Predictive Pest Management for Sustainable Agriculture

A PROJECT REPORT

Submitted by

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ABSTRACT

This paper introduces a platform that aims to assist farmers in dealing with pest problems, in their crops. The systems main component is a learning model that has been trained using a dataset of 10,988 images. It can identify pests, including ants, bees, beetles and more. By uploading images of pests found on their crops farmers can promptly receive solutions for pest eradication. This innovative approach not provides cost effective pest management but also gathers valuable data, on pest behaviour contributing to more informed agricultural practices. Overall, this platform holds promise in advancing pest control methods and ultimately improving crop health and productivity. This version summarizes the effort creation of a digital platform based on a deep learning model its significance assisting farmers in pest control the approach image-based pest detection and the accomplishments offering quick remedies and rich data insights.

INTRODUCTION

Effective pest management is vital for the health and yield of crops, in a sector where more than 70% of the population depends on agriculture. Due to the high labour intensity, expert knowledge requirement and time constraints it is no longer feasible for conventional methods of detecting pests using manual work as well as substantial experience in plant diseases. This research sets out a new approach to diagnose pest related plant diseases based on the use of picture processing and machine learning models to cope with these challenges. We have a deep learning model which will predict the pest in the image.

As agricultural pests become more prevalent, farmers increasingly rely on innovative technological solutions. This paper introduces a future-looking digital platform that will change the way they manage pests. A cutting-edge deep learning model will be used to identify agricultural pests, including ants, bees, and beetles, among others, using an extensive dataset of 10,988 images.

By implementing this technology, farming will be redefined in terms of pest control. In addition to facilitating immediate identification of pests, the platform will provide effective pest eradication strategies by allowing farmers to upload images directly from their fields. In addition to streamlining pest management, this approach promises to reduce the associated costs and environmental impact associated with traditional pest control methods by significantly.

By integrating machine learning techniques with everyday agricultural practices, this work offers a technologically sophisticated solution that is also practically applicable. In addition to addressing immediate pest control needs, this project will also contribute to a broader understanding of pest behavior patterns by developing a comprehensive tool. Agricultural strategies and interventions will be informed by this accumulation of data.

It is expected that the completion of this work will make a significant contribution to agriculture in the future. As well as providing farmers with practical tools, it will pave the way for more efficient, sustainable, and data-driven farming practices. It is intended to enhance crop health and productivity on a global scale by providing a key component of pest management in agriculture.

Now that this introduction is aligned with the guidelines, we emphasize the current and future implications of the work, its significance in a broader agricultural context, as well as anticipated outcomes.

To identify the harmful or damaged part of plants, the side effects of the pests play a key role. As a result, an automatic identification method for plant disease recognition is in urgent demand. Use of pesticide is only the solution to control disease. At the same time, overdose of pesticide results into the food safety issues and environmental pollution. The task of deciding the appropriate amount of pesticide and applying it as per the requirement is very crucial task. Automatic pest management system will help to monitor crop and manage pesticides. In this paper, different approaches for automatic detection of leaf affectedness are studied. For agriculture diseases, leaf images can be identified by analysing crop images and processed for recognition based on various features, such as color, texture, and shape etc. Integrated Pests Management (IPM) supports for providing acceptable solution in agricultural field. It helps to improves crop yield production. Along with its good initiatives, it also facing different challenges like improper use of pesticides degrades the quality.

Pest detection using Deep Learning:

Deep learning is state of art technique and has been proven in various applications. Basically, it is using neural network for training purpose, features are extracted by using different hidden layers. There are many deep learning model which follows different architectures. Traditional image classification techniques use model working on specific features. So appropriate feature extractor model is to be built to give more accurate result. Whereas, deep learning techniques automatically extract features from large dataset. The major challenge is to prepare dataset with large number of instances to extract deep features. Above fig provides the comparison between traditional method and deep learning techniques for various parameter .

Difference	***Machine Learning techniques***	***Deep Learning Techniques***
Input Data	Model can be trained on small dataset	Model needs large amount of data
Feature extraction	Different feature extractor models are used	Automatic feature extraction is done
Training Time	Comparatively less time to train the model	Comparatively more time to train the model
Hardware Requirement	These models can be used with low end machines	These models need high end machines

. COMPARISON BETWEEN TRADITIONAL TECHNIQUES AND DEEP LEARNING TECHNIQUES

Design And Implementation

We have a deep learning model which will predict the pest in the image .We have a dataset of pest images to train our model on with pest images belonging to the below classes: Ants, bees, beetle, caterpillar, earthworms, earwig, grasshopper, moth, slug, snail, wasp, weevil.

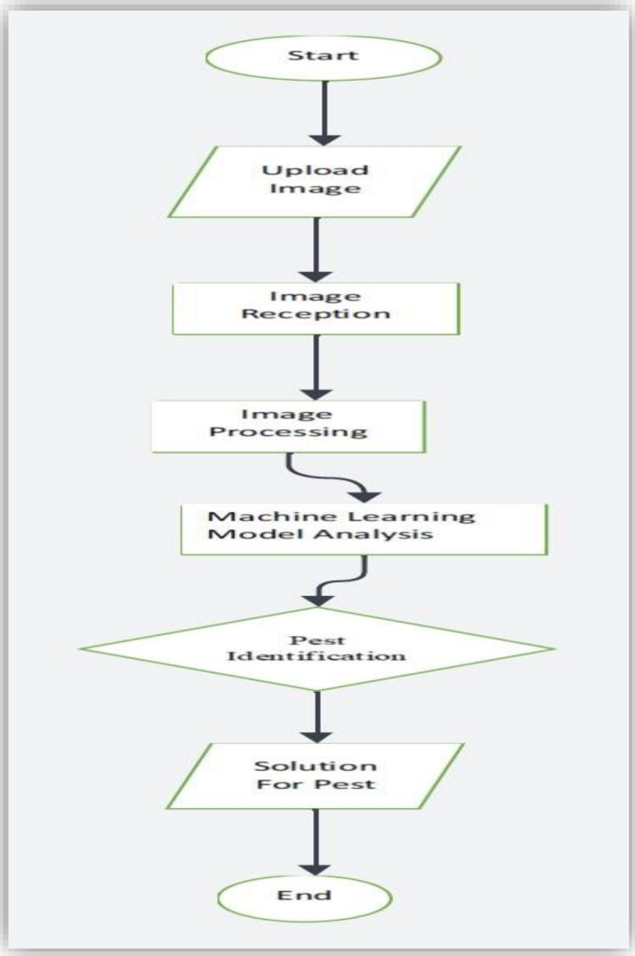
We have 10988 training images and these are individual class wise counts

Snail	1000
Bees	1000
Ants	998

Wasp	996
Moth	994
Weevil	970
Grasshopper	970
Earwig	932
Caterpillar	868
Beetle	832
Slug	782
Earthworms	646

The image data set is imported as batches before it enters the model for training. This is to reduce the memory loading issues that can happen due to training the entire dataset at once. These batches are further divided into training and validating datasets in the ratio of 80% for training and 10% for validation. The remaining 10% is spared for testing the accuracy of the built model.

The following flowchart represents different steps involved in the training process.



Modelling

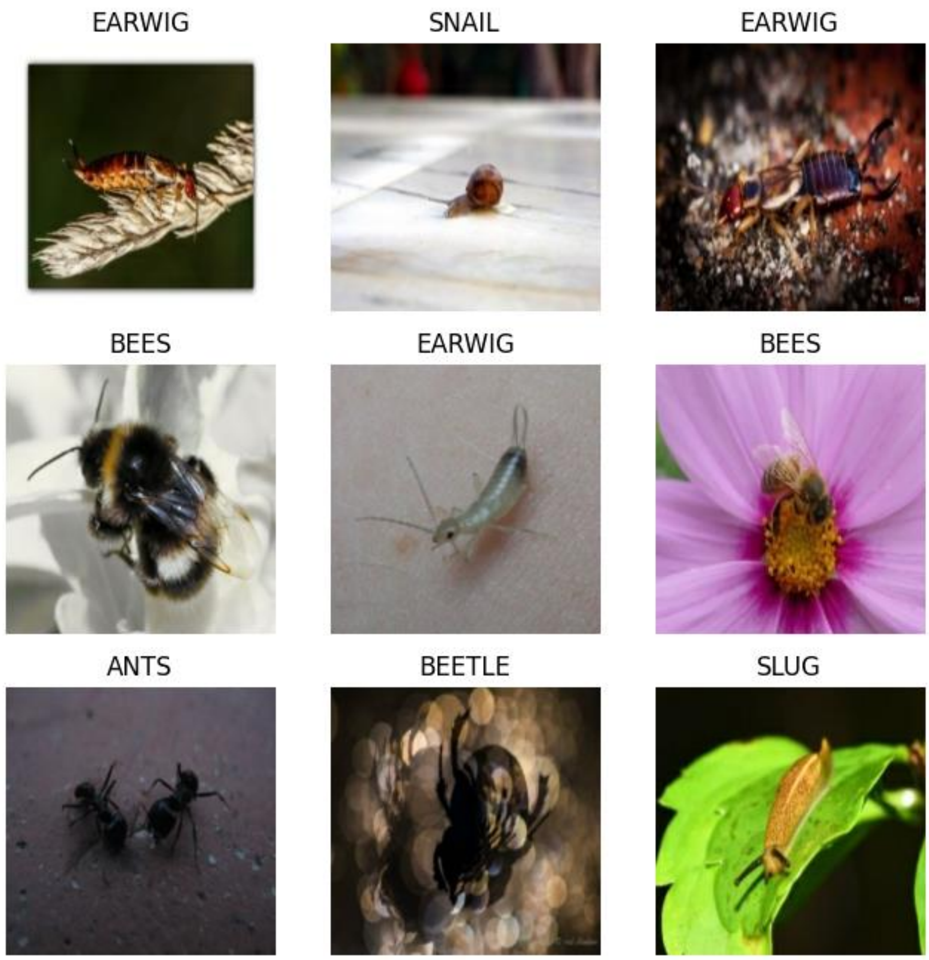
In ResNets, we employ a network with residual blocks instead of typical neural networks, where each layer feeds into the next layer and straight into the layers approximately 2-3 hops away. This prevents over-fitting (a situation when validation loss stops decreasing at a point and then keeps increasing while training loss still decreases). This makes it possible to train deep neural networks and aids in preventing the vanishing gradient problem. Then we define our Image Classification Base class whose functions are:

• Training step: To measure the model's "falsity" after the training or validation process. In addition to an accuracy measure that is presumably not going to be differentiable, we are using this function (this would mean that it would be impossible to calculate the gradient, this is necessary for the model to improve throughout training).

• Validating step: Although an accuracy measure cannot be used to train a model, it is still possible to utilise it in the future. Accuracy is described by a threshold and will be considered if the dissimilarity between the actual and predicted label was small than the threshold0value.

• Epoch end: We also want to disclose validation losses/accuracies, train losses, and learning rate after each epoch since we utilise a learning rate scheduler that updates the learning rate after each batch of training

- Sample images of training data:



That the data size is Train data:4620 , Test data: 2645 and Validation data:815

Training techniques used:

Used **RandomFlip** and **RandomRotation** for enhancing our training dataset by providing different versions of the original images for each training epoch, which can help improve the model's generalisation and robustness. Used RESNET50 pretrained model and added 3 dense layers

```
pretrained_model = tf.keras.applications.ResNet50(
    input_shape=(224, 224, 3),
    include_top=False,
    weights='imagenet',
    pooling='max'
)

pretrained_model.trainable = False
```

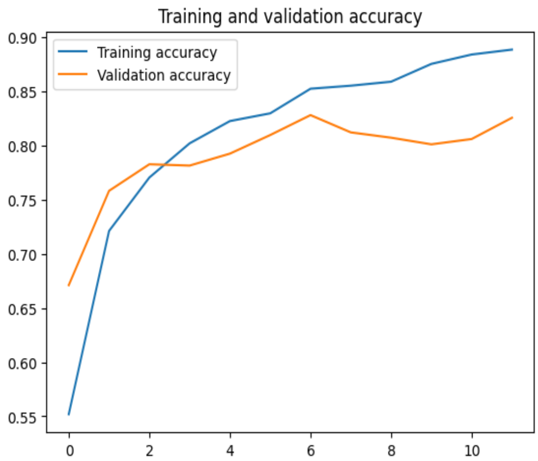
Results And Discussions:

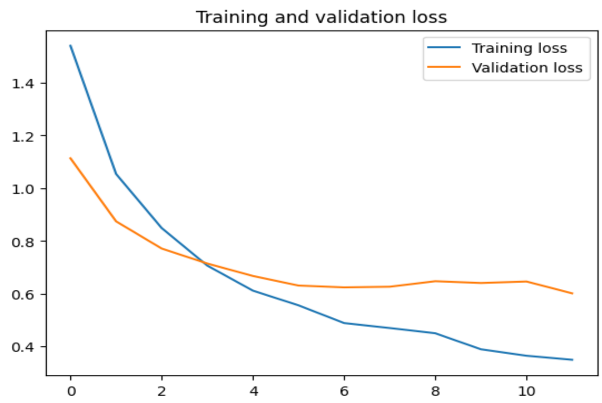
Model Performance: The Accuracy of the deep learning model demonstrated impressive accuracy rates in identifying various pests within the dataset.

	precision	recall	f1-score	support
0	0.927126	0.938525	0.932790	244.000000
1	0.925000	0.956897	0.940678	232.000000
2	0.855491	0.783069	0.817680	189.000000
3	0.892241	0.911894	0.901961	227.000000
4	0.915152	0.949686	0.932099	159.000000
5	0.889447	0.776316	0.829040	228.000000
6	0.880000	0.932203	0.905350	236.000000
7	0.975000	0.987342	0.981132	237.000000
8	0.958333	0.904494	0.930636	178.000000
9	0.979339	0.987500	0.983402	240.000000
10	0.951220	0.951220	0.951220	246.000000
11	0.930041	0.986900	0.957627	229.000000
accuracy	0.924764	0.924764	0.924764	0.924764
macro avg	0.923199	0.922170	0.921968	2645.000000
weighted avg	0.924275	0.924764	0.923821	2645.000000

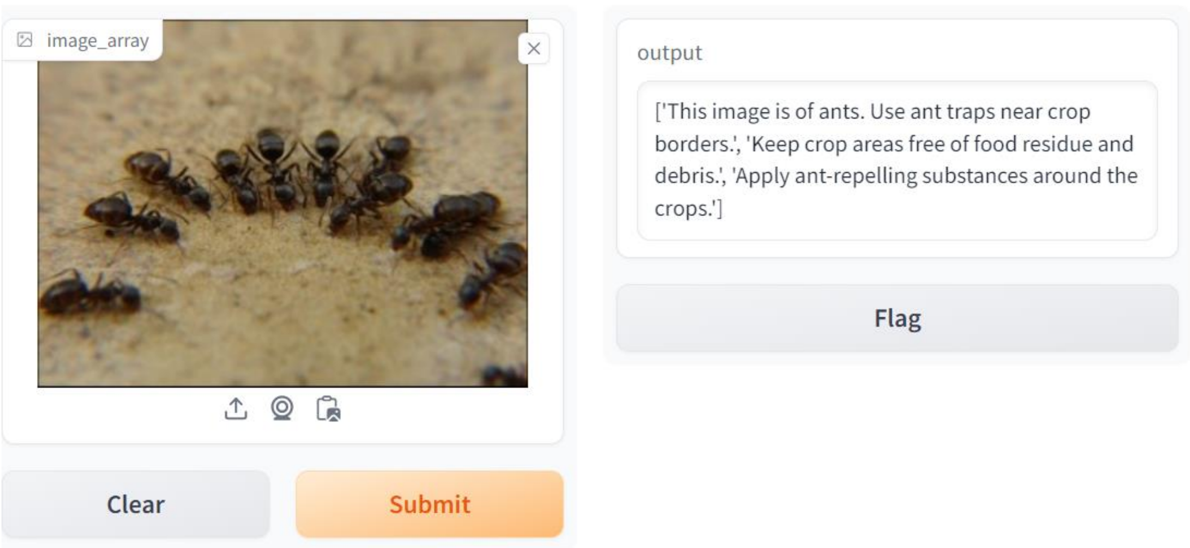
On test dataset these are the accuracies. Our model which is using pretrained resnet 50 is giving **92.4%** accuracy.

During training, the model was fine-tuned using the validation set. This iterative process ensured that the model's parameters were optimized for pest identification.





This collection of images provides compelling visual evidence of the diverse pest challenges faced in agricultural settings. The consistent presence of various pests, as exemplified by the ant infestation, underscores the critical need for a multi-faceted approach to pest management. The implementation of proactive measures, including regular monitoring, the use of specific traps, and environmentally conscious repellents, is essential to safeguard crop health and yield. These findings advocate for an integrated pest management framework tailored to the unique ecological conditions of each crop area.



Conclusion:

In conclusion, our pest identification platform is a game-changer for farmers. It helps them spot and deal with pests, making farming easier and more eco-friendly. We will keep making it better, and together with farmers and experts, we are shaping the future of farming. We trained a ResNet50 model on our dataset and obtained an accuracy of 92.4%. The model was trained for 12 epochs using the Adam optimizer. The input image was resized to 224x224 pixels and pre-processed using standard mean normalization. The model consists of 50 layers a utilized skip connections to improve the gradient flow during training. We used a training set of 10988 images belonging to 6 classes and a validation set of 2328 images belonging to 6 classes.

References

1) C. S. Rao, M. Rahul, S. Dasgupta and R. Hegde, "Sustainable Pesticide usage in Agriculture," 2021 IEEE Mysore Sub Section International Conference (MysuruCon), pp. 628-633, 2021
2) Tanha Talaviya, Dhara Shah, Nivedita Patel, Hiteshri Yagnik, Manan Shah, “Implementation of artificial intelligence in agriculture for optimisation of irrigation and application of pesticides and herbicides”, Artificial Intelligence in Agriculture, vol 4, pp 58-73, 2020.
3) Hussain M., Bird J.J., Faria D.R. “A Study on CNN Transfer Learning for Image Classification”, Advances in Computational Intelligence Systems, Advances in Intelligent Systems and Computing, vol 840, pp 191-202, 2019.
4) Dr. Ishan Y Pandya, “Pesticides and Their Applications in Agriculture”, Asian Journal of Applied Science and Technology vol 2, Issue 2, pp 894-900, 2018.

5) K. Saranya, P. Uva Dharini, P. Uva Darshni and S. Monisha, "IoT Based Pest Controlling System for Smart Agriculture," 2019 International Conference on Communication and Electronics Systems (ICCES), pp. 1548-1552, 2019.