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AGRICULTURAL PROJECT USING DEEP LEARNING ARCHITECTURE

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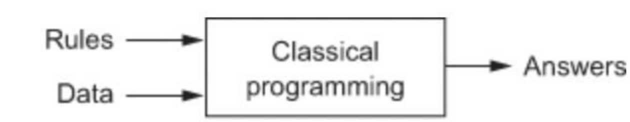
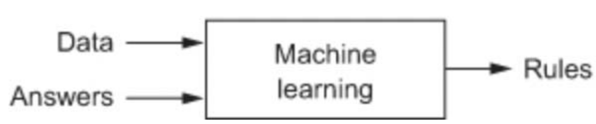
Abstract:In-depth learning develops the most advanced, sophisticated method of processing images and data analysis, yielding promising results and great power. In-depth learning has recently entered the agricultural field after being used successfully in other fields. In this Thesis, we conduct a survey of research efforts that employ in-depth learning strategies in a variety of agricultural and food production challenges. We investigate specific agricultural issues that are still being researched, specific models and frameworks, resources, the environment, and data pre-processing, as well as overall performance as measured by the metrics used in each study project. Furthermore, we learn to compare in-depth reading with other popular strategies available, based on classification or functional retardation differences. Our findings show that in-depth reading outperforms existing widely used image processing methods in terms of accuracy**.**

***IndexTerms* - Deep learning, data analysis, accuracy, image processing.**

I. INTRODUCTION

Deep Learning is a subset of Machine Learning that maps input to output using mathematical functions. These functions can extract non-redundant information or patterns from data, allowing them to establish a link between the input and the output.This is referred to as learning, and the process of learning is referred to as training.Traditional computer programming combines input and a set of rules to produce the desired output. In both machine learning and deep learning, input and output are linked to rules.When these rules are combined with new input, they produce the desired results.





To extract information, modern deep learning models employ artificial neural networks, also known as neural networks.These neural networks are made up of simple mathematical functions that can be stacked on top of each other and arranged in layers to give them a sense of depth, hence the term Deep Learning.Deep learning can also be viewed as an approach to Artificial Intelligence, a clever combination of hardware and software used to solve tasks that require human intelligence.

Agriculture ensures food security for the country, which is why it is the country's backbone. It is critical to the majority of the country's external trade. Agriculture provides a living for approximately 75% of the world's population. Because of the increase in population, there is a need to increase yield in the field of agriculture, so we must improve the status of agriculture. Farmers are looking for cost-effective ways to increase crop production while utilising available resources efficiently. This contributes to the new application of digital technologies in agriculture to assist farmers in making better decisions and increasing yields. We can now overcome various problems and challenges in agriculture fields by using deep learning methods. Everything nowadays is digitalized, from home appliances to spacecraft, and this is only possible because of intelligent systems that use artificial intelligence and their associated applications. At the moment, machine learning improves our lives. Deep learning is a subset of machine learning in which the goal is to create neural networks that simulate the human brain for analytical learning. It interprets data like text, images, video, and sound by simulating how the human brain works. It is applied to complex problems such as image recognition, natural language processing, image classification, image segmentation, and object detection. Deep Learning necessitates a large training dataset because the classification precision of a DL classifier is entirely dependent on the size and quality of the dataset.

II. RELATED WORKS

Modern technology has enabled humanity to produce enough food to feed more than 7 billion people. However, many factors continue to threaten food security, including climate change (Tai et al., 2014), pollinator decline, plant diseases, and others. Plant diseases are not only a threat to global food security, but they can also be disastrous for smallholder farmers who rely on healthy crops. Smallholder farmers produce more than 80% of agricultural production in developing countries, and crop losses due to pests and diseases account for more than 50% of crop losses. Furthermore, the vast majority of hungry people (50%) live on small farms, making smallholder farmers vulnerable to pathogen-induced food supply disruption.

Several efforts have been made to halt the spread of plant diseases. Integrated pest management (IPM) methods have greatly improved historical approaches to the widespread use of pesticides over the last decade. Alternatively, diagnosing the disease as soon as it appears is an important step in proper disease management. Historically, agricultural extension organisations or other institutions, such as local botanical clinics, have supported diagnostics. In recent years, such efforts have been aided by the availability of online disease diagnostic information, which has expanded the Internet's global reach. Even more recently, mobile-based tools have proliferated, capitalising on the world's instantaneous historical discovery of mobile technology.

Because of their computing power, high-resolution displays, and numerous built-in resources, such as advanced HD cameras, smartphones, in particular, offer newer ways to assist in disease diagnosis. By 2020, it is expected that there will be between 5 billion and 6 billion smartphones in the world. By the end of 2015, 69% of the world's population had access to portable broadband coverage, and mobile broadband coverage reached 47% in 2015. since 2007, a 12-fold increase (ITU, 2015). The combination of common smartphone features, HD cameras, and efficient processors on mobile devices creates a situation in which diagnostic-based diagnostics, if technically feasible, can be made available at an unprecedented level. We show technological feasibility using an in-depth study method with 54,306 images of 14 plant species with 26 (or healthy) diseases made public through the Plant Village project.

Computer vision, particularly object recognition, has made significant advances in recent years. The PASCAL VOC Challenge, and more recently the ImageNet-based Image Scale (ILSVRC) database, have been widely used as benchmarks in the computer industry for many visual-related problems, including object classification. In 2012, a large, large convolutional neural network achieved an error rate of 5- 16.4% for image classification across 1000 categories. Various advances in deep convolution neural networks over the next three years reduced the error rate to 3.57%. While training large neural networks takes time, trained models can split images quickly, making them ideal for consumer applications on smartphones.

The most efficient model receives an F1 rating of 0.9934 points (total accuracy of 99.35%), indicating that our approach is technically feasible. Our findings are the first step. Deep neural networks have recently been used successfully as end-of-study models in a variety of domains. Similar to a pair of diseases, neural networks provide a map between inputs — such as a picture of a sick plant — and outputs. The neural network nodes are mathematical functions that take numbers from the incoming edges and provide numerical output as an exit curve. Deep neural networks simply map the input layer to the output layer using stacked layer nodes. The goal is to build a deep network in such a way that the network structure and functions (nodes) as well as edge weights correctly map out the input in-put. Deep neural networks are trained by fine-tuning network parameters in order to improve mapping during the training process. This process is computer-generated, and it has recently been greatly improved due to the value of both intellectual and engineering achievements.

We need a large, verified database of sick and healthy plant images in order to create accurate image detectors for plant disease diagnostic purposes. Such a data set did not exist until recently, and even small data sets were not free. To address this issue, the Plant Village project has begun gathering tens of thousands of photos of healthy and diseased plants and making them freely available. We present the classification of 26 diseases in 14 plant species using a convolution neural network and 54,306 images. Our models' performance is measured by their ability to predict the correct pair of plant diseases based on approximately 38 classes. The most efficient model receives an F1 rating of 0.9934 points (total accuracy of 99.35%), indicating that our approach is technically feasible. Our findings are the first step towards developing a plant-based diagnostic programme that is supported by smartphones.

III. METHOD

In-depth neural networks that incorporate both encryption techniques and encryption methods, which have been studied in a variety of fields. Strategies such as Hopfield neural networks and the time of turmoil do not cause neural networks to be delayed. In-depth testing has been performed on automated coding networks. Because the proposed networks are based on the aforementioned strategies, they revitalise productive networks and automated coding frameworks in particular.

Conventional algorithms, on the other hand, maintain their prominence because the aforementioned techniques can be used in a variety of programmes outside of research studies. The high calculation time required to implement a few matrix functions and automatic in-depth learning encoders makes the technology difficult to adapt to real-time applications.

Many studies have synchronised and evaluated cryptanalysis and cryptographic application in in-depth learning models in recent years. Instead of focusing solely on in-depth learning methods, a combination of common encryption techniques and highly modified neural networks was used to improve performance. Default encoders use neural networks to handle data encoding and decoding. Examples of useful results obtained by default encoder applications that integrate speech spectrogram, image processing, and deionizing.

The encryption process can also be performed with pre-installed auto encoders, but they are computer-expensive and lack security because the encoder and decoder are trained accordingly. However, because it promotes continuous pressure with the deleted photos, the quality of the photos will be much higher. Many autoencoder applications have not been cryptographically tested. Another in-depth learning method is the Chaotic Hopfield neural network, which hides blank text using binary sequences during encryption. 'Neural cryptography analysis' is a significant and ancient method that is based on both learning methods, but it is very obvious in attack.

Aside from cryptographic techniques, adversarial production networks (GANs) are more common production networks that take random sound as input and produce realistic images. This network operates without bias in the creation of productive networks that negotiate image quality.

You can determine a website's privacy level using unique privacy. Deciding what is best for consumer privacy protection will allow the individual to explore various options. We will calculate the risk that someone will be able to leak confidential data into the database and how much data will be leaked the most after recognising our level of data protection. Sound in effects is another method used by various privacy organisations to protect individual privacy.

Unique location privacy: audio is used in each data centre independently of the database. Different local privacy may increase the model's efficiency in cases where different customers want to collaborate without exchanging raw data.

Once the database has been retrieved from raw data, processed, and deleted, the problem must be interpreted. In this case, the problem must be translated into the name of the company and the label. A label is an event or location, a sequential model that attempts to predict, and a person, object, or event defined by a label is referred to as a business.

Recommended Encoder E weights and E-dimensions are generated at random and are not trained for any purpose, as E's function is to convert the n-dimensional image vector into a p-dimensional floating point vector that represents the output layer E. Without knowing the parameters and the entire E structure, it is not possible to restore the back engineer image from coding. Decoder R takes an encoded vector and produces an 8-bit RGB matrix image. Decoder D is a highly productive neural network that accepts a coded vector as input and outputs an n-dimensional image vector that is reconstructed into an 8-bit RGB matrix and processed to create an image. D has been trained to have difficulty retracting from the large number of image code pairs found in E in order to generate a true image from coding. As a result, D does not rely on E to be trained in any way as long as a large codec data set from E is detected, and can be viewed as an adversary net attempting to learn a hidden relationship in E that converts an image into code.

The parameters can be developed in ways other than the gradient descent (GD) method used by many machine learning models. In short, the algorithm begins by implementing the assignment w in the model parameters, and in some cases, this parameter is also provided to the first-aid variable. Gradient g_i is calculated in the ith iteration by selecting the subset set of training B as follows:

$$g_i = \sum_{z \in B_i} F'(w_{i-1}, z), \tag{1}$$

Where F is a prepared function. At the same time, the parameters of the problem should also be reviewed with the review function φ such as:

$$(w_i, a_i) = \varphi(w_{i-1}, a_{i-1}, g_i), \tag{2}$$

Where wi is the new assignment made to problem parameters and ai new assignment made of the auxiliary variables. The whole process is repeated several times leading to the final vector of weight and is used as a result of the learning process.The main purpose of privacy diversity is to evaluate work in the database in a confidential manner and to develop processes in a way that enhances privacy throughout the mathematical process. In this process, confidentiality is guaranteed by boundaries in the form of two categories: ϵ, δ ≥. Function f: X * → Y is known as (ϵ, δ) -DP if all S Y, and every pair of D dataset that holds it differs from the single D ′ □ X * record, such as:

$$\Pr[f(D) \in S] \leq e^{\in}\Pr[f(D') \in S] + \delta, \tag{3}$$

When it comes to internal randomization opportunities, f. During the calculation, only a small amount of information from the database will be displayed for each record, according to this definition. Another way to convert a non-private function f into a private function is to add audio to the database at random. Given the key conditions, this necessitates the Lipschitz-smooth function f:

$$\left|\left|f(D) - f\left(D'\right)\right|\right| \leq \Delta\left|D - D'\right|. \tag{4}$$

When Rand is tried for distribution, a distribution must be determined in such a way that the function D f(d) + Rand has the necessary sequestration.

The proposed work's primary goal is to simplify the process of converting data from raw structure to a specific matrix. As a result, it can upload to the deep learning operation.The following factors initiate the operation architecture: It performs extractor data sanctification and raw data processing, and it transforms parsimoniously into a series of time stamped datasets. Each learner represents a feature binder, and each learner provides a point vector and a marker. It defines the classification problem for the operation and interacts with the learner to provide results.

IV. DATA PROCESSING

We have pictures of Cotton plants and cotton leaves.
Data is divided into 4 classes.

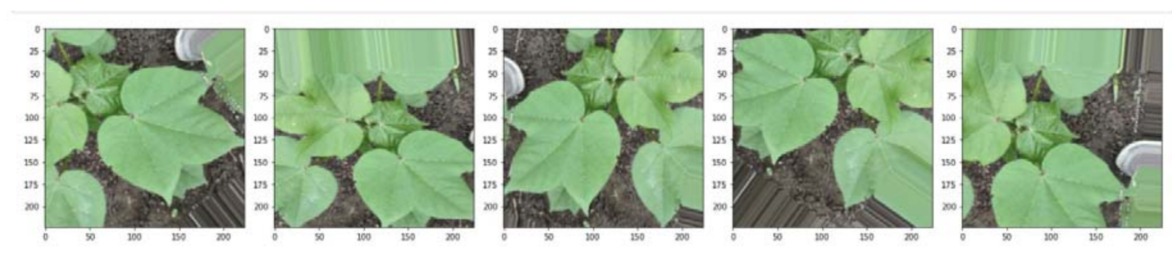
- Sick cotton plant
- New cotton plant
- A sick cotton leaf
- A new cotton leaf.

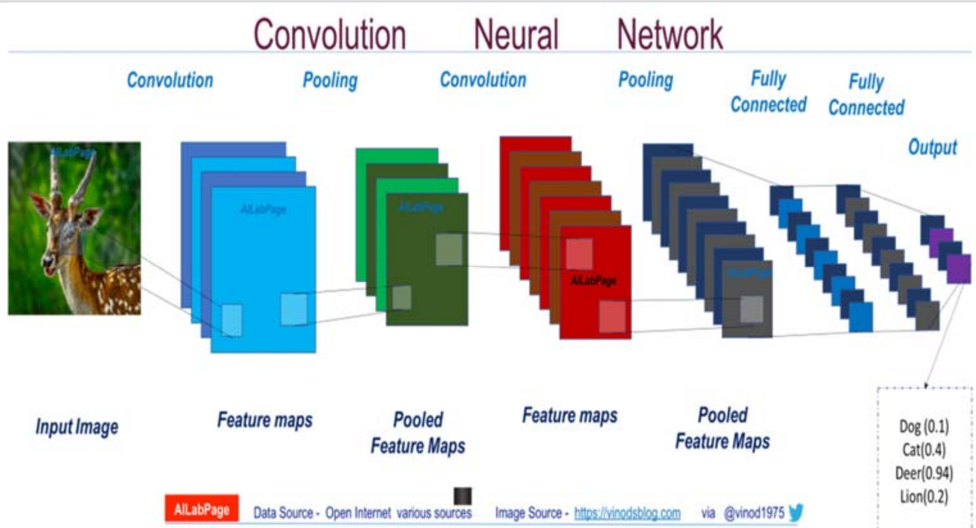
V. DATA AGUMENTATION

Data augmentation is a method of automatically creating new training data from existing training data. This is accomplished by generating new and distinct training models using domain-based techniques based on examples from training data.

Why is data augmentation necessary?

We don't know what kind of image we'll get from a user in a production that may have a title or zoom in or zoom out, so we'll need to augment data in training classes to successfully classify any type of image.

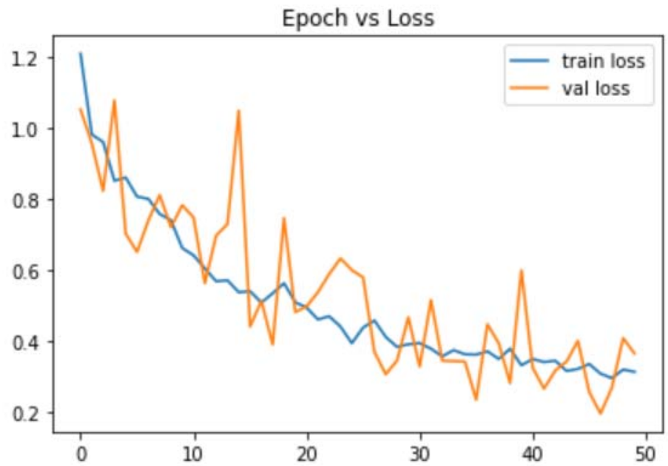




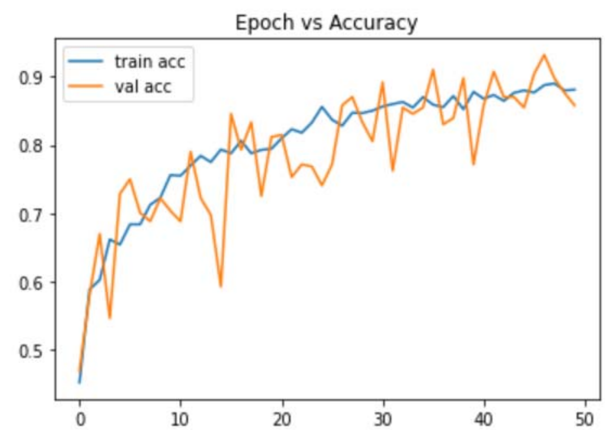
VI. RESULTS

CNN Model
At the end of the 50th epoch
training_data_set_accuracy = 0.88
Valdation_data_set_accuracy=0.85

Epoch vs Loss

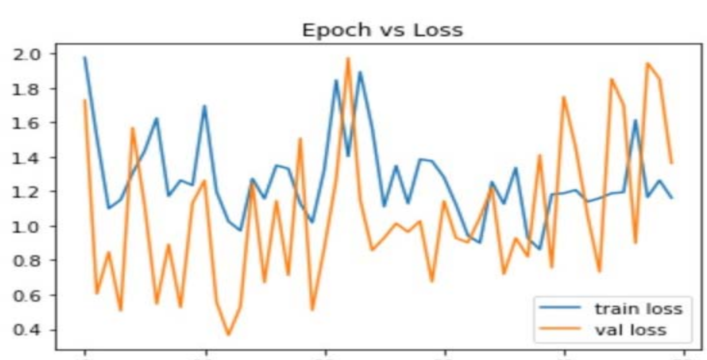


Epoch vs Accuracy

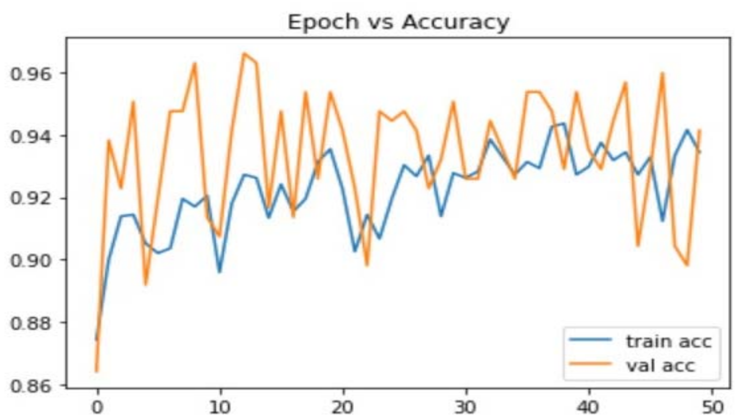


InceptionV3 model
At the end of 50th epoch
training accuracy = 0.93
validation accuracy = 0.94

Epoch vs Loss



Epoch vs Accuracy



VII. CONCLUSION

In this paper, we conducted a survey of deep learning-based research efforts in the agricultural domain. We examined the specific area and problem they focus on, technical details of the models used, data sources used, pre-processing tasks and data augmentation techniques used, and overall performance based on the performance metrics used by each paper. In terms of performance, we then compared deep learning to other existing techniques. Our findings show that deep learning outperforms other popular image processing techniques in terms of performance. In the future, we intend to apply the general concepts and best practises of deep learning, as described in this survey, to other areas of agriculture where this modern technique has not yet been fully utilised.

Our hope is that this survey will encourage more researchers to experiment with deep learning, using it to solve various agricultural problems involving classification or prediction, computer vision and image analysis, or data analysis more broadly. Deep learning's overall benefits are encouraging for its future application in smarter, more sustainable farming and more secure food production.

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