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Cultivation of Crops using Machine Learning and Deep Learning

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ABSTRACT
To assist you with the entire farming operation, we use cutting-edge machine learning and deep learning technologies. Make educated decisions about your area's demographics, the factors that influence your crop, and how to keep them safe for a super awesome good yield. With the rise of big data technology and high-performance computing, machine learning has opened up new possibilities for data-intensive research in the multi-disciplinary agri-technologies domain. (a)Plant disease forecast, (b) fertilizer recommendation, and (c) crop recommendation The papers presented have been filtered and classified to show how machine learning technology can support agriculture. Farm management systems are evolving into real-time artificial intelligence powered programmes that provide rich suggestions and insights for farmer decision support and action through applying machine learning to sensor data.

KEYWORDS*: Crop recommendation; Fertilizer recommendation; Plant disease prediction; planning; precision agriculture*

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I. INTRODUCTION

In this project, I present a website in which the following applications are implemented; Crop recommendation, Fertilizer recommendation and Plant disease prediction, respectively. In the crop recommendation application, the user can provide the soil data from their side and the application will predict which crop should the user grow. For the fertilizer recommendation application, the user can input the soil data and the type of crop they are growing, and the application will predict what the soil lacks or has excess of and will recommend improvements. For the last application, that is the plant disease prediction application, the user can input an image of a diseased plant leaf, and the application will predict what disease it is and will also give a little background about the disease and suggestions to cure it

Agriculture plays a critical role in the global economy. Pressure on the agricultural system will increase with the continuing expansion of the human population. Agri-technology and precision farming, now also termed digital agriculture, have arisen as new scientific fields that use data intense approaches to drive agricultural productivity while minimizing its environmental impact. The data generated in modern agricultural operations is provided by a variety of different sensors that enable a better understanding of the operational environment (an interaction of dynamic crop, soil, and weather conditions) and the operation itself (machinery data), leading to more accurate and faster decision making.

Machine learning (ML) has emerged together with big data technologies and high-performance computing to create new opportunities to unravel, quantify, and understand data intensive processes in agricultural operational environments and Ease of Use

A. Machine Learning Terminology and Definitions

Typically, ML methodologies involves a learning process with the objective to learn from "experience" (training data) to perform a task. Data in ML consists of a set of examples. Usually, an individual example is described by a set of attributes, also known as features or variables. A feature can be nominal (enumeration), binary (i. e. , 0 or 1), ordinal (e. g. , A+ or B−), or numeric (integer, real number, etc.). The performance of the ML model in a specific task is measured by a performance metric that is improved with experience over time. To calculate the performance of ML models and algorithms, various statistical and mathematical models are used. After the end of the learning process, the trained model can be used to classify, predict, or cluster new examples (testing data) using the experience obtained during the training process.

B. Tasks of Learning

ML tasks are classified into two main categories, that is, supervised and unsupervised learning, depending on the learning signal of the learning system. In supervised learning, data are presented with example inputs and the corresponding outputs, and the objective is to construct a general rule that maps inputs to outputs. In some cases, inputs can be only partially available with some of the target outputs missing or given only as feedback to the actions in a dynamic environment (reinforcement learning). In the supervised setting, the acquired expertise (trained model) is used to predict the missing outputs (labels) for the test data. In unsupervised learning, however, there is no distinction between training and test sets with data being unlabeled. The learner processes input data with the goal of discovering hidden patterns.

C. Analysis of Learning

Dimensionality reduction (DR) is an analysis that is executed in both families of supervised and unsupervised learning types, with the aim of providing a more compact, lower-dimensional representation of a dataset to preserve as much information as possible from the original data. It is usually performed prior to applying a classification or regression model in order to avoid the effects of dimensionality

II. REVIEW

The reviewed articles have been, on a first level, classified in four generic categories; namely, crop management, livestock management, water management, and soil management. The applications of ML in the crop section were divided into sub-categories including yield prediction, disease detection, weed detection crop quality, and species recognition. The applications of ML in the livestock section were divided into two sub-categories; animal welfare and livestock production.

2.1. Crop Management

- Enter the corresponding nutrient values of your soil, state and city. Note that, the N-P-K (Nitrogen-Phosphorous-Pottasium) values to be entered should be the ratio between them.
- Note: When you enter the city name, make sure to enter mostly common city names. Remote cities/towns may not be available in the Weather API from where humidity, temperature data is fetched.
- Yield prediction, one of the most significant topics in precision agriculture, is of high importance for yield mapping, yield estimation, matching of crop supply with demand, and crop management to increase productivity.
- Examples of ML applications include in those in the works of an efficient, low-cost, and non-destructive method that automatically counted coffee fruits on a branch.
- The method calculates the coffee fruits in three categories: harvestable, not harvestable, and fruits with disregarded maturation stage.
- In addition, the method estimated the weight and the maturation percentage of the coffee fruits.
- The aim of this work was to provide information to coffee growers to optimise economic benefits and plan their agricultural work. Avoid combining SI and CGS units, such as current in amperes and magnetic field in oersteds.

2.2. Fertilizer suggestion system

- Enter the nutrient contents of your soil and the crop you want to grow.
- The algorithm will tell which nutrient the soil has excess of or lacks. Accordingly, it will give suggestions for buying fertilizers.
- The accurate detection and classification of crop quality characteristics can increase product price and reduce waste.
- The method was based on ML techniques applied on chemical components of samples.
- More specifically, the main goal was the classification of the geographical origin of rice, for two different climate regions in Brazil.

2.3. Disease Detection System

- Upload an image of leaf of your plant.
- The algorithm will tell the crop type and whether it is diseased or healthy.
- If it is diseased, it will tell you the cause of the disease and suggest you how to prevent/cure the disease accordingly.
- Note that, for now it only supports following crops

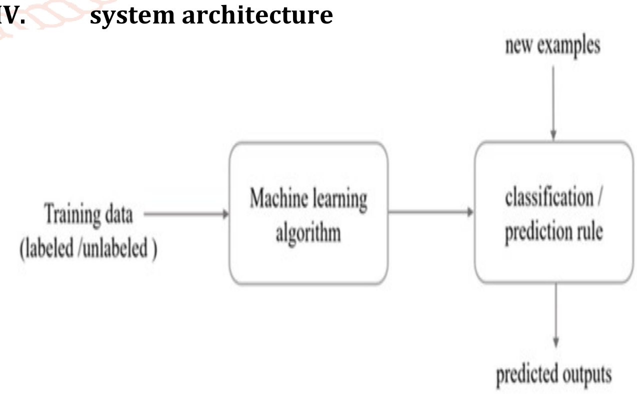
III. Supported crops

- Apple
- Blueberry
- Cherry
- Corn
- Grape
- Pepper
- Orange
- Peach
- Potato
- Soybean
- Strawberry
- Tomato
- Squash
- Raspberry

A. Species Recognition

The last sub-category of crop category is the species recognition. The main goal is the automatic identification and classification of plant species in order to avoid the use of human experts, as well as to reduce the classification time. A method for the identification and classification of three legume species, namely, white beans, red beans, and soybean, via leaf vein patterns has been presented in Vein morphology carries accurate information about the properties of the leaf. It is an ideal tool for plant identification in comparison with color and shape.

IV. system architecture



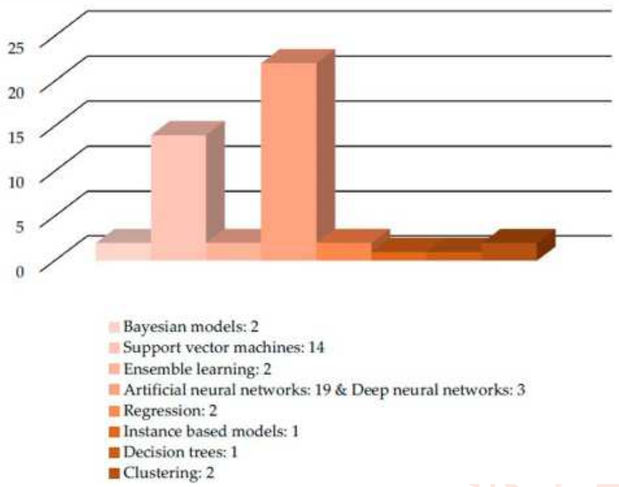
1. Abbreviations for machine learning models.

Abbreviation	Model
ANNs	artificial neural networks
BM	bayesian models
DL	deep learning
DR	dimensionality reduction
DT	decision trees
EL	ensemble learning
IBM	instance based models
SVMs	support vector machines

2. Abbreviations for machine learning algorithms

Abbreviation	Algorithm
ANFIS	adaptive-neuro fuzzy inference systems
Bagging	bootstrap aggregating
BBN	bayesian belief network
BN	bayesian network
BPN	back-propagation network CART
	classification and regression trees
CHAID	chi-square automatic interaction detector
CNNs	convolutional neural networks
CP	counter propagation
DBM	deep boltzmann machine
DBN	deep belief network
DNN	deep neural networks
ELMs	extreme learning machines
EM	expectation maximisation
ENNs	ensemble neural networks
GNB	gaussian naive bayes
GRNN	generalized regression neural network
KNN	k-nearest neighbor
LDA	linear discriminant analysis
LS-SVM	least squares-support vector machine
LVQ	learning vector quantization
LWL	locally weighted learning
MARS	multivariate adaptive regression splines
MLP	multi-layer perceptron
MLR	multiple linear regression
MOG	mixture of gaussians OLSR
	ordinary least squares regression

3. Presentation of machine learning (ML) models with their total rate.



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