

**SUGARCANE PEST DETECTION AND CONTROL MANAGEMENT
USING CNN**

Submitted in partial fulfilment of the required for the award of

Masters of Computer Science

by

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DEPARTMENT OF COMPUTER SCIENCE

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SATHYABAMA

INSTITUTE OF SCIENCE AND TECHNOLOGY

(DEEMED TO BE UNIVERSITY)

Accredited with Grade “A++” by NAAC

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of
ANITA STELLA F R (42734002) who carried out the project entitled
**"SUGARCANE PEST DETECTION AND CONTROL MANAGEMENT
USING CNN"** under our supervision from JANUARY 2024 TO APRIL 2024.

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ABSTRACT

Sugarcane cultivation faces significant challenges due to pest infestations and leaf diseases, which can lead to substantial yield losses if not addressed promptly. In this study, we propose a novel approach to tackle these challenges by integrating advanced technologies. Firstly, a Convolutional Neural Network (CNN) model is trained to classify sugarcane leaf images into categories representing healthy leaves, leaf diseases, and five major sugarcane insect pests, including cicada, sugarcane rhinoceros beetle, sugarcane white-tipped locust grasshopper, sugarcane soldier fly larvae, and white grub. The CNN model leverages a comprehensive dataset of labelled images encompassing various disease manifestations and pest species. Furthermore, an Arduino-based system is developed to facilitate real-time detection of pests and diseases in sugarcane fields. Upon detection, the system triggers a relay connected to a water pump, enabling precise administration of fertilizers targeted at mitigating the identified threats. Through extensive testing in real-world sugarcane cultivation environments, the proposed system demonstrates promising capabilities in early pest and disease detection, as well as automated fertilizer application, thus offering a sustainable and efficient solution for enhancing sugarcane productivity and yield.

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CHAPTER 1

INTRODUCTION

Sugarcane, scientifically known as *Saccharum officinarum* L., is an essential crop on a global scale. It plays a crucial role in sugar production and makes a considerable contribution to the agricultural economy. Nevertheless, the production of sugarcane encounters certain obstacles, notably the widespread presence of insect pests and leaf diseases. These challenges not only endanger the quality and productivity of sugarcane, but also provide significant economic risks to farmers.

In India, a country that is one of the top producers of sugarcane, the obstacles are especially noticeable because of the varied agro-climatic conditions in different locations. Sugarcane farming in the country is divided into two distinct agro-climatic zones: the tropical region, which includes states such as Maharashtra, Tamil Nadu, and Karnataka, and the subtropical region, which includes states like Uttar Pradesh, Bihar, and Punjab. Each of these places possesses its own distinct array of pest and disease challenges, requiring specific and focused management approaches.

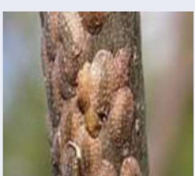
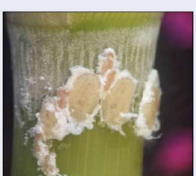
NAME	SCIENTIFIC NAME	FAMILY	IMAGES	INFERENCE
EARLY SHOOT BORER	<i>Chilo Infuscatellus</i>	Pyralidae		• Dead heart shows in 1-3 months old crop. • Caterpillar bores into and feeds on rotten portion of the straw coloured shoot emits an offensive odour. • A number of bore holes at the base of the shoot is just above the ground level.
TOP SHOOT BORER	<i>Scirpophaga Excerptalis</i>	Crambidae		• Larva bore into unfolded leaves and shows parallel row of shot holes in the emerging leaves. • Bore holes at the top of the shoot and shows bunchy top appearance.

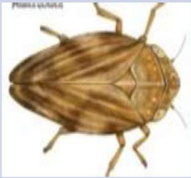
NAME	SCIENTIFIC NAME	FAMILY	IMAGES	INFERENCE
TERMITES	Odontotermes Assmuthi	Termitidae		• Characteristic semi- circular feeding marks on the margin of the leaves in the standing crop. • Poor germination of setts (after planting) • Causes yellowing and drying of outer leaves first followed by the inner leaves. • Entire shoot dries up and can be pulled out. • Setts hollow inside and may be filled with soil.
SUGAR CANE WOOLY APHID	Ceratovacuna lanigera	Aphididae		• Congregation of large number of white coloured nymphs and adults on the under surface of leaf. • Yellowing and drying of leaves from the tip along the margins. • Leaves become brittle and dries completely. • Heavy secretion of honey dew leads to development of sooty mold. • Deposition of woolly matter on ground / soil distinctly visible.

The influence of insect pests on sugarcane production is significant, with approximations indicating that there can be a reduction in yield of up to 20-25%. Furthermore, the fact that there are over 200 bug species that infest sugarcane, and many of them cause significant harm, highlights the need for immediate implementation of efficient pest control methods. Moreover, leaf diseases such as red rot, smut, and leaf scald not only worsen yield losses but also pose a threat to the long-term viability of sugarcane farming.

PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
EARLY SHOOT BORER				
TOP SHOOT BORER				

PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
TERMITES				
SUGARCANE WOOLY APHID				
PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
INTERNODE BORER				
STALK BORER				
PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
WHITE GRUB				
MEALY BUG				

PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
WHITE FLIES				
PINK STEM BORER				
PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
SUGARCANE SOLDIER FLY				
SUGARCANE LEAF HOPPER				
PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
APHIDS				
SUGARCANE SCALE				

PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
SUGARCANE FROGHOPPER				
SUGARCANE RHINOCEROS BEETLE				
PEST	ANGLE 1	ANGLE 2	ANGLE 3	ANGLE 4
CICADA				
SUGARCANE THRIPS				

To tackle these difficulties, it is necessary to employ new and integrated strategies that make use of improvements in technology. Machine learning techniques, including Convolutional Neural Networks (CNNs), have demonstrated impressive effectiveness in picture classification tasks, such as identifying plant diseases and pests, in recent years. Moreover, the incorporation of IoT (Internet of Things) devices, such as Arduino microcontrollers, presents possibilities for immediate monitoring and intervention in agricultural systems.

1.1 BACKGROUND

Sugarcane (*Saccharum officinarum* L.) is a crucial cash crop cultivated in various parts of the world for its high sugar content. It serves as a primary raw material for sugar production, biofuel production, and various other industrial applications. However, sugarcane cultivation is susceptible to numerous biotic and abiotic stresses, including pest infestations and disease outbreaks, which significantly impact crop yield and quality.

Insect pests pose a considerable threat to sugarcane cultivation, causing direct damage to plants by feeding on foliage, stems, and roots. Additionally, they can serve as vectors for various plant pathogens, exacerbating the spread of diseases within sugarcane fields. Among the numerous insect pests that affect sugarcane, some of the most economically damaging species include the sugarcane borer (e.g., stalk borer, shoot borer), white grubs, and locust grasshoppers. Leaf diseases also pose significant challenges to sugarcane production, affecting the photosynthetic capacity of plants and ultimately reducing sugar yield. Common sugarcane leaf diseases include red rot (*Colletotrichum falcatum*), smut (*Sporisorium scitamineum*), leaf scald (*Xanthomonas albilineans*), and rust (*Puccinia melanocephala*), among others. These diseases can spread rapidly under favorable environmental conditions, leading to severe losses if left uncontrolled.

In India, which is one of the world's largest producers of sugarcane, the management of pest and disease pressures is of paramount importance to sustainably meet the demand for sugar and related products. The country's diverse agro-climatic zones present unique challenges, with different regions facing varying pest and disease profiles. Effective management strategies tailored to local conditions are essential to mitigate losses and ensure the economic viability of sugarcane cultivation.

Traditional pest and disease management approaches often rely on the indiscriminate use of chemical pesticides and fertilizers, which can have

adverse environmental and health impacts. Therefore, there is a growing need for sustainable and integrated pest management (IPM) practices that minimize reliance on synthetic chemicals while maximizing crop productivity. Leveraging advancements in technology, such as machine learning and IoT, offers promising avenues for developing smart and eco-friendly solutions to pest and disease management in sugarcane cultivation.

1.2 AIM OF THE PROJECT

The aim of this study is to develop a smart pest and disease management system for sugarcane cultivation that integrates CNN-based image classification with Arduino-controlled fertilizer administration, thereby enhancing crop health and productivity.

1.3 OBJECTIVES

To collect a comprehensive dataset of labeled sugarcane leaf images encompassing various disease manifestations, as well as images of five major sugarcane insect pests.

To train a Convolutional Neural Network (CNN) model using the collected dataset for accurate classification of sugarcane leaf images into categories representing healthy leaves, leaf diseases, and specific insect pests.

To develop a mechanism for Arduino-controlled administration of fertilizers, triggered upon the detection of pests or diseases in sugarcane plants.

To evaluate the performance of the integrated system through field trials in sugarcane cultivation environments, assessing its accuracy in pest and disease detection and the effectiveness of fertilizer administration.

CHAPTER 2

LITERATURE SURVEY

Tanmay Thorat, et.al, 2023, “Intelligent Insecticide And Fertilizer Recommendation System Based On TPF-CNN For Smart Farming”, SCIEDIRECT. Nowadays, artificial intelligence and sensor technology play a vital role in the agriculture field. The use of excess insecticides and fertilizers in farming poses a risk to human health. It is necessary to control them to ensure healthy crop production. Many techniques are used to identify the pest, suggest medications, and do soil nutrient analysis techniques separately. This paper applies the dual operator, Transition Probability Function (TPF), and Convolution Neural Network (CNN) to process the pest's image discretely and continuously for applying the recommended insecticide. The mathematical model with the objective function is derived in this paper. The proposed system combines two major aspects in farming: pest identification and insecticide recommendation using machine vision and CNN. Secondly, the soil nutrient analysis uses a soil NPK sensor with the recommendation of fertilizers according to the obtained nutrient values. On-spot results are obtained, and the time required for insecticide recommendation is within 10 s, and for fertilizer recommendation, it is within 80 s. Successful identification of five pests, namely aphids, bollworms, leaf folder, leaf miner, and green stink bug, was done with more than 90% accuracy. The proposed approach is also compared with the other intelligent approaches, such as Artificial Neural Network (ANN), K-Nearest Neighbour (KNN), and Support Vector Machine (SVM), and it is observed that the proposed TPF-CNN approach gives higher accuracy in the shortest time.

Sachin Kumar, et.al, 2017, “Precision Sugarcane Monitoring Using SVM Classifier”, Research Gate. India is an agriculture based economy and sugarcane

is one of the major crops produced in northern India. Productivity of sugarcane decreases due to inappropriate soil conditions and infections caused by various types of diseases; timely and accurate disease diagnosis, plays an important role towards optimizing crop yield. This paper presents a system model for monitoring of sugarcane crop, the proposed model continuously monitors parameters (temperature, humidity and moisture) responsible for healthy growth of the crop in addition KNN clustering along with SVM classifier is utilized for infection identification if any through images obtained at regular intervals. The data has been transmitted through a wireless network from the site to the control unit. Model achieves an accuracy of 96%. on a sample of 200 images; the model was tested at Lolai, near Malhaur, Gomti Nagar.

Murali Krishna Senapaty, et.al, 2023, “IoT-Enabled Soil Nutrient Analysis and Crop Recommendation Model for Precision Agriculture”, MDPI. Healthy and sufficient crop and food production are very much essential for everyone as the population is increasing globally. The production of crops affects the economy of a country to a great extent. In agriculture, observing the soil, weather, and water availability and, based on these factors, selecting an appropriate crop, finding the availability of seeds, analysing crop demand in the market, and having knowledge of crop cultivation are important. At present, many advancements have been made in recent times, starting from crop selection to crop cutting. Mainly, the roles of the Internet of Things, cloud computing, and machine learning tools help a farmer to analyse and make better decisions in each stage of cultivation. Once suitable crop seeds are chosen, the farmer shall proceed with seeding, monitoring crop growth, disease detection, finding the ripening stage of the crop, and then crop cutting. The main objective is to provide a continuous support system to a farmer so that he can obtain regular inputs about his field and crop. Additionally, he should be able to make proper decisions at each stage of farming. Artificial intelligence, machine learning, the

cloud, sensors, and other automated devices shall be included in the decision support system so that it will provide the right information within a short time span. By using the support system, a farmer will be able to take decisive measures without fully depending on the local agriculture offices. We have proposed an IoT-enabled soil nutrient classification and crop recommendation (IoTSNA-CR) model to recommend crops. The model helps to minimise the use of fertilisers in soil so as to maximise productivity. The proposed model consists of phases, such as data collection using IoT sensors from cultivation lands, storing this real-time data into cloud memory services, accessing this cloud data using an Android application, and then pre-processing and periodic analysis of it using different learning techniques. A sensory system was prepared with optimised cost that contains different sensors, such as a soil temperature sensor, a soil moisture sensor, a water level indicator, a pH sensor, a GPS sensor, and a colour sensor, along with an Arduino UNO board. This sensory system allowed us to collect moisture, temperature, water level, soil NPK colour values, date, time, longitude, and latitude. The studies have revealed that the Agrinex NPK soil testing tablets should be applied to a soil sample, and then the soil colour can be sensed using an LDR colour sensor to predict the phosphorus (P), nitrogen (N), and potassium (K) values. These collected data together were stored in Firebase cloud storage media. Then, an Android application was developed to fetch and analyse the data from the Firebase cloud service from time to time by a farmer. In this study, a novel approach was identified via the hybridisation of algorithms. We have developed an algorithm using a multi-class support vector machine with a directed acyclic graph and optimised it using the fruit fly optimisation method (MSVM-DAG-FFO). The highest accuracy rate of this algorithm is 0.973, compared to 0.932 for SVM, 0.922 for SVM kernel, and 0.914 for decision tree. It has been observed that the overall performance of the proposed algorithm in terms of accuracy, recall, precision, and F-Score is high compared to other methods. The

IoTSNA-CR device allows the farmer to maintain his field soil information easily in the cloud service using his own mobile with minimum knowledge. Additionally, it reduces the expenditure to balance the soil minerals and increases productivity.

Plk Plk, et.al, 2023, “Sugar Cane Leaf Disease Classification And Identification Using Deep Machine Learning Algorithms”, Research Gate. The identification of crop diseases is one of the major concerns that the agricultural industry has to deal with. The detection and classification of leaves is essential in agriculture, forestry, rural medicine, and other commercial applications, among other things. The diagnosis of sugar cane plant leaf disease is required for automatic weed identification in precision agriculture. This paper discusses a novel approach to the development of a plant disease recognition model that is based on sugar cane leaf image classification and employs deep convolutional networks to recognise disease in sugar cane plants. The method used for identification and automatic recognition investigates the possibility of using k-NN and SVM in pre-training with ANN, followed by CNN-based approaches for recognition.

Himanshu Pal, et.al, 2022, “A Survey On Iot-Based Smart Agriculture To Reduce Vegetable And Fruit Waste”, IOPSCIENCE. Agriculture automation is a top focus and developing area for a number of countries right now. We are seeing a surge in demand for Internet of Things (IoT) in various industries these days. One of the most essential applications of IoT is agriculture. Today, we notice that the world's population is quickly rising, and an agro product plays a critical part in this population's existence. We are conscious of the fact that resources are limited. If we continue to farm in the traditional manner, it will be extremely difficult for the rising population to survive. Due to improper fertilizers, quantity of water, chemicals and huge amount of pesticides decreases the fertility of land. There is a need for smart agriculture to monitor all these

factors which affect the fertility of soil. When the fertility is decreasing it will impact on the growth of fruits and vegetables. In this paper we are going to study how we can manage our resources through Internet of Things, multispectral camera, hyper spectral camera, and thermal camera and RGB camera. Plant diseases, pesticide control, weed control, proper irrigation, and water management are all problems in agriculture that can be readily solved with the various automated and control approaches stated above.

Ramesh, et.al, 2023, “IoT-Enabled Device for Effective Crop Yielding using Deep Learning Techniques”, IJMTST. The agriculture sector, including India, plays a critical role in the economy of many countries. However, farmers face various challenges such as uncertainty in crop yields, pest and disease infestations, water scarcity, and lack of knowledge in crop management. Recent advances in technology such as Deep Learning and IoT have the potential to revolutionize the way farmers manage their crops. By using Deep Learning algorithms, farmers can identify plant diseases accurately, which is crucial for disease control and prevention. The use of sensors to detect environmental factors such as temperature, humidity, soil moisture, and nutrient levels can provide real-time monitoring of fields. Analyzing this data using machine learning techniques can optimize crop growth and yield. For example, smart irrigation systems can be developed to ensure that crops receive the right amount of water based on the moisture content of the soil. This approach can help reduce water usage and increase crop yield. Data analytics can also help farmers identify the best crop to grow in a particular location based on environmental conditions, soil quality, and market demand. This approach can help farmers make informed decisions about crop selection and maximize their profits. In summary, the combination of Deep Learning and IoT has the potential to transform the agriculture sector by providing farmers with real-time information on crop growth, disease control, and environmental conditions. This

approach can help farmers increase crop yields, reduce water usage, and make informed decisions about crop management.

Gowthami, et.al, 2023, “Automatic Pest Monitoring and Fertilizer Healing by Sprayer for Enhancing Growth of Plants Using IoT”, IJSET. Farming has extraordinary future for innovative propel, Agriculture field is utilized through internet of things (IOT). And Agricultural unwellness and bug pests square measure one among the foremost necessary factors that seriously threaten agricultural production. Early detection and identification of pests will effectively scale back the economic losses caused by pests. Normally, the plants ought to be water that is employed for general plant automotive as a part of caring or little and huge gardens. Automatic water system in light-weight of soil moisture and temperature will accomplish by inserting Node MCU board with easy receptive soil sensors. And also, during this technology, the humidity and temperature of plants square measure exactly controlled. In advancement associate degree golem based mostly Blynk App interface are going to be organized to use mobile interface to form a far off measurement framework to be utilized as a district of the sector of agriculture. During this study , we tend to propose helpful, low value power economical for star based mostly by orientation of solar array within the direction of the sun for providing the required power supply in remote areas or within the field of agriculture wherever it's unfeasible to provide(to produce)charge through a stable current supply. This method isn't such a lot advanced however rather simpler with the good agriculture observation system. With the assistance of image process we are able to establish the pesticides what we'd like to produce the plant for a more robust growth. Additionally with the assistance nutrients detector we are able to verify the kind of nutrient what required and thus helps to counterpoint the expansion of the plant.

Vijaypal Singh Dhaka, et.al, 2023, “Role of Internet of Things and Deep Learning Techniques in Plant Disease Detection and Classification: A Focused Review”, NCBI. The automatic detection, visualization, and classification of plant diseases through image datasets are key challenges for precision and smart farming. The technological solutions proposed so far highlight the supremacy of the Internet of Things in data collection, storage, and communication, and deep learning models in automatic feature extraction and feature selection. Therefore, the integration of these technologies is emerging as a key tool for the monitoring, data capturing, prediction, detection, visualization, and classification of plant diseases from crop images. This manuscript presents a rigorous review of the Internet of Things and deep learning models employed for plant disease monitoring and classification. The review encompasses the unique strengths and limitations of different architectures. It highlights the research gaps identified from the related works proposed in the literature. It also presents a comparison of the performance of different deep learning models on publicly available datasets. The comparison gives insights into the selection of the optimum deep learning models according to the size of the dataset, expected response time, and resources available for computation and storage. This review is important in terms of developing optimized and hybrid models for plant disease classification.

Akanksha Gupta, et.al, 2022, “Classification and Yield Prediction in Smart Agriculture System Using IoT”, Research Square. The Modern agriculture industry is datacentred, precise and smarter than ever. Advanced development of Internet-ofThings (IoT) based systems redesigned “smart agriculture”. This emergence in innovative farming systems is gradually enhancing the crop yield, reduces irrigation wastages and making it more profitable. Machine learning (ML) methods achieve the requirement of scaling the learning performance of the model. This paper introduces a hybrid ML model with IoT for yield

prediction. This work involves three phases : preprocessing, feature selection(FS) and classification. Initially, the dataset is preprocessed and FS is done on the basis of Correlation based FS (CBFS) and the Variance Inflation Factor algorithm (VIF). Finally, a two-tier ML model is proposed for IoT based smart agriculture system. In the first tier, the Adaptive k-Nearest Centroid Neighbour Classifier (aKNCN) model is proposed to estimate the soil quality and classify the soil samples into different classes based on the input soil properties. In the second tier, the crop yield is predicted using the Extreme Learning Machine algorithm (ELM). In the optimized strategy, the weights are updated using modified Butterfly Optimization algorithm (mBOA) to improve the performance accuracy of ELM with minimum error values. PYTHON is the implementation tool for evaluating the proposed system. Soil dataset is utilized for performance evaluation of the proposed prediction model. Various metrics are considered for the performance evaluation such as accuracy, RMSE, R2, MSE, MedAE, MAE, MSLE, MAPE and Explained Variance Score (EVS).

SH Bhojani, et.al, 2022, “Wheat Crop Yield Prediction Using New Activation Functions In Neural Network”, MDPI. This research mainly based on multilayer perceptron (MLP) neural networks technique of data mining to forecast the wheat crop yield at the district level. There are many statistical and simulation models available, but the proposed algorithm with new activation function provides promising results in a shorter time with more accuracy. Sigmoid and hyperbolic tangent activation functions are widely used in the neural network. In this research study, variable numbers of hidden layers are tested with the variable number of neurons per hidden layer for the agriculture dataset. Variable values of momentum, seed and learning rate are also used in this study. Experiments show that newly created activation functions provide better results compared to ‘sigmoid’ default neural network activation function for agriculture datasets.

CHAPTER 3

METHODOLOGY

3.1 EXISTING SYSTEM

The current system for managing pests and illnesses in sugarcane farming still relies heavily on conventional approaches, including visual inspection by farmers and manual application of chemical pesticides. Nevertheless, these techniques possess significant constraints. Relying solely on visual examination can be problematic, especially in expansive sugarcane fields, resulting in delays in taking action and inadequate management of pests and diseases. Furthermore, the process of manually applying pesticides frequently leads to ineffective allocation of resources, since there is a possibility of either excessive or insufficient use based on subjective evaluations of pest intensity. This not only exacerbates environmental degradation and poses health hazards for farmworkers, but also escalates production expenses. In addition, conventional scouting techniques may suffer from a lack of promptness and precision, as they are unable to offer up-to-the-minute information on the occurrence of pests and diseases. Hence, there is a requirement for enhanced and automated methods to tackle these difficulties and enhance pest and disease control in sugarcane farming. In spite of attempts to implement integrated pest management (IPM) techniques, worries about sustainability remain due to the dependence on chemical pesticides and the accompanying hazards of pesticide resistance and environmental harm. Thus, utilizing cutting-edge technologies like machine learning, IoT, and precision agriculture shows potential for creating intelligent and environmentally-friendly solutions that allow for immediate monitoring, early identification, and focused intervention. This ultimately improves the health, productivity, and sustainability of sugarcane cultivation.

DISADVANTAGES

Reliance on visual inspection leads to subjective assessments, prone to human error.

Manual pesticide application results in inefficient use, with risks of overuse or underuse.

Conventional scouting methods lack timeliness, leading to delayed pest and disease control measures.

Chemical pesticides pose risks of environmental pollution, harm to non-target organisms, and health hazards for farmworkers.

Overreliance on chemical pesticides threatens soil health, water quality, and long-term effectiveness due to pesticide resistance.

3.2 PROPOSED SYSTEM

The proposed system represents a comprehensive solution to the challenges of pest and disease management in sugarcane cultivation, integrating advanced technologies to offer timely and targeted interventions. At its core, a Convolutional Neural Network (CNN) model trained on a diverse dataset of sugarcane leaf images enables accurate classification of plant health status, distinguishing between healthy plants, diseased plants, and specific insect pests. This CNN-based image classification is complemented by real-time monitoring facilitated by IoT devices deployed in sugarcane fields, which capture and transmit images for analysis. An Arduino-based system serves as the control hub, automating the detection of pests and diseases and triggering appropriate interventions based on the CNN model's classifications. This may involve activating a water pump to administer targeted fertilizers or pesticides to affected areas. Additionally, data analytics techniques are employed to analyze historical data on pest and disease occurrences, weather patterns, and crop management practices, providing insights for optimizing intervention strategies. A user-friendly interface, potentially through a mobile application, empowers

farmers with real-time updates on pest and disease status in their fields, along with recommendations for targeted interventions. The scalability and adaptability of the system ensure its applicability across diverse sugarcane cultivation environments, contributing to improved crop health, productivity, and sustainability while minimizing environmental impacts and resource use.

ADVANTGAES

The system can catch pests and diseases in sugarcane plants early, preventing significant damage.

It targets affected areas precisely, reducing the need for excessive pesticide or fertilizer use.

It automates detection and treatment processes, saving time and effort for farmers.

Data analysis helps optimize strategies, making interventions more effective.

Farmers receive alerts about pest and disease status in their fields instantly.

It can be used in different sugarcane growing conditions, adapting to various environments.

By minimizing chemical use, it promotes eco-friendly farming practices.

3.3 BLOCK DIAGRAM

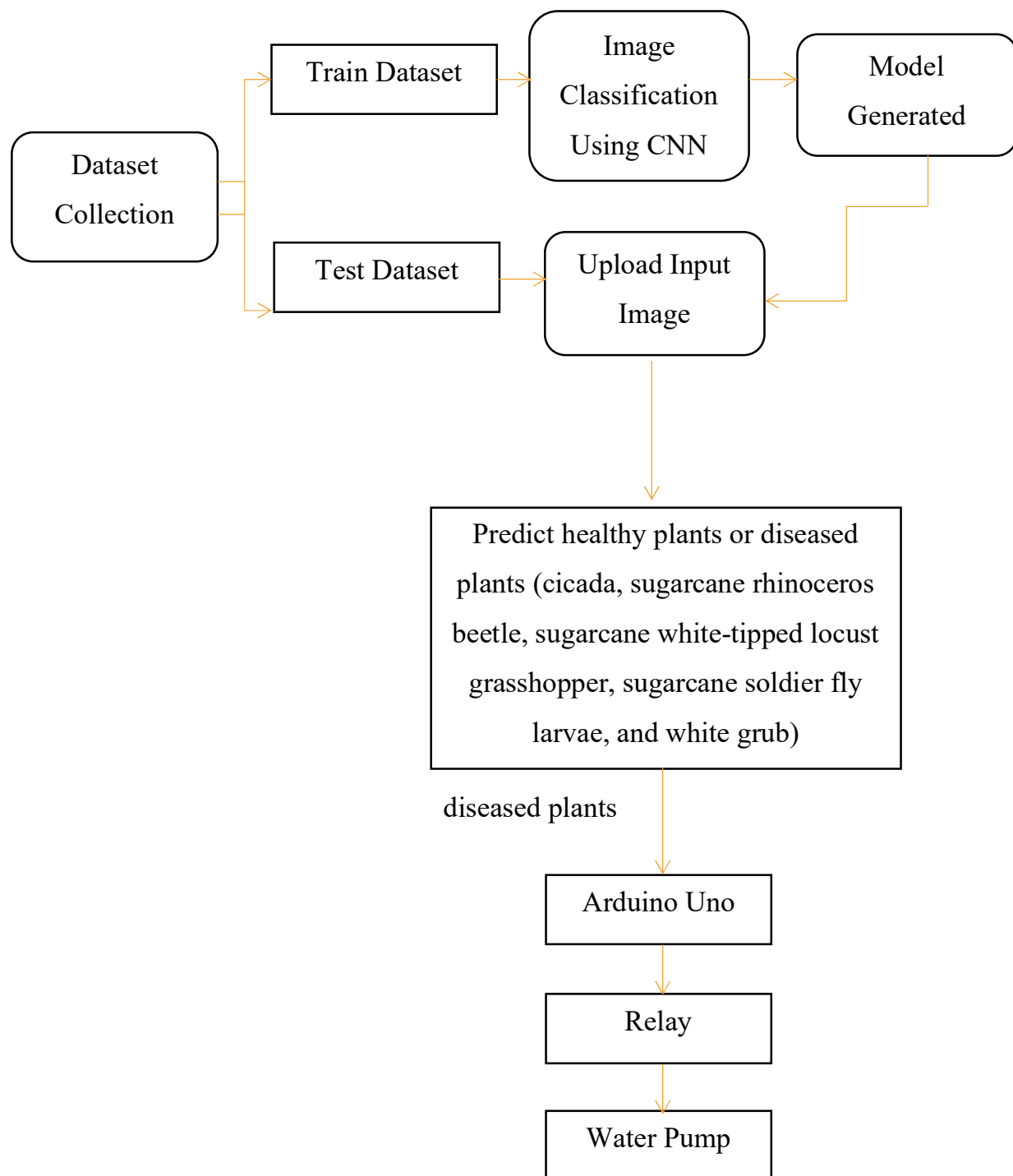


Figure 1

3.4 SYSTEM REQUIREMENT

Hardware Requirements

- System: Intel core I3 3.80 GHz 64 bit.
- Monitor: LED.
- Mouse: Logitech.
- Ram: 4.00 GB.

Software Requirements

- Operating system : Windows 10
- Language : Python
- Platform : Anaconda3
-

3.5 ER DIAGRAM

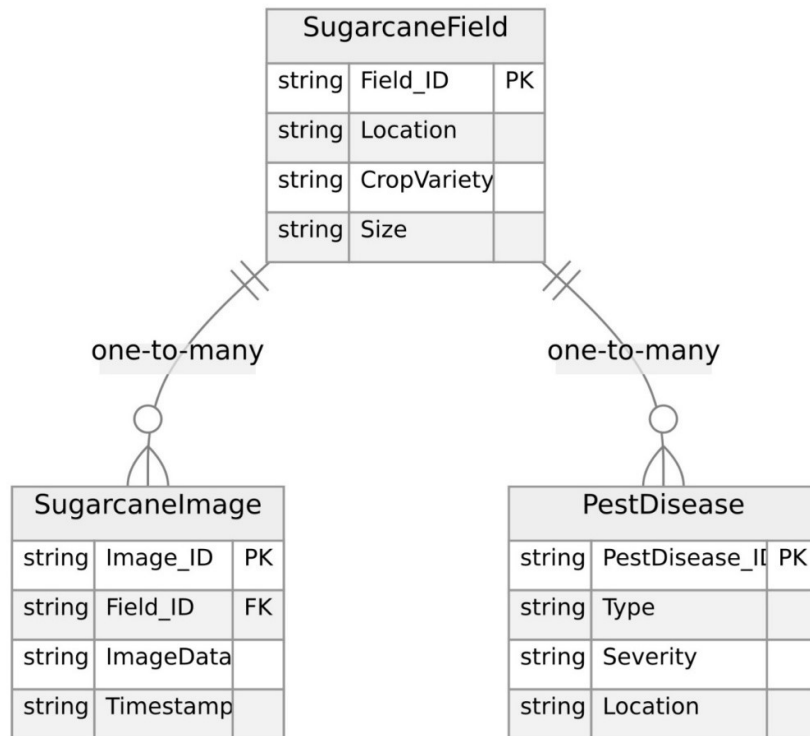


Figure 2

3.6 CLASS DIAGRAM

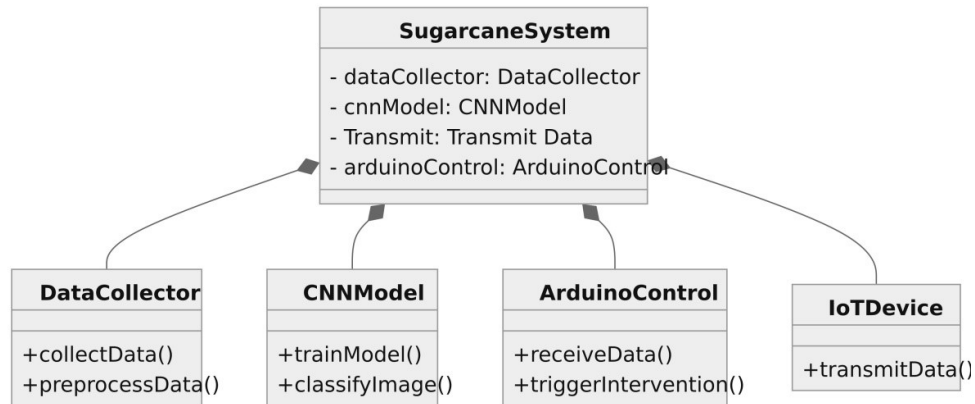


Figure 3

3.7 MODULE DESCRIPTION

3.7.1 Data Collection and Preparation

- In this module, a diverse dataset of sugarcane leaf images is collected, encompassing various conditions such as healthy plants, plants affected by different diseases, and images of specific insect pests like the cicada, sugarcane rhinoceros beetle, etc.
- The collected data is preprocessed to ensure consistency and suitability for training the CNN model. This preprocessing may involve tasks such as resizing images to a uniform size, normalizing pixel values to a standard range, and augmenting the dataset with techniques like rotation, flipping, or adding noise to increase diversity.

3.7.2 CNN-Based Image Classification

- This module focuses on training a Convolutional Neural Network (CNN) model using the prepared dataset.
- The CNN architecture is designed to effectively learn features from sugarcane leaf images and classify them into distinct categories such as healthy, diseased, or pest-infested.

- The training process involves feeding the labeled images into the CNN, optimizing its parameters through techniques like gradient descent and backpropagation to minimize classification errors, and validating the model's performance using a separate validation dataset.

3.7.3 Arduino-Controlled Intervention

- An Arduino-based control system is integrated into the setup to automate the process of detecting and responding to pest or disease threats.
- Upon receiving image data from the laptop, the Arduino triggers predetermined actions based on the analysis results. For example, if a diseased leaf or pest infestation is detected, the Arduino may activate a water pump connected to a fertilizer or pesticide dispenser to administer targeted treatments to the affected area.

3.7.4 CNN ALGORITHM

A Convolutional Neural Network, sometimes known as a CNN, is a form of deep learning algorithm that was developed in particular for the purpose of processing and analyzing visual input, such as pictures and movies. picture classification, object detection, and picture segmentation are three examples of the kind of problems that benefit greatly from the application of CNNs. They are modeled after the anatomy and operation of the human visual system, which served as their primary source of inspiration. These models have shown to be extremely useful in a wide variety of computer vision applications.

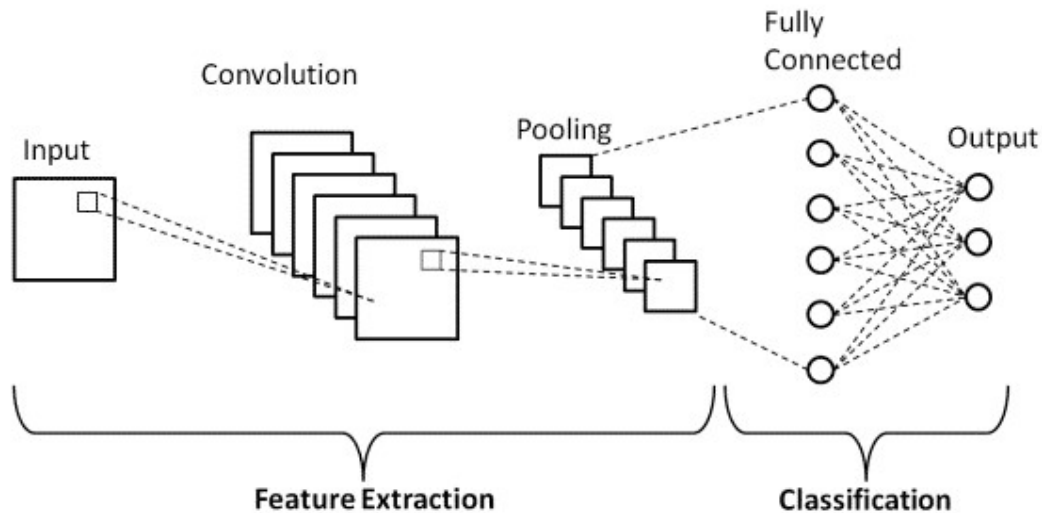


Figure 4 - CNN Architecture

The operation of a CNN can be broken down into the following steps:

1. Convolutional Layer is the most important part of a CNN because it performs the main operation. This layer is made up of several feature extraction filters, also referred to as kernels. Filters and kernels are both terms that refer to tiny matrices. Each filter performs element-wise multiplications and additions on the input image as it scans it by sliding over it in short steps called strides. Convolution is the name given to this process. The end product is a feature map, which draws attention to distinct motifs or characteristics that are visible in the image.
2. Activation Function: Following the convolution operation, an activation function is applied element-wise to the feature map. This activation function is often a Rectified Linear Unit, which stands for Rectified Linear Unit. The activation function brings non-linearity into the network, which enables the network to comprehend the intricate connections between the data points.
3. Pooling Layer: Pooling layers, also known as max-pooling, are utilized to minimize the spatial dimensions of the feature maps while simultaneously maintaining the integrity of the critical information. The size of the feature map can be efficiently reduced via max-pooling by selecting the largest value from a

tiny window within the feature map. This helps to preserve dominating features while at the same time reducing the size of the feature map.

4. The Fully Connected Layer: After being flattened, the feature maps that were produced from the Convolution and Pooling Layers are then input into one or more Fully Connected Layers. These layers are very much like the ones that are seen in conventional neural networks. They then create the final output, which may be a classification label or a regression value, based on what they have learned about the complicated interactions between the characteristics.

5. Backpropagation and Training : Convolutional neural networks (CNNs) are educated by a method known as backpropagation. Iterative adjustments are made to the network's parameters (weights and biases) throughout the training phase in order to bring the gap between the projected outputs and the actual targets as close as possible. To accomplish this, optimization procedures, such as stochastic gradient descent, are utilized to update the parameters in a manner that has the effect of lowering the loss function of the network.

6. Convolutional Neural Networks (CNNs) are created with numerous convolutional and pooling layers stacked on top of each other in a hierarchical structure. This architecture provides a hierarchy of features, with beginning layers detecting simple patterns (edges, textures), and deeper layers learning more complicated patterns and objects. This architecture also creates a hierarchy of features. This hierarchical representation is essential for the network to have in order to comprehend and categorize complicated visual data.

7. Pretrained Models and Transfer Learning: In order to train CNNs from scratch, you may need to have access to enormous amounts of data as well as computational resources. As a direct consequence of this, models that have been pretrained by being trained on big datasets such as ImageNet have gained popularity. These models have gained an understanding of a wide array of features and patterns that are generally applicable to a variety of visual tasks.

CHAPTER 4

SOFTWARE SPECIFICATION

4.1 PYTHON:

Python is a high-level, general-purpose programming language that is interpreted at a high level. Python uses dynamic typing and trash collection. It's compatible with a wide variety of programming styles, including procedural, object-oriented, and functional. Because of its extensive standard library, Python is often called a "batteries included" language. There are Python interpreters for a wide variety of OSes. CPython is an open source reference implementation that is developed and maintained by a global community of programmers. The Python Software Foundation is a nonprofit that oversees and guides the development of Python and CPython.

Python is a powerful scripting language because it is high-level, interpreted, interactive, and object-oriented. Python was created to be easily understood. It contains fewer syntactical structures than other languages and makes extensive use of English terms where punctuation is used in other languages.

Python is Interpreted – The interpreter performs the processing of Python during execution. Your programme can be run without first being compiled. That's quite PHP/PERL-like.

Python is Interactive – You can write programmes in Python by entering commands into the interpreter at a prompt.

Python is Object-Oriented – Python is compatible with the Object-Oriented programming paradigm, which is characterised by the encapsulation of code within objects.

Python is a Beginner's Language – Python is an excellent language for novice programmers since it can be used to create a wide variety of programmes, from text-processing utilities to web browsers to games.

4.2 ANACONDA



You'll find everything you need to do your scientific Python work and more in the Anaconda package. The enormous power of Python may be harnessed by a Data Scientist with the help of the various tools included in this package. The Anaconda Community Edition is open-source and available for no cost. This facilitates simple and quick entry into the world of Anaconda usage. The populace of Anaconda has ballooned to unprecedented proportions. Connecting to a wide variety of scientific, Machine Learning, and Data Science tools is a breeze with Anaconda.

4.2.1 Key Features:

- Neural Networks
- Machine Learning
- Predictive Analytics
- Data Visualization
- Bias Mitigation

4.2.2 Anaconda Navigator

You can run programmes and control your conda packages, environments, and channels from the convenience of your desktop using the Anaconda Navigator GUI, which is bundled with the Anaconda distribution. In addition to searching

for packages in Anaconda Cloud, Navigator may also search for packages in a local Anaconda Repository, install them in an environment, run them, and update them. Windows, macOS, and Linux users can get it.

The following applications are available by default in Navigator:

JupyterLab

Jupyter Notebook

QtConsole

Spyder

Glue

Orange

RStudio

Visual Studio Code

4.3 FEASIBILITY STUDY

During this stage, the project's viability is evaluated, and a business proposal outlining the project's broad strokes and some preliminary cost estimates is presented. The practicality of the proposed system is to be investigated during system analysis. This is done so that the suggested solution won't cost the business too much. To conduct a feasibility study, it is necessary to have some familiarity with the system's primary requirements. There are three main factors to think about while doing a feasibility study:

4.3.1 Economic Feasibility

The purpose of this analysis is to determine how much of a financial toll the implementation of this technology will have on the company. The corporation can only devote so much money to the system's development and research. All costs must be adequately explained. As a result, the produced system is both functional and cost-effective, with the latter being made possible

by the widespread availability of the technologies employed. Only the personalised items will require a purchase.

4.3.2 Technical Feasibility

Examining the system's technological requirements and viability is the purpose of this research. Any new system can't put too much strain on the world's computing infrastructure. The client will have to deal with a lot of pressure as a result. The developed system should have low requirements, as there should be few or no adjustments necessary to put it into action.

4.3.3 Operational Feasibility

The goal of the research is to determine how well received the system is by its target audience. Training the user to make the most of the system is part of this procedure. The user should feel safe using the system and not afraid of it. The approaches used to familiarise and inform the user are the sole determinants of the system's level of adoption. As the system's end user, he has to feel more certain in his abilities before he can offer any constructive criticism, which is always appreciated.

4.4 SYSTEM TESTING

The goal of testing is to unearth flaws. The goal of testing is to identify and eliminate any potential problems with a product. Assemblies, subassemblies, and final products can all be tested for functionality with this method. Software testing is the practise of putting a programme through its paces to make sure it won't crash or else behave badly under use. There are numerous kinds of examinations. There are various kinds of tests, and each one caters to a different need.

4.5 POWER SUPPLY

A power supply (sometimes known as a power supply unit or PSU) is a device or system that supplies electrical or other types of energy to an output load or group of loads. The term is most commonly applied to electrical energy supplies, less often to mechanical ones, and rarely to others.

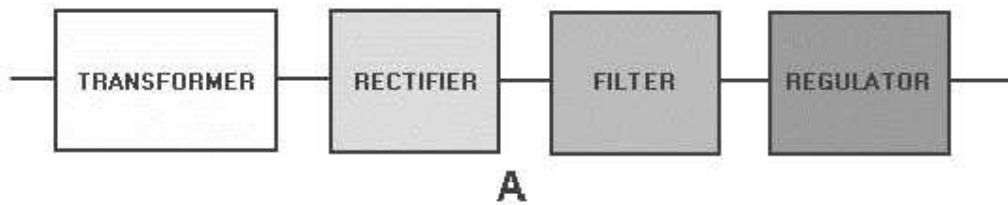


Figure 5

4.5.1 Block diagram of a basic power supply

The transformer raises or lowers the input line voltage and isolates the power supply. RECTIFIER converts alternating current input signal to pulsating direct current. However, this chapter will show that pulsing dc is undesirable. Therefore, a FILTER section converts pulsing dc to a purer, better dc voltage.

Final part, REGULATOR, does what it says. It keeps power supply output consistent despite heavy load current or input line voltage variations. Let's trace an ac signal through the power supply now that you know what each part accomplishes. You must now observe how each power supply section changes this signal. See how these modifications occur later in the chapter. In view B of figure 4-1, the transformer primary receives 115 volts ac. The transformer is a 1:3 step-up transformer. To compute the output for this transformer, multiply the input voltage by the ratio of turns in the primary and secondary. For example, $115 \text{ volts ac} \times 3 = 345 \text{ volts ac (peak-to-peak)}$ at the output. Each rectifier diode carries 180 degrees of the 360-degree input, therefore the output is half, or 173 volts, of pulsing dc. The filter portion, a

network of resistors, capacitors, or inductors, controls the signal's rise and fall time, keeping it at a constant dc level. Discussion of filter circuits will clarify the filter process. The filter outputs 110 volts dc with ac ripple. The lower average voltage will be discussed later in this chapter. Electronic equipment (the load) uses the regulator's 110-volt dc output.

4.5.2 Simple 5V power supply for digital circuits

Brief description of operation: Gives out well regulated +5V output, output current capability of 100 mA

Circuit protection: Built-in overheating protection shuts down output when regulator IC gets too hot

Circuit complexity: Very simple and easy to build

Circuit performance: Very stable +5V output voltage, reliable operation

Availability of components: Easy to get, uses only very common basic components

Design testing: Based on datasheet example circuit, I have used this circuit successfully as part of many electronics projects

Applications: Part of electronics devices, small laboratory power supply

Power supply voltage: Unregulated DC 8-18V power supply

Power supply current: Needed output current + 5 mA

Component costs: Few dollars for the electronics components + the input transformer cost

4.6 CIRCUIT DESCRIPTION

This design is a modest +5V power supply for digital electronics experiments. All electronics stores and supermarkets sell small, affordable wall transformers with variable output voltage. These transformers are readily available, but their voltage control is weak, making them unsuitable for digital circuit experimenters until they can be improved. This circuit solves the

problem.

This design can output +5V at 150 mA, however effective cooling on the 7805 regulator chip can increase it to 1 A. The circuit is overloaded and thermally protected.

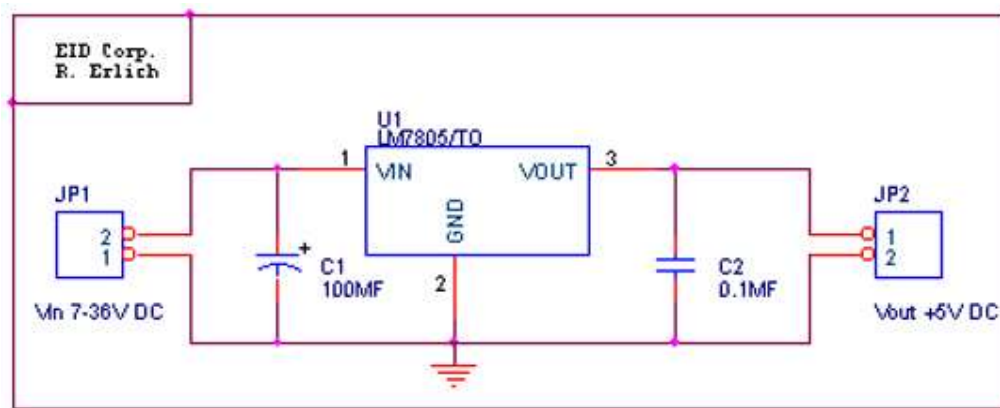


Figure 6 - Circuit diagram of the power supply

4.6.1 Circuit diagram of the power supply

The capacitors must have enough high voltage rating to safely handle the input voltage feed to circuit. The circuit is very easy to build for example into a piece of Vero board.

4.6.2 Pinout of the 7805 regulator IC

Unregulated voltage in

Ground

Regulated voltage out

4.6.3 Component list

7805 regulator IC

100 uF electrolytic capacitor, at least 25V voltage rating

10 uF electrolytic capacitor, at least 6V voltage rating

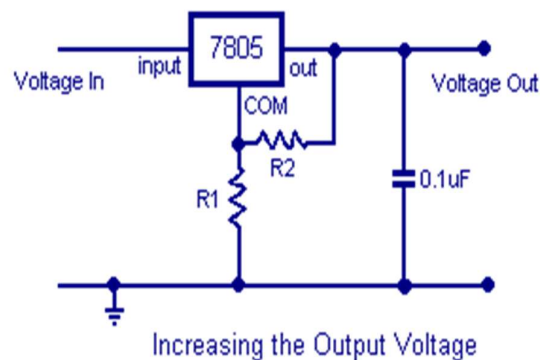
100 nF ceramic or polyester capacitor

4.6.4 More output current

If you need more than 150 mA of output current, you can update the output current up to 1A doing the following modifications:

Change the transformer from where you take the power to the circuit to a model which can give as much current as you need from output

Put a heat sink to the 7805 regulator (so big that it does not overheat because of the extra losses in the regulator)



4.6.5 Other output voltages

If you need other voltages than +5V, you can modify the circuit by replacing the 7805 chips with another regulator with different output voltage from regulator 78xx chip family. The last numbers in the chip code tells the output voltage. Remember that the input voltage must be at least 3V greater than regulator output voltage to otherwise the regulator does not work well.

4.7 ARDUINO UNO

Arduino is an open-source project that created microcontroller-based kits for building digital devices and interactive objects that can sense and control physical devices. The project is based on microcontroller board designs, produced by several vendors, using various microcontrollers. These systems provide sets of digital and analog input/output (I/O) pins that can interface to various expansion boards (termed shields) and other circuits. The boards feature serial communication interfaces, including Universal Serial Bus (USB) on some models, for loading programs from personal computers. For programming the microcontrollers, the Arduino project provides an integrated development environment (IDE) based on a programming language named Processing, which also supports the languages C and C++.

4.7.1 PRODUCT DESCRIPTION

Arduino Uno is a microcontroller board based on the ATmega328P. It has 14 digital input/output pins (of which 6 can be used as PWM outputs), 6 analog inputs, a 16 MHz quartz crystal, a USB connection, a power jack, an ICSP header and a reset button. It contains everything needed to support the microcontroller; simply connect it to a computer with a USB cable or power it with a AC-to-DC adapter. Arduino Uno has a number of facilities for communicating with a computer, another Arduino board, or other microcontrollers.



Figure 7 – Arduino UNO

4.7.2 ATMEGA328P-PU microcontroller

The most important element in Arduino Uno R3 is ATMEGA328P-PU is an 8-bit Microcontroller with flash memory reach to 32k bytes. It's features as follow:

High Performance, Low Power AVR

Advanced RISC Architecture

- 131 Powerful Instructions – Most Single Clock Cycle Execution
- 32 x 8 General Purpose Working Registers
- Up to 20 MIPS Throughput at 20 MHz
- On-chip 2-cycle Multiplier

High Endurance Non-volatile Memory Segments

- 4/8/16/32K Bytes of In-System Self-Programmable Flash program memory
- 256/512/512/1K Bytes EEPROM
- 512/1K/1K/2K Bytes Internal SRAM
- Write/Erase Cycles: 10,000 Flash/100,000 EEPROM
- Data retention: 20 years at 85°C/100 years at 25°C
- Optional Boot Code Section with Independent Lock Bits
- In-System Programming by On-chip Boot Program
- True Read-While-Write Operation
- Programming Lock for Software Security

Peripheral Features

- Two 8-bit Timer/Counters with Separate Prescaler and Compare Mode
- One 16-bit Timer/Counter with Separate Prescaler, Compare Mode, and Capture Mode
- Real Time Counter with Separate Oscillator
- Six PWM Channels
- 8-channel 10-bit ADC in TQFP and QFN/MLF package
- Temperature Measurement
- 6-channel 10-bit ADC in PDIP Package
- Temperature Measurement
- Programmable Serial USART
- Master/Slave SPI Serial Interface
- Byte-oriented 2-wire Serial Interface (Philips I2 C compatible)
- Programmable Watchdog Timer with Separate On-chip Oscillator
- On-chip Analog Comparator
- Interrupt and Wake-up on Pin Change

Special Microcontroller Features

- Power-on Reset and Programmable Brown-out Detection
- Internal Calibrated Oscillator
- External and Internal Interrupt Sources
- Six Sleep Modes: Idle, ADC Noise Reduction, Power-save, Power-down, Standby, and Extended Standby

I/O and Packages

- 23 Programmable I/O Lines
- 28-pin PDIP, 32-lead TQFP, 28-pad QFN/MLF and 32-pad QFN/MLF

Operating Voltage

- 1.8 - 5.5V

Temperature Range

- -40°C to 85°C

Speed Grade

- 0 - 4 MHz@1.8 - 5.5V, 0 - 10 MHz@2.7 - 5.5V, 0 - 20 MHz @ 4.5 - 5.5V

Power Consumption at 1 MHz, 1.8V, 25°C

- Active Mode: 0.2 mA
- Power-down Mode: 0.1 μ A
- Power-save Mode: 0.75 μ A (Including 32 kHz RTC)

4.7.3 PIN CONFIGURATION

(PCINT14/RESET) PC6	1	28	PC5 (ADC5/SCL/PCINT13)
(PCINT16/RXD) PD0	2	27	PC4 (ADC4/SDA/PCINT12)
(PCINT17/TXD) PD1	3	26	PC3 (ADC3/PCINT11)
(PCINT18/INT0) PD2	4	25	PC2 (ADC2/PCINT10)
(PCINT19/OC2B/INT1) PD3	5	24	PC1 (ADC1/PCINT9)
(PCINT20/XCK/T0) PD4	6	23	PC0 (ADC0/PCINT8)
VCC	7	22	GND
GND	8	21	AREF
(PCINT6/XTAL1/TOSC1) PB6	9	20	AVCC
(PCINT7/XTAL2/TOSC2) PB7	10	19	PB5 (SCK/PCINT5)
(PCINT21/OC0B/T1) PD5	11	18	PB4 (MISO/PCINT4)
(PCINT22/OC0A/AIN0) PD6	12	17	PB3 (MOSI/OC2A/PCINT3)
(PCINT23/AIN1) PD7	13	16	PB2 ($\overline{SS}$ /OC1B/PCINT2)
(PCINT0/CLKO/ICP1) PB0	14	15	PB1 (OC1A/PCINT1)

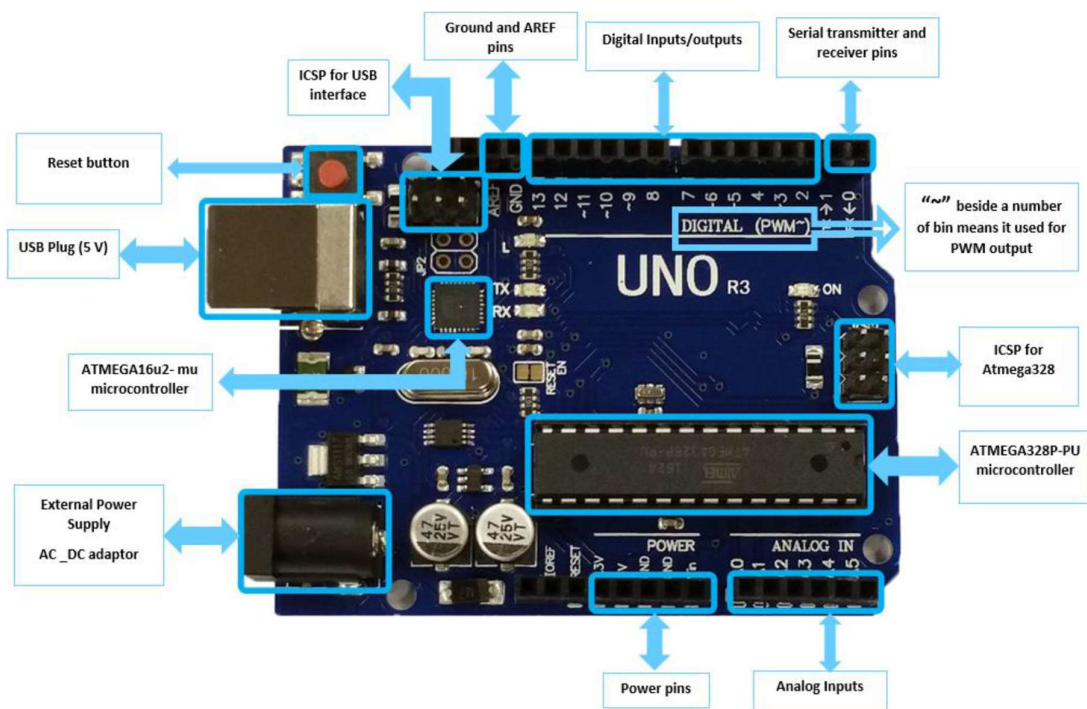


Figure 8

4.7.4 FEATURES

- Microcontroller: ATmega328P
- Operating voltage: 5V
- Input voltage: 7-12V
- Flash memory: 32KB
- SRAM: 2KB
- EEPROM: 1KB

4.7.5 APPLICATIONS

- Real time biometrics
- Robotic applications
- Academic applications
-

4.8 RELAY BOARD

Relays are simple switches which are operated both electrically and mechanically. Relays consist of an electromagnet and also a set of contacts. The switching mechanism is carried out with the help of the electromagnet. The main operation of a relay comes in places where only a low-power signal can be used to control a circuit. It is also used in places where only one signal can be used to control a lot of circuits. They were used to switch the signal coming from one source to another destination. The high end applications of relays require high power to be driven by electric motors and so on. Such relays are called contactors.

4.8.1 PRODUCT DESCRIPTION

A relay is an electromechanical switch which is activated by an electric current. A four relay board arrangement contains driver circuit, power supply circuit and isolation circuit. A relay is assembled with that circuit. The driver circuit

contains transistors for switching operations. The transistor is use for switching the relay. An isolation circuit prevents reverse voltage from the relay which protects the controller and transistor from damage. The input pulse for switching the transistor is given from the microcontroller unit. It is used for switching of a four device.

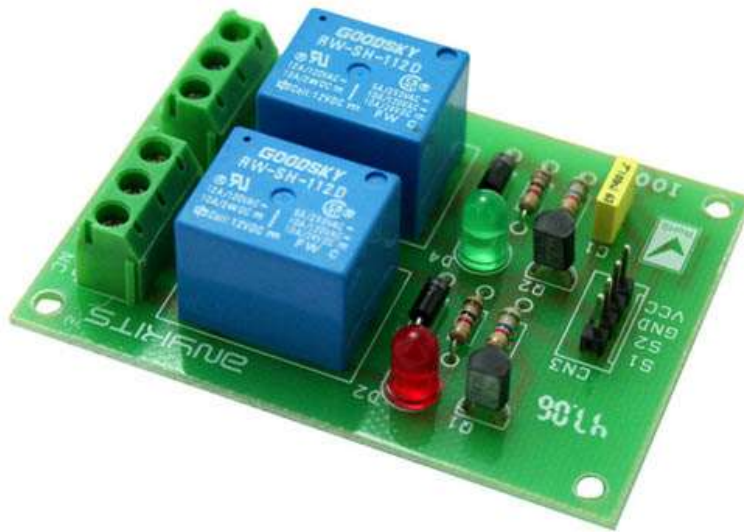


Figure 9

4.8.2 FEATURES

- Input voltage: 12VDC
- Driver unit: BC547
- Isolation unit: In4007
- Fast switching
- Motor forward and reverse operation

4.8.3 APPLICATIONS

- Ac load Switching applications
- Dc load Switching applications
- Motor switching applications

4.9 WATER PUMP

As the name implies, water pumps pump water. Whether that be in a vehicle, at a business, in the home, or in a well, shoppers can probably find a water pump to fit their vehicle or to help them draw water from the ground in a self-dug well to be used in pressure tanks within the location. Vehicle water pumps help regulate the flow of water through a vehicle's cooling system; when the seal on these go bad, the whole pump must be replaced. Located within the home or business, pressure water pumps regulate the water pressure year round, controlling water flow to different areas of the location.

4.9.1 PRODUCT DESCRIPTION

A pump motor is a DC motor device that moves fluids. A DC motor converts direct current electrical power into mechanical power. DC or direct current motor works on the principal, when a current carrying conductor is placed in a magnetic field, it experiences a torque and has a tendency to move. This is known as motoring action. Pumps operate by some mechanism (typically reciprocating or rotary), and consume energy to perform mechanical work by moving the fluid. Pumps operate via many energy sources, including manual operation, electricity, engines, or wind power, come in many sizes, from microscopic for use in medical applications to large industrial pumps.



Figure 10 – Water Pump Motor

4.9.2 FEATURES

- Reduced noise
- Available in DC and AC
- Supply voltage: +12VDC
- Supply voltage: 230V AC

4.9.3 APPLICATIONS

- Priming a pump
- To pump water supply, including pneumatic systems and in places where no suction lift is required
- Pump motor as public water supply
- In domestic water supply system

CHAPTER 5

CONCLUSION AND FUTURE ENHANCEMENT

The suggested system for pest and disease management in sugarcane agriculture offers a comprehensive strategy that utilizes cutting-edge technologies such as image processing, Internet of Things (IoT), and automation to tackle the difficulties encountered by farmers. The system intends to improve crop health, productivity, and sustainability by incorporating features such as data collecting, CNN-based picture categorization, real-time monitoring, and automated intervention.

By gathering and preparing photos of sugarcane leaves, the system establishes the groundwork for training a Convolutional Neural Network (CNN) model that can effectively classify images into categories such as healthy, ill, or infested with pests. The utilization of IoT devices for real-time monitoring facilitates the prompt identification of pest and disease risks in sugarcane fields. Additionally, an intervention system controlled by Arduino enables automated responses that are determined by the analysis outcomes.

The intuitive interface enables farmers to receive real-time information on the current condition of pests and diseases, as well as recommendations for specific actions. This promotes informed decision-making and proactive management strategies. The suggested method has the potential to greatly benefit sugarcane growers and contribute to the sustainability of agricultural operations by optimizing resource consumption, minimizing environmental impacts, and enhancing overall crop management efficiency.

The suggested system is a promising advancement in pest and disease control for sugarcane farming. Its goal is to modernize and improve this aspect of agriculture, with the ultimate purpose of ensuring food security, economic prosperity, and environmental stewardship in the agricultural sector.

APPENDIX

SOURCE CODE

```
[ ]: import numpy as np
import os
import cv2
from sklearn.model_selection import train_test_split
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, MaxPooling2D, Flatten, Dense

[ ]: %matplotlib inline

[ ]: # Define constants
CATEGORIES = ['Aphididae', 'healthy', 'Crambidae', 'Pyralidae', 'Termitidae']
IMG_SIZE = 60
DIRECTORY = r'Dataset' # Update this with your dataset directory

[ ]: data = []
for category in CATEGORIES:
    path = os.path.join(DIRECTORY, category)
    for img in os.listdir(path):
        img_path = os.path.join(path, img)
        try:
            arr = cv2.imread(img_path, cv2.IMREAD_GRAYSCALE)
            # Convert the image to grayscale
            gray = cv2.cvtColor(image, cv2.COLOR_BGR2GRAY)
            # Apply Gaussian blur to reduce noise
            blurred = cv2.GaussianBlur(gray, (5, 5), 0)

            # Perform thresholding to separate the leaf from the background
            _, thresh = cv2.threshold(blurred, 100, 255, cv2.THRESH_BINARY_INV)

            # Find contours in the thresholded image
            contours, _ = cv2.findContours(thresh, cv2.RETR_EXTERNAL, cv2.CHAIN_APPROX_SIMPLE)

            # Create a mask for the contours
            mask = np.zeros_like(gray)
            cv2.drawContours(mask, contours, -1, (255, 255, 255), thickness=cv2.FILLED)
            if arr is None:
                raise Exception(f"Failed to read image: {img_path}")
            new_arr = cv2.resize(arr, (IMG_SIZE, IMG_SIZE))
            data.append([new_arr, CATEGORIES.index(category)])
        except Exception as e:
            print(f"Error processing image: {img_path}")
            print(e)

[ ]: # Shuffle the data
np.random.shuffle(data)

# Split the data into features and labels
X = np.array([entry[0] for entry in data]).reshape(-1, IMG_SIZE, IMG_SIZE, 1) # Features
y = np.array([entry[1] for entry in data]) # Labels

# Normalize pixel values to the range [0, 1]
X = X / 255.0

[ ]: X

[ ]: y
```

```
[1]: # Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Define the CNN model
model = Sequential([
    Conv2D(32, (3, 3), activation='relu', input_shape=(IMG_SIZE, IMG_SIZE, 1)),
    MaxPooling2D((2, 2)),
    Conv2D(64, (3, 3), activation='relu'),
    MaxPooling2D((2, 2)),
    Flatten(),
    Dense(64, activation='relu'),
    Dense(len(CATEGORIES), activation='softmax')
])

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
model.fit(X_train, y_train, epochs=100, validation_data=(X_test, y_test))

# Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f'Test Loss: {loss}, Test Accuracy: {accuracy}')

# Save the model
model.save('leaf_model.h5')
```

```
-----
NameError                                Traceback (most recent call last)
Cell In[1], line 2
      1 # Split the data into training and testing sets
----> 2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
      4 # Define the CNN model
      5 model = Sequential([
      6     Conv2D(32, (3, 3), activation='relu', input_shape=(IMG_SIZE, IMG_SIZE, 1)),
      7     MaxPooling2D((2, 2)),
      (...)
     12     Dense(len(CATEGORIES), activation='softmax')
     13 ])
NameError: name 'train_test_split' is not defined
```

```
[2]: import cv2
import keras
import serial
import time

SerialObj = serial.Serial('COM10') # COMxx format on Windows
# ttyUSBx format on Linux
SerialObj.baudrate = 9600 # set Baud rate to 9600
SerialObj.bytesize = 8 # Number of data bits = 8
SerialObj.parity = 'N' # No parity
SerialObj.stopbits = 1 # Number of Stop bits = 1
time.sleep(3)

import numpy as np
CATEGORIES = ['Aphididae', 'healthy', 'Crambidae', 'Pyralidae', 'Termitidae']

def image(path):
    img = cv2.imread(path, cv2.IMREAD_GRAYSCALE)
    new_arr = cv2.resize(img, (60, 60))
    new_arr = np.array(new_arr)
    new_arr = new_arr.reshape(-1, 60, 60, 1)
    return new_arr

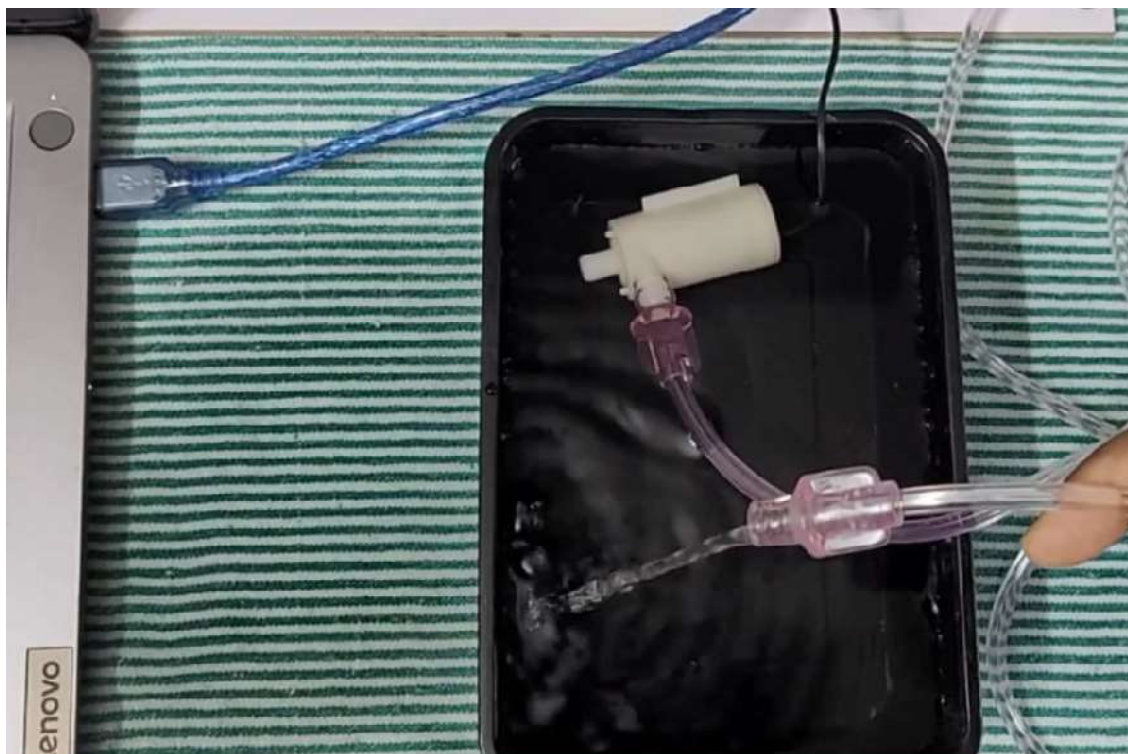
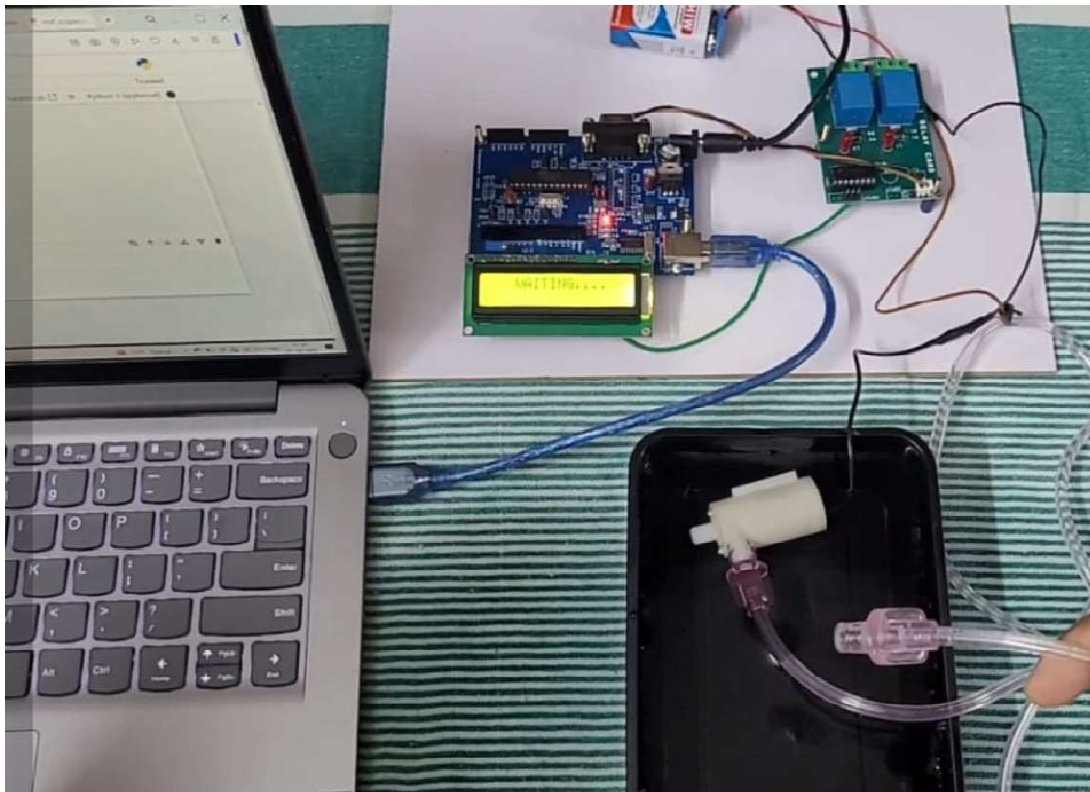
model = keras.models.load_model('leaf_model.h5')

prediction = model.predict([image('termite.jpg')])
print(prediction)
print(CATEGORIES[prediction.argmax()])
if CATEGORIES[prediction.argmax()] != 'healthy':
    print("Relay On")
    SerialObj.write(b'A') #transmit 'A' (8bit) to micro/Arduino
    SerialObj.close() # Close the port
else:
    print("Relay Off")
```

```
WARNING:absl:Compiled the loaded model, but the compiled metrics have yet to be built. `model.compile_metrics` will be empty until you train or evaluate the model.
WARNING:absl:Error in loading the saved optimizer state. As a result, your model is starting with a freshly initialized optimizer.

1/1 ----- 0s 79ms/step
[[1. 0. 0. 0. 0.]]
Aphididae
Relay On
```

SCREENSHOT



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