as an image or a sound wave. To recognize the structure, the structure comprises convolutional, and pooling layers for feature extraction and the convolutional and pooling layers both serve as classifiers. Also, CNN might be used in several ways in the agricultural industry, such as disease detection on crops and plant leaves, the classifying of land cover, plant recognition, weed identification, and fruit counting.

2.2.2 Neuron-inspired neural networks (RNN)

Nodes are stacked in layers that are essentially neuron-like. These directed connections, also called one-way connections, are employed in many agricultural disciplines, including soil cover categorization, crop yield calculation, weather prediction, soil moisture content estimate, and animal research. In addition, a recurrent neural network is a good fit for processing time-series data.

2.2.3 A kind of generative adversarial network (GAN)
GANs are made of two neural network models in competition with each other. This data from the training set may be inspected, interpreted, and simulated using these models. To expand on this, GAN has often been used to enhance datasets. In this example, two neural networks can work together to provide high-quality data. Despite being a different form of the neural network, it is clear that GAN is also highly effective for image processing.

2.2.4 Short-Long Term Memory (LSTM)
This is the most often used deep learning method. A big, versatile computer, like the iMac, can do Image recognition tasks together with other types of data processing (for example, voice or video). Classifying and predicting time series data are good uses for these terms. LSTM is often used for agricultural applications such as classifying crop kinds, forecasting crop yields, and forecasting weather. Additionally, LSTM is suitable for handwriting and voice recognition.

3.0 Result and Discussion
A deep learning framework is a software interface or tool that helps you create deep learning models swiftly and efficiently.

3.1 Using tensors
TensorFlow is a publicly accessible Deep Learning and Machine Learning library that utilizes a wide range of Deep Neural Networks. The concept of using graphs to generate neural network models is what is used in neural network models. In other words, nodes represent mathematical operations, whereas edges represent data arrays, which may have more than one dimension, and between which data flows. In addition, TensorFlow comes with TensorBoard, a suite of visualization tools designed to provide visual feedback on TensorFlow calculations.

3.2. Convolution Architecture for Feature Extraction
Caffe is a free and open-source platform for creating numerous DL architectures. This C++ framework is optimized for GPU computations using CUDA (Compute Unified Device Architecture). The tools included in this program bundle additionally provide MATLAB and Python interfaces. It can also handle several deep learning architectures for Image segmentation and classification. Fully connected neural network topologies are compatible with CNN, LSTM, and the CNN+LSTM architecture.

3.3. The PyTorch
PyTorch is an open-source machine learning platform for research and development (ML). This is a utility that's used to aid the DNN model development. It includes a diverse set of deep learning algorithms. It is based on Torch, a framework for developing and training deep neural networks. PyTorch provides a straightforward methodology for training and creating deep learning models, making it easy to do both.

3.4. Theano
Theano is an open-source Python-based framework for deep and machine learning. Theano is a versatile computation engine capable of executing on both the CPU and GPU. It is, however, faster on the GPU than on the CPU (CPU). Theano is a machine learning library used to train deep neural network algorithms.

3.5. How deep learning is used in agriculture
Deep learning offers a plethora of applications in agriculture. Table 1 summarises some of the pertinent prior work in agriculture that has used deep learning.

4. Conclusion
As the World's population grows every day, there is a corresponding rise in the need for food production. To enhance food yield, the government pushes farmers to employ contemporary technology. As a result, farmers use IoT data to get key insights that help them maximize profits. As previously stated, there are several recognized uses of analytics based on IoT, such as detecting soil temperature, nutrients, moisture, and the evaluation and control of water usage for plant development. "Both deep learning and the Internet of Things have done a lot to assist people, cities, and the environment." As the relationship between IoT and Deep Learning, the relationship between DL and Makers is frequently described as a relationship between customers and producers, with Makers providing data broken down using DL (DL) strategies.

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