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## CNN-BASED CROP PEST CLASSIFICATION MODEL

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### Abstract

It is great to hear about this project that offers a pest identification system for classifying helpful and harmful pests in crops. The use of a Convolutional Neural Network (CNN) for pest identification and classification is an innovative approach, and the use of a dataset of 1,500 photos of 9 distinct pests for training the model is commendable. The accuracy rate of 90% achieved by the proposed technique is indeed impressive and suggests that the model is effective in identifying and categorizing pests. It is also good to know that the system has been validated against other traditional classification models and has been evaluated with a large amount of data. However, it is essential to note that the accuracy of the model may depend on the quality and quantity of the training dataset, and it is important to ensure that the dataset used for training is representative of the real-world scenarios. Additionally, the effectiveness of the system in identifying pests in different crops and environments may also need to be evaluated. Overall, this project offers a promising solution for pest identification and classification in crops, and it has the potential to be a valuable tool for farmers and researchers in the field of agriculture.

**Keywords:** Convolutional Neural Network, Classification, Deep Learning. Python – Keras, Tensor flow, Accuracy.

### I. Introduction

Pests can have a significant impact on agricultural productivity in Bangladesh. In order to address this issue, scientists have been exploring various solutions, including the use of deep learning techniques to distinguish between harmful and harmless pests. This is important because many farmers in Bangladesh are inexperienced and lack the knowledge to differentiate between the two types of pests. As a result, they may attempt to eliminate both, which can ultimately reduce productivity in the long run.

There are various approaches that can be used to address the issue of pests in agriculture. For example, farmers can use natural methods to control pests, such as crop rotation, biological control, and the use of organic fertilizers. In addition, they can use chemical pesticides to

control pests, although this approach has its drawbacks, such as the potential for harm to the environment and human health.

Overall, it is clear that addressing the issue of pests in agriculture is a complex and multifaceted problem that requires a range of solutions. By using a combination of natural and chemical methods, as well as utilizing new technologies such as deep learning, it is possible to help farmers in Bangladesh to increase their productivity and achieve more sustainable agricultural practices.

### II. Literature Review

**2.1 V. Singh, V. and P. A. K. Misra, "Detection of unhealthy region of plant leaves using Image Processing and Genetic Algorithm," in 2015 International Conference on Advances in Computer**

**Engineering and Applications (ICACEA), Ghaziabad, India, 2015.**

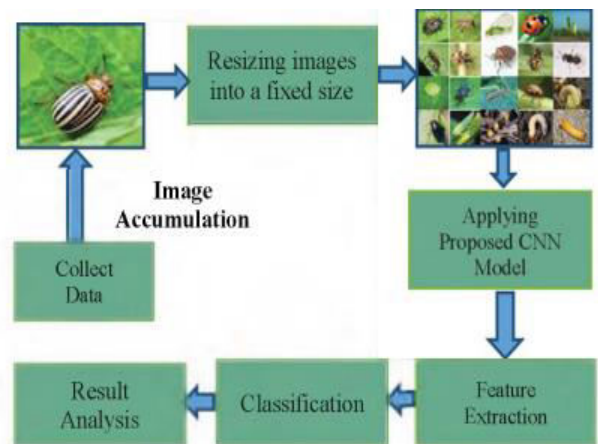
Agricultural productiveness is the single most important factor in the Indian economy. This is among the reasons why aliment recognition in plants is so important in the agriculture area, because plant aliment was rather common. If appropriate precautions are not provided, given in this area, major consequences occur on flowers, affecting product quality, volume, and productiveness. Plant aliment detection using an automated method is hugely advantageous since it lowers a tremendous amount of screening work in large farms of crops, and it detects the signs and indications of ailments at an early stage when they appear on leaf tissue. This work presents a photo segmentation technique for digital detection and classification of plant leaf diseases, as well as a survey of unique disease classification strategies that can be employed for plant leaf disease detection. The usage of a genetic algorithm is used to do image segmentation, which is a necessary component for detecting disorder in plant leaf disease.

**2.2 W. Ding and G. Taylor, "Automatic moth detection from trap images for pest management", Computers and Electronics in Agriculture, vol. 123, pp. 17-28, 2016. Available: 10.1016/j.compag.2016.02.003.**

We advocate an automated moth detection pipeline according to convolutional neural networks. A set of strategies for enhancing uncooked moth entice pictures is described. On a dataset of codling moth pictures collected in the area, our approach showed excellent overall effectiveness. Our species-agnostic technique can easily be adjusted to unique pests and/or settings. In pheromone-based pest management systems, controlling the range of insect pests is vital. In this study, we suggest a computerized recognition method for identifying and quantifying pests in photos taken inside area traps that is based entirely on deep learning. When applied to a dataset of industrial codling moths, our method shows promise in both qualitative and quantitative terms. Despite of prior pest-detection endeavours, our technique employs no pest-specific engineering, allowing it to acclimatize to a wide range of species and habitats while requiring little human intervention. It can be implemented on parallel hardware, making it suitable for deployment in situations where real-time actual quality is necessary.

**III. Proposed System**

TensorFlow, a powerful Python package, was used to create the proposed model. The suggested model, like existing CNN architectures, has three layers: input, hidden, and output. Model we've suggested comprises of four Convolutional layers and equal number of activation functions. The model has four max polling layers, a later flattened layer, and a fully linked layer to connect the output layer. The suggested model has 48x48x32 neurons, 22x22x64 neurons, 9x9x128, 2x2x200 neurons, and 1x1x64 neurons.



**Fig 1: Proposed Model**

**3.1 Algorithm Implementation**

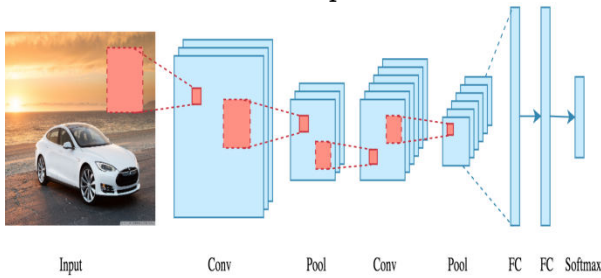
CNNs have become the de facto standard for image-related problems, and their success can be attributed to their ability to learn features without requiring human intervention. This is achieved through the use of convolutional layers that scan the input image and identify local patterns, such as edges, textures, and shapes. These patterns are then combined in higher layers to form more complex features that correspond to specific objects or concepts.

Apart from image recognition, CNNs have been successfully applied in a wide range of domains, including natural language processing, speech recognition, and recommender systems. In these applications, the input is not necessarily an image but could be a sequence of words, an audio signal, or a set of user preferences. However, the underlying principles of feature learning and hierarchical representation remain the same. Furthermore, CNN architectures have evolved rapidly in recent years, with deeper and more complex models being developed to handle larger and more diverse datasets. These models have achieved state-of-the-art performance in various tasks, such as object detection,



segmentation, and classification. However, they also come with challenges, such as longer training times, overfitting, and computational constraints.

In summary, CNNs have revolutionized the field of deep learning and have become an indispensable tool for solving image-related problems. Their success has spurred interest in other domains and has paved the way for new architectures and techniques.



#### IV. Dataset Information

| Sample Value | Sample Value |
|--------------|--------------|
| 1            | 0.00162259   |
| 2            | -0.0245922   |
| 3            | 0.00017747   |
| 4            | -0.01512071  |
| 5            | -0.03885242  |
| 6            | -0.05341309  |
| 7            | -0.07121147  |
| 8            | -0.08777473  |
| 9            | -0.08747025  |
| 10           | -0.069102    |
| 11           | -0.08356939  |
| 12           | -0.09599775  |
| 13           | -0.1035412   |
| 14           | -0.10899775  |
| 15           | -0.10799148  |
| 16           | -0.10734907  |
| 17           | -0.10701723  |
| 18           | -0.1071306   |
| 19           | -0.10699361  |
| 20           | -0.11372489  |
| 21           | -0.11743015  |
| 22           | -0.11743582  |
| 23           | -0.11212912  |
| 24           | -0.10043244  |
| 25           | -0.08862765  |
| 26           | -0.08295276  |
| 27           | -0.07121293  |
| 28           | -0.06390846  |
| 29           | -0.05708992  |
| 30           | -0.05770024  |
| 31           | -0.06242623  |
| 32           |              |

Fig 2: Dataset Details

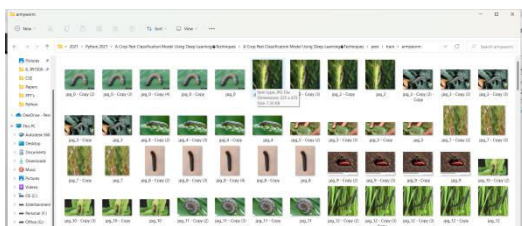


Fig 3: Dataset Sample Images

#### V. Results and Discussion

Here we are presenting our results

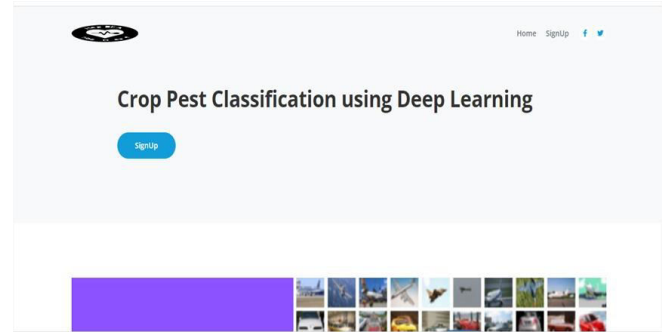


Fig 4: The Above Screen is Our Project Main page

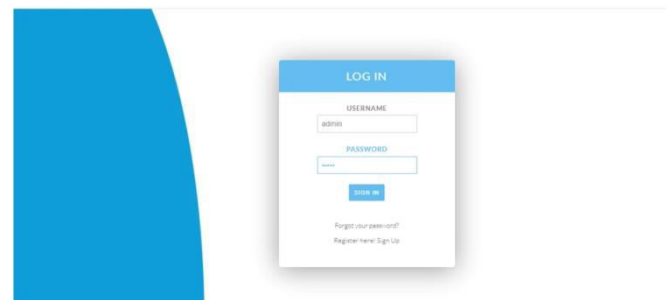


Fig 4: In the above screen user can login by using valid input name and password if the username and password correct then only the user can login otherwise it will show some error.



Fig 6: In the above screen we can see the output our project. first we have to upload input image based on that we get pest information

#### VI. Conclusion

It is great to see advancements in technology being utilized to help farmers in identifying beneficial and harmful pests. The use of CNN-based classification models for pest identification is a promising approach, and the

proposed model seems to have provided excellent results.

It is also encouraging to hear that the proposed CNN structure is less complex and faster in execution than extraction and transfer models. This means that it can be easily adopted and used by farmers in real-time, which is crucial for timely pest detection and prevention.

The future prospects of creating a more accurate and robust model are also exciting, as this can further improve the precision of the pest-identification framework. The idea of developing a smartphone application for farmers to use is also a great initiative. It can provide a user-friendly interface for quick and easy pest detection and display essential information about them to the farmers.

Overall, the proposed CNN-based classification model for pest identification is a significant step forward in the agriculture industry, and I look forward to seeing further advancements in this field.

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