JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

AN AUTOMATIC FERTILIZER SPRAYER USING MACHINE LEARNING ALGORITHM

T.V.Thirisa[1], V. Priyadharshini [2], S.Padmapriya[3], A.R.Padmapriya[4]
Mr. S. Selvakumar[5]
1234 Final Year Students, Department of Electronics and Communication Engineering,
5Assistant Professor, Department of Electronics and Communication Engineering,
Electronics and Communication Engineering,
K.L.N.College Of Engineering , Sivagangai , India

Abstract : An automatic fertilizer sprayer using machine learning algorithm and Raspberry Pi camera would describe a system that incorporates computer vision and machine learning techniques to optimize the application of fertilizer in agricultural fields. The system would consist of a Raspberry Pi camera that captures images of the plants, which are then processed using a machine learning algorithm. The algorithm would analyze the images and use the data to generate a customized fertilizer spraying plan that takes into account the specific needs of each area of the field. The sprayer would be fully automated, with the algorithm controlling the flow rate and direction of the fertilizer, ensuring that the correct amount is delivered precisely where it is needed. This would reduce the amount of fertilizer needed, decrease labor costs, and increase crop yields, making it an attractive solution for farmers. The integration of the Raspberry Pi camera would enhance the system's ability to identify and respond to changes in soil and crop conditions in real-time, resulting in more efficient and effective fertilizer application.

***Index Terms* – Machine Learning , Raspberry Pi , Fertilizer Sprayer**

I. INTRODUCTION

In farms, the farmers need to spray pesticides and have to stay up in the sun and spend a lot of time. Since they cannot look at each plant separately, they tend to spray pesticide on all the plants, which also wastes the pesticides because some plants might not need it and it damages the soil. In case of larger field, the labor costs also increase. Therefore, to minimize these issues we have designed our project . The algorithm would analyze the images and use the data to generate a customized fertilizer spraying plan that takes into account the specific needs of each area of the field. The sprayer would be fully automated with the algorithm controlling the flow rate and direction of the fertilizer, ensuring that the correct amount is delivered precisely where it is needed. This would reduce the amount of fertilizer needed, decrease labor costs, and increase crop yields, making it an attractive solution for farmers. The integration of the Raspberry Pi camera would enhance the system's ability to identify and respond to changes in soil and crop conditions in real-time, resulting in more efficient and effective fertilizer application. This paper suggests the effective use of technology to meet the agricultural growth. This a cost effective and one time investment project. It saves labor cost which also saves total cost for a farmer.

II. MACHINE LEARNING

Machine learning is a subfield of artificial intelligence (AI) that involves building algorithms that can automatically learn and improve from data without being explicitly programmed. It is based on the idea that machines can learn from and make predictions or decisions based on data inputs. In machine learning, algorithms can recognize patterns and relationships in large datasets, and can use these patterns to make predictions or decisions about new data. Machine learning has become increasingly popular in recent years due to the explosion of big data and the availability of powerful computing resources. It has the potential to revolutionize many industries, from healthcare and finance to transportation and manufacturing. However, it also raises important ethical and social concerns, including issues around bias, fairness, and accountability.

III. RASPBERRY PI

The Raspberry Pi 3 Model B+ is a powerful and versatile single-board computer that offers several improvements over its predecessor, the Raspberry Pi 3 Model B. It features a Broadcom BCM2837B0 processor, which is a Cortex-A53 64-bit SoC running at 1.4GHz. The board comes with 1GB LPDDR2 SDRAM, and it has a microSD card slot for operating system and data storage. The Raspberry Pi 3 Model B+ also features built-in Gigabit Ethernet, as well as 2.4GHz and 5GHz IEEE 802.11.b/g/n/ac wireless LAN and Bluetooth 4.2 BLE, making it easy to connect to networks and devices wirelessly. Additionally, the board has HDMI, MIPI DSI display port, and MIPI CSI camera port, providing video and audio output options. Overall, the Raspberry Pi 3 Model B+ is a great choice for various applications, including home automation, media centers, and well suited for machine learning .

Abbreviations and Acronyms

1. CNN - Convolutional Neural Network: Refers to a type of artificial neural network designed specifically for image recognition and processing.

2. Conv - Convolution: Refers to the mathematical operation that performs a dot product between two matrices and generates a feature map that represents the presence of a particular pattern in the input image.

3. Pooling - Pooling Layer: Refers to the layer in a CNN that downsamples the output of a convolutional layer to reduce the dimensionality of the input.

4. ReLU - Rectified Linear Unit: Refers to the activation function commonly used in CNNs that applies a non-linear function to the output of a convolutional layer.

5. FC - Fully Connected Layer: Refers to a type of layer in a CNN that connects every neuron in one layer to every neuron in the next layer, similar to a traditional neural network.

6. Dropout - Dropout Layer: Refers to a regularization technique used in CNNs that randomly drops out a percentage of neurons during training to prevent overfitting.

7. BatchNorm - Batch Normalization: Refers to a technique used in CNNs to normalize the input to a layer, making the optimization process more stable.

8. SGD - Stochastic Gradient Descent: Refers to the optimization algorithm commonly used in CNNs to update the weights of the network during training.

9. FCN - Fully Convolutional Network: Refers to a type of CNN that replaces the fully connected layers with convolutional layers to enable pixel-wise prediction, commonly used for image segmentation.

10. IoU - Intersection over Union: Refers to the evaluation metric used in CNNs for object detection and segmentation tasks to measure the overlap between the predicted and ground truth bounding boxes or masks.

RESEARCH METHODOLOGY

This system can be divided into different modules Dataset creation , plant detection and recognition and the hardware part.

3.1 Dataset Creation

CLASSIFICATION: You want an algorithm to answer binary yes-or-no questions (cats or dogs, good or bad, sheep or goats, you get the idea) or you want to make a multiclass classification (grass, trees, or bushes; cats, dogs, or birds etc.) You also need the right answers labeled, so an algorithm can learn from them. Check our guide on how to tackle data labeling in an organization.

CLUSTERING: You want an algorithm to find the rules of classification and the number of classes. The main difference from classification tasks is that you don’t actually know what the groups and the principles of their division are. For instance, this usually happens when you need to segment your customers and tailor a specific approach to each segment depending on its qualities.

REGRESSION: You want an algorithm to yield some numeric value. For example, if you spend too much time coming up with the right price for your product since it depends on many factors, regression algorithms can aid in estimating this value.

RANKING: Some machine learning algorithms just rank objects by a number of features. Ranking is actively used to recommend movies in video streaming services or show the products that a customer might purchase with a high probability based on his or her previous search and purchase activities. It's likely that your business problem can be solved within this simple segmentation and you may start adapting a dataset accordingly. The rule of thumb on this stage is to avoid over-complicated problems.

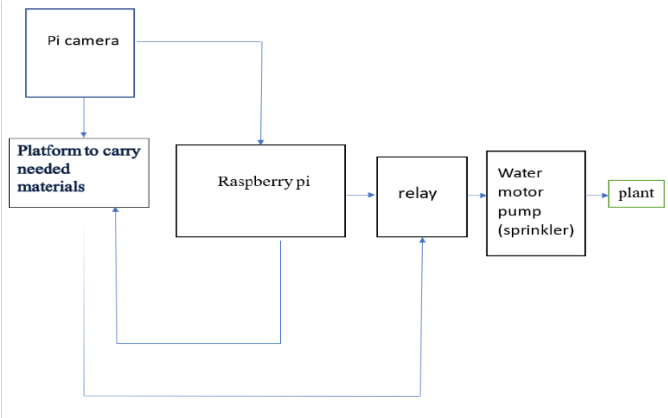

Fig .1 Block Diagram

3.2 Plant Detection

Modern technologies have given human society the ability to produce enough food to meet the demand of more than 7 billion people. However, food security remains threatened by a number of factors including climate change . The decline in pollinators (Report of the Plenary of the Intergovernmental Science-Policy Platform on Biodiversity Ecosystem and Services on the work of its fourth session, 2016), plant diseases (Strange and Scott, 2005), and others. Plant diseases are not only a threat to food security at the global scale, but can also have disastrous consequences for smallholder farmers whose livelihoods depend on healthy crops. In the developing world, more than 80 percent of the agricultural production is generated by smallholder farmers (UNEP, 2013), and reports of yield loss of more than 50% due to pests and diseases are common (Harvey et al., 2014). Furthermore, the largest fraction of hungry people (50%) live in smallholder farming households, making smallholder farmers a group that's particularly vulnerable to pathogen-derived disruptions in food supply.

Various efforts have been developed to prevent crop loss . Historical approaches of widespread application of pesticides have in the past decade increasingly been supplemented by integrated pest management (IPM) approaches (Ehler, 2006). Independent of the approach, identifying a disease correctly when it first appears is a crucial step for efficient disease management. Historically, disease identification has been supported by agricultural extension organizations or other institutions, such as local plant clinics. In more recent times, such efforts have additionally been supported by providing information for disease diagnosis online, leveraging the increasing Internet penetration worldwide. Even more recently, tools based on mobile phones have proliferated, taking advantage of the historically unparalleled rapid uptake of mobile phone technology in all parts of the world

Deep neural networks have recently been successfully applied in many diverse domains as examples of end to end learning. Neural networks provide a mapping between an input—such as an image of a diseased plant—to an output—such as a plant pair. The nodes in a neural network are mathematical functions that take numerical inputs from the incoming edges, and provide a numerical output as an outgoing edge. Deep neural networks are simply mapping the input layer to the output layer over a series of stacked layers of nodes. The challenge is to create a deep network in such a way that both the structure of the network as well as the functions (nodes) and edge weights correctly map the input to the output. Deep neural networks are trained by tuning the network parameters in such a way that the mapping improves during the training process. This process is computationally challenging and has in recent times been improved dramatically by a number of both conceptual and engineering breakthroughs

In order to develop accurate image classifiers for the purposes of plant disease diagnosis, we needed a large, verified dataset of images of diseased and healthy plants. Until very recently, such a dataset did not exist, and even smaller datasets were not freely available. To address this problem, the Plant Village project has begun collecting tens of thousands of images of healthy and diseased crop plants and has made them openly and freely available. Here, we report on the classification of 26 diseases in 14 crop species using 54,306 images with a convolutional neural network approach. We measure the performance of our models based on their ability to predict the correct crop-diseases pair, given 38 possible classes. The best performing model achieves a mean F_1 score of 0.9934 (overall accuracy of 99.35%), hence demonstrating the technical feasibility of our approach. Our results are a first step toward a smartphone-assisted plant disease diagnosis system.

3.3 Theoretical framework

To get a sense of how our approaches will perform on new unseen data, and also to keep a track of if any of our approaches are overfitting, we run all our experiments across a whole range of train-test set splits, namely 80–20 (80% of the whole dataset used for training, and 20% for testing), 60–40 (60% of the whole dataset used for training, and 40% for testing), 50–50 (50% of the whole dataset used for training, and 50% for testing), 40–60 (40% of the whole dataset used for training, and 60% for testing) and finally 20–80 (20% of the whole dataset used for training, and 80% for testing). It must be noted that in many cases, the PlantVillage dataset has multiple images of the same leaf (taken from different orientations), and we have the mappings of such cases for 41,112 images out of the 54,306 images; and during all these test-train splits, we make sure all the images of the same leaf goes either in the training set or the testing set. Further, for every experiment, we compute the mean precision, mean recall, mean F_1 score, along with the overall accuracy over the whole period of training at regular intervals (at the end of every epoch). We use the final mean F_1 score for the comparison of results across all of the different experimental configurations.

3.4 Hardware

This agricultural robot decreases farmers general attempts and also improves the work's pace and precision. This robot has been created to improve application precision and yield. As a microcontroller, Raspberry pi is used. Only raspberry pi controls the live video motion, spraying impact and robot movement.

This agricultural robot can display 3 processes, i.e.

(a) movement of machine

(b) uploading of video and

(c) spraying process for pesticides.

For the operation of the robot and the spray unit, the operator uses the Android application. The Raspberry pi is connected to an ordinary USB web cam, which is mounted on the robot to stream live video to the operator-connected PC. We use Raspberry Pi programmed with Python's programming code to identify and classify the disease in crops.

3.4.1. Robot Movement

DC motors are used for the robot's motion that are governed electronically by Raspberry pi with the assistance of L293D.andreceives signals from the input and sends them to the controller, which in turn spins the engine. By obtaining the signal, DC motors are switched ON and OFF by allowing Arduino to have a specific pin. An adequate velocity is provided by 300rpm DC motors.

3.4.2. Photo Capturing

With the aid of the USB webcam and Raspberry pi we stream the video to the operator PC. Video streaming can be achieved in many ways, i.e. by installing gstreamer software on both the raspberry pi and the operator PC or by installing VLC player on both the transmitter side and the receiver side [2]. We prefer to use VLC player to stream the video with https:// followed by raspberry pi's IP address, so it seems simple for operators to take snapshots from the streaming video to detect further disease.

3.4.3. Fertilizer Spraying Mechanism

The floating sensor and submersible pump were mounted inside the pesticide tank. The submersible pump is linked to one end of the tiny diameter pipe and the other end is linked to the sprayer nozzle. The operator can use the Android app to spray particular pesticide if the algorithm says the plant .

3.4.2.1 Model for CNN

Convolutional Neural Networks also known as CNNs or ConvNets, are a type of feed-forward artificial neural network whose connectivity structure is inspired by the organization of the animal visual cortex. Small clusters of cells in the visual cortex are sensitive to certain areas of the visual field. Individual neuronal cells in the brain respond or fire only when certain orientations of edges are present. Some neurons activate when shown vertical edges, while others fire when shown horizontal or diagonal edges. A convolutional neural network is a type of artificial neural network used in deep learning to evaluate visual information. These networks can handle a wide range of tasks involving images, sounds, texts, videos, and other media

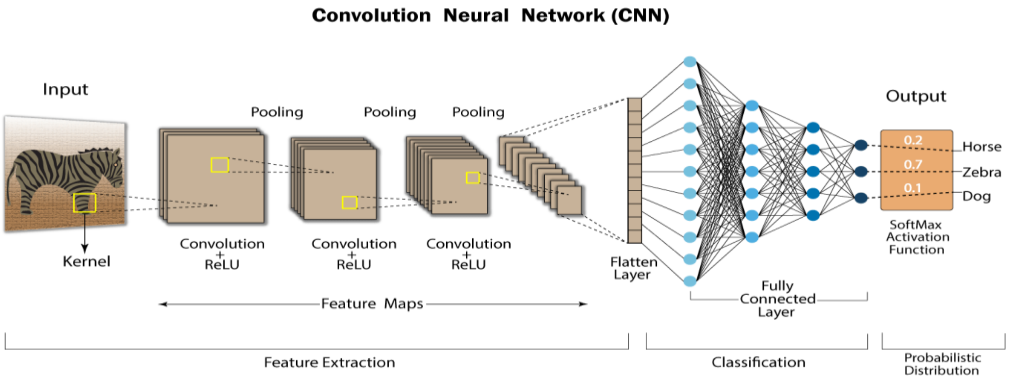

Fig .2. Convolutional Neural Network

3.4.2.2 Importing Some Relevant Libraries

```
import NumPy as np
%matplotlib inline
import matplotlib.image as mpimg
import matplotlib.pyplot as plt
import TensorFlow as tf
tf.compat.v1.set_random_seed(2019)
```

3.4.2.3.Loading the MNIST Dataset

```
(X_train,Y_train),(X_test,Y_test) = keras.datasets.mnist.load_data()
```

Scaling our Data

```
X_train = X_train / 255
X_test = X_test / 255
```

3.4.2.4.flatenning

```
X_train_flattened = X_train.reshape(len(X_train), 28*28)
X_test_flattened = X_test.reshape(len(X_test), 28*28)
```

3.4.2.5.Designing Neural Network

```
model = keras.Sequential([

keras.layers.Dense(10, input_shape=(784,), activation='sigmoid')

])

model.compile(optimizer='adam',

loss='sparse_categorical_crossentropy',

metrics=['accuracy'])

model.fit(X_train_flattened, Y_train, epochs=5)
```

IV. RESULTS AND DISCUSSION

As the vehicle moves it keeps monitoring the entire space , as per our concept if it finds a plant the motors will stop and the fertilizer is sprayed through a pump and submersible motor . When it finds other objects other than the plants the fertilizer is not sprayed and the main aim of this project is successfully completed that the fertilizer is not wasted and it can be used as multi purpose machine

4.1 Results of Descriptive Statics of Study Variables

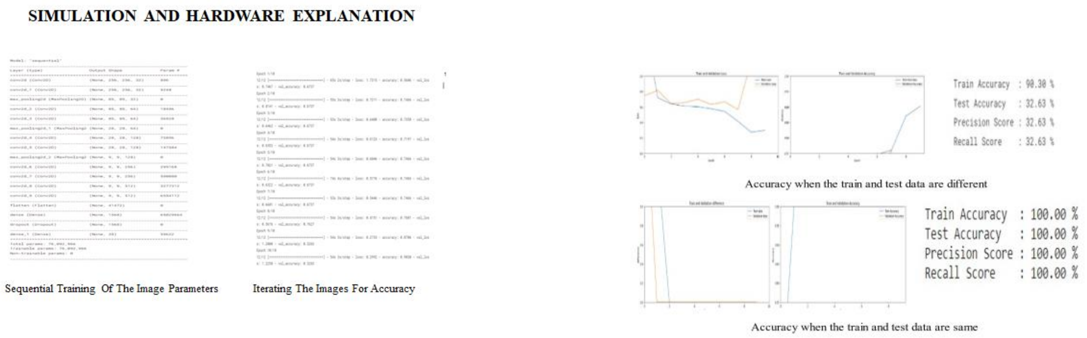

Fig .3. Simulation and Accuracy

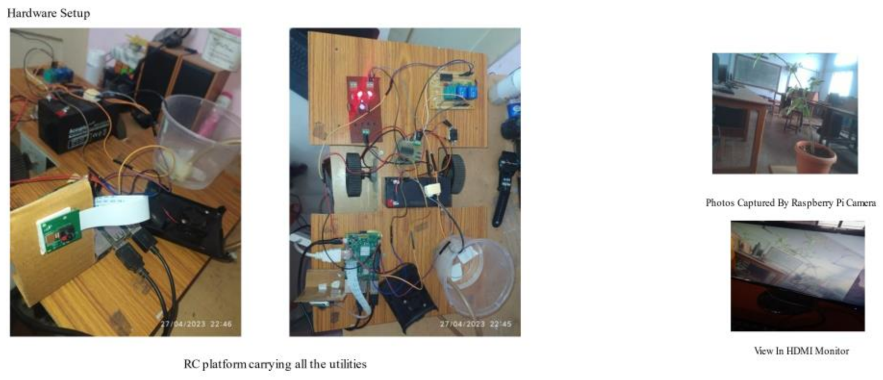

Fig .4 . Hardware Setup

Figures

The figures represent the simulation , block diagram and the simulation . “Fig .1” represents the block diagram of the entire project setup which represents both the hardware and software part. “Fig .2” represents the diagram with entire explanation of the convolutional neural network . “Fig .3” represents the simulation and accuracy of the datasets compared. “Fig .4” is the entire hardware setup.

V. ACKNOWLEDGMENT

First and foremost we thank and praise the almighty god for his guidance and protection throughout the course of our study. It is worth to quote that "Behind every successful efforts there lays contribution from numerous sources irrespective of their magnitude". At this juncture we take this opportunity to express our sincere and whole hearted thanks to all.

We extend our gratitude to our college President, **Er.K.N.K.KARTHIK,** K.L.N. College of Engineering for making us march towards the glory of success.

We extend our sincere thanks to our college Secretary and Correspondent **Dr. K.N.K.GANESH,** K.L.N. College of Engineering, for the motivation throughout the academic works. We express our thanks to our principal **Dr. A.V.RAMPRASAD,** for his kind cooperation and then keen interest by which our project ends in no vain.

We would like to express our gratefulness to our beloved Head of the Department, **Dr.V.KEJALAKSHMI M.E., Ph.D.,** for her continuous motivation for completing this project and Project Co-ordinator **Mr. KUMARESH AP(Sr.Gr)/ECE** for his invaluable guidance and encouragement for completing this project work.

We express our deep gratitude to our project guide **Mr.S.SELVAKUMAR M.E,** Assistant Professor, Department of Electronics and Communication Engineering, who greatly supported us and helped us to complete this project successfully. Last but not least, we also thank our parents, all staffs in our department and friends who have given a lot of motivation, valuable suggestions and helped us to complete the project in time.

Finally, we thank each and every one who helped us to do this project.

VI. REFERENCES

[1] Prakash M. Manikar, Shreekant Ghorpade, Mayur Adawadkar, "Plant Leaf Disease Detection and Classification Using Image Processing Techniques," International Engineering Journal, Volume 2, Issue 4, 2015

[2] Prof. Bhavana Patil, Mr. Hemant Panchal, Mr. SHUBHAM Yadav, Mr. Arvind Singh, Mr. Dinesh Patil, "Plant Monitoring Using Image Processing, Raspberry PI and IOT," Journal of Engineering and Technology, Volume 4, Issue 10, 2017

[3] Navin V. Dumare, Prof. S. S. Mungona, "Identification of Cotton Leaf Diseases Using Raspberry PI," Volume 5, Issue 5, 2017