ABSTRACT

Traditional farming is going out of date nowadays. Technologies are being introduced in the farming sector for the past decade and in recent years it is seen that the participation of deep learning and machine learning is playing an integral role in solving traditional problems. The introduction of new technology has increased the productivity of farmers and also increased the yields and quality of the crops too. Plant diseases are a serious concern for the consumers and the farmers too. It does not only carry some harmful bacteria within itself however it compromises the yield of the crops too. The identification of such plant diseases has been a continuous problem for cultivators and researchers. Deep learning-enabled developments in the field of computer vision have paved the path for computerassisted plant disease diagnosis. Deep Learning has achieved great success in the categorization of a number of plant diseases by exploiting its ability to recognize objects with the help of convolutional neural networks. Various deep learning algorithm like AlexNet and LeNet-5 is applied on a publicly available dataset (plantvillage dataset) so that the neural network can capture the various features of a specific disease and diagnose it accordingly using a human-like decision making skill

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LIST OF SYSMBOLS

NOTATION	
NUTATION	

S.NO	NAME	NOTATION	DESCRIPTION
1.	Class	+ public -private -attribute -attribute	Represents a collection of similar entities grouped together.
2.	Association	Class A Class B Class A Class B Class A Class B	Associations represents static relationships between classes. Roles representsthe way the two classes see each other.
3.	Actor		It aggregates several

				classes into a single classes.
4.	Aggregation	Class A Class B	Class A Class B	Interaction between the system and external environment

5.	<i>Relation</i> (uses)	uses	Used for additional process communication.
6.	Relation (extends)	EXTENDS	Extends relationship is used when one use case is similar to another use case but does a bit more.
7.	Communication		Communication between various use cases.

8.	State	State	State of the processs.
9.	Initial State	$0 \longrightarrow$	Initial state of the object
10.	Final state	\longrightarrow	F inal state of the object
11.	Control flow		Represents various control flow between the states.
12.	Decision box	$\leftarrow \bigcirc \rightarrow$	Represents decision making process from a constraint
13.	Usecase	Usescase	Interact ion between the system and

		external environment.
14.	Component	Represents physical modules which is a collection of components.
15.	Node	Represents physical modules which are a collection of components.
16.	Data Process/State	A circle in DFD represents a state or process which has been triggered due to some event or acion.
17.	External entity	Represents external entities such as keyboard,sensors,etc.

18.	Transition		Represents communication that occurs between processes.
19.	Object Lifeline		Represents the vertical dimensions that the object communications.
20.	Message	Message	Represents the message exchanged.

1. INTRODUCTION

India being an agriculture country, about 70% of the population depends on it as their main source of income and food. Agriculture plays and important part of the Indian economy as it contributes about 17% of the total GDP. Farmers have wide range in selecting their crops and finding a suitable pesticide for it but in spite of all their efforts it can all be vain if they can't identify the disease plaguing their crops. Thus, disease on crops can significantly reduce the quality and quantity of agricultural products along with economical damage to the farmers. To successfully cultivate crops without incurring much loss we need to properly identify the disease and remedy it, this requires a lot of work and processing time as detecting each and every plant can be tedious can time consuming. To lessen the burden of the farmers along with their losses we propose the use of a system which can detect infected plants so that we can curb the spread of infection and diseases at an earlier step thus reducing losses and crop failure.

In most cases symptoms like fungal infection and rot can be seen on the leaves, stem and fruit. This project provides an insight into how we deal with the problem and further discuss the challenges of our work and how we can improve upon it in future work.

1.1 OUTLINE OF THE PROJECT

Overview of the system:

- Define a problem
- Gathering image data set
- Evaluating algorithms
- Detecting results

The steps involved in Building the data model is depicted below.

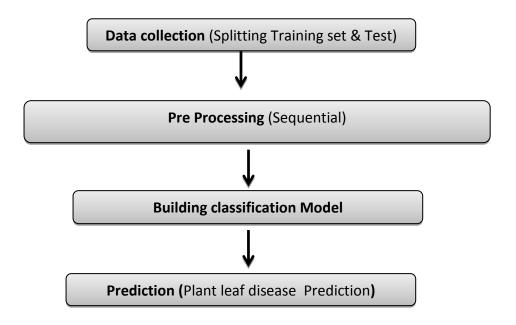


Fig 1: Data flow diagram for CNN model

1.2 OBJECTIVE :

Smart farming system using necessary infrastructure is an innovative technology that helps to improve the quality and quantity of agricultural production in the country. Disease in plants has long been one of the major threats to food security as it dramatically reduces the crop yield and compromises the quality. The identification of such diseases has been a significant challenge to cultivators and researchers. Deep learning-enabled developments in the field of computer vision have paved the path for computer-assisted plant disease diagnosis. Deep learning with convolutional neural networks (CNN) has achieved tremendous success in the categorization of a number of plant diseases by exploiting its ability to recognise objects, and the solution provides an efficient technique for detecting plant disease. Various CNN algorithm like AlexNet and LeNet-5 is applied on a publicly available dataset (plant village dataset) so that the neural network can capture the various features of specific disease and diagnose it accordingly using a human-like decision making skill.

The presented work presents a color based segmentation techniques for extraction of yellow rust in whet crop images. Accurate segmentation of yellow rust in wheat crop images is very part of assessment of disease penetration into the wheat crop. And in turn to take the necessary preventive action for minimizing the crop damage. The jpeg images acquired from CCD camera are read into the matlab tool and a color-based segmentation algorithm is performed to segment the yellow rust. The segmentation of color is performed base on k-means algorithm.

TITLE: Comparative study of Leaf Disease Diagnosis system using Texture features and Deep Learning Features

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YEAR: 2018

The feature extraction technique plays a very critical and crucial role in automatic leaf disease diagnosis system. Many different feature extraction techniques are used by the researchers for leaf disease diagnosis which includes colour, shape, texture, HOG, SURF and SIFT features. Recently Deep Learning is giving very promising results in the field of computer vision. In this manuscript, two feature extraction techniques are discussed and compared. In first approach, the Gray Level Covariance Matrix(GLCM) is used which extracts 12 texture features for diagnosis purpose. In second appraoch, the pretrained deep learning model, Alexnet is used for feature extraction purpose. There are 1000 features extracted automatically with the help of this pretrained model. Here Backpropagation neural network (BPNN) is used for the classification purpose. It is observed that the deep learning features are more dominant as compared to the texture features. It gives 93.85% accuracy which is much better than the texture feature extraction technique used here.