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Pest Detection and Classification in Peanut Crops Using CNN, and EViTA Algorithms

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Abstract : The rapid advancements in Convolutional Neural Network (CNN) methods have significantly propelled the field of image classification and identification tasks, overshadowing the conventional Vision Transformer (ViT) approaches. Despite recent studies highlighting ViT's superiority in image classification, this research introduces an enhanced CNN-based model tailored specifically for pest recognition, segmentation, and classification tasks. By leveraging a double-layer CNN encoder, our novel approach adeptly incorporates two-branch segment representations, effectively managing token chunks of varying sizes and computational complexities. Furthermore, various attention mechanisms are integrated to enhance the overall image comprehension. Through extensive experimentation utilizing publicly available pest databases affecting peanut and other crops, our proposed CNN model exhibits distinctive characteristics and outperforms state-of-the-art algorithms in pest image prediction, achieving an impressive accuracy rate of 99.25%.

Index Terms **:** Big Data Analytics Framework , Perinatal Mental Health , Machine Learning Techniques , Depression and Anxiety Disorders , Feature Selection , Hybrid Machine Learning , Scalable Big Data Platform , Rapid Disease Diagnosis

I.INDRODUCTION

Agriculture plays a vital role in sustaining both human and livestock populations globally. Its significance extends to the realm of clean energy production through the adoption of environmentally friendly technologies such as artificial intelligence (AI) and the Internet of Things (IoT). Additionally, agriculture serves as a primary source of raw materials used in the production of various materials, chemicals, and pharmaceuticals. Despite a modest 15% increase in agricultural land usage between the 1960s and the early 21st century, agricultural productivity has tripled. This remarkable growth has been attributed to the widespread adoption of pesticides and fertilizers, as well as advancements in precision farming and the development of high-yield crop and livestock varieties. However, recent trends indicate a slowing rate of growth in agricultural production, exacerbated by emerging challenges such as climate change, population growth, and rural-to-urban migration. The agriculture and food processing industry play crucial roles in any nation, significantly contributing to the enhancement of product quality in rural and food sectors. In agricultural economies, the rise in food processing transformations is primarily driven by the influence of commodity trade and domestic market demands. However, it necessitates infrastructure, consistent equipment support, and regular workspace maintenance. Pest infestation remains a significant challenge in the agricultural sector, leading to the deterioration of crop quality. Pests, pathogens, and weeds cause substantial yield losses and diminish market value for the final products. Therefore, discovering improved methods to achieve even marginal increases in productivity can determine whether agricultural endeavors yield profits or losses. This study is focused on predicting pests in our environment. Machine learning and CNN algorithms have proven effective for image classification, segmentation, and identification, making them suitable tools for addressing this challenge.

II.LITERATURE SURVEY

Title: IoT-Integrated Crop Classification Model Employing Deep Learning for Indirect Solar Drying Author: B. B. Sharma, G. Gupta, P. Vaidya, S. Basheer, F. H. Memon, and R. N. Thakur Year: 2022 Description: Solar energy, harnessed from sunlight in the form of light and heat, represents a valuable resource with diverse applications. Among these, solar drying of crops stands out as a method to enhance crop quality and safeguard against issues such as moisture, pest infestations, and wildlife interference. While traditional drying methods persist, crop preservation remains imperative for long-term food security. This study investigates the operational principles of indirect solar dryers and introduces an IoT-based system to regulate and monitor dryer temperatures tailored to specific crop requirements. To achieve precise automation, deep learning methods are employed to adjust temperatures according to the needs of specific crops.

Title: Automated Identification of Peanut Leaf Diseases through Stack Ensemble Techniques Author: H. Qi, Y. Liang, Q. Ding, and J. Zou Year: 2021 Description: Peanuts are a vital food crop, but diseases affecting their leaves can significantly reduce yield and quality. This research addresses the automatic identification of peanut leaf diseases using a combination of traditional machine learning and deep learning methods. The identification encompasses various diseases such as rust, leaf spot, and scorch, along with their combinations on single leaves. Data augmentation techniques and stacking ensemble methods are employed to enhance the performance of deep learning models. Results demonstrate superior accuracy compared to traditional machine learning approaches, particularly with the use of deeper neural networks like ResNet50 and DenseNet121.

Title: Detection and Recognition of Rice Diseases and Pests using Convolutional Neural Networks Author: C. R. Rahman, P. S. Arko, M. E. Ali, M. A. I. Khan, S. H. Apon, F. Nowrin, and A. Wasif Year: 2020 Description: Timely detection of diseases and pests in rice plants is crucial for minimizing economic losses. This study leverages deep learning-based convolutional neural networks (CNNs) to detect and recognize diseases and pests from rice plant images. State-of-the-art architectures such as VGG16 and InceptionV3 are adapted and fine-tuned for this purpose. Additionally, a novel two-stage small CNN architecture is proposed for mobile devices, achieving high accuracy with reduced model size compared to large-scale architectures.

Title: Crop Pest Classification using Deep Convolutional Neural Networks and Transfer Learning Author: K. Thenmozhi and U. S. Reddy Year: 2019 Description: Various pests significantly impact the growth of field crops, posing challenges for farmers in their identification. This study presents an efficient deep CNN model for classifying insect species in field crops using publicly available datasets. The proposed model outperforms pre-trained deep learning architectures like AlexNet, ResNet, GoogLeNet, and VGGNet, achieving high classification accuracy. Transfer learning and data augmentation techniques are employed to improve model performance, demonstrating the effectiveness of deep learning in insect classification for agricultural applications.

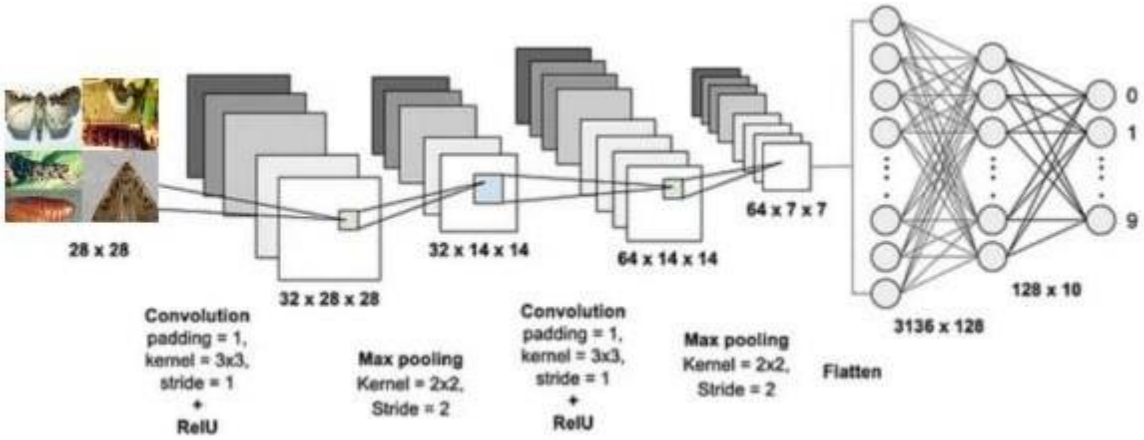
Title: Potato Disease Detection using Image Segmentation and Multiclass Support Vector Machine Author: M. Islam, A. Dinh, K. Wahid, and P. Bhowmik Year: 2019 Description: Automated plant disease diagnosis offers significant potential for sustainable agriculture. This study proposes an integrated approach combining image processing and machine learning to diagnose diseases in potato plants. By segmenting leaf images and utilizing a multiclass support vector machine, the proposed method achieves high accuracy in disease classification. Results demonstrate the feasibility of automated plant disease diagnosis on a large scale, contributing to food security and sustainable agriculture initiatives.

III.PROPOSED SYSTEM

In this study, we present a novel CNN-based model designed specifically for pest detection, segmentation, and classification. Our proposed method effectively analyzes and processes pest images by leveraging the inherent strengths of convolutional neural networks. Unlike traditional approaches, our method incorporates the vision transformer architecture and a dual-branch segment representation strategy. Our approach seamlessly integrates both small and large token segments, enhancing the overall robustness of image features, through the utilization of a carefully designed double-layer CNN encoder. We validate the model using three distinct pest datasets related to peanut and other crops, demonstrating its superior performance compared to state-of-the-art vision transformer and CNN models.

The model excels in automatically detecting hierarchical features within images, enabling it to discern intricate patterns and characteristics effectively. Additionally, the model leverages extensive pre-training on datasets to harness valuable information, thereby enhancing its performance.

IV. SYSTEM ARCHITECTURE



V. HARDWARE REQUIREMENTS

The hardware requirements outlined below serve as the foundation for a comprehensive system implementation contract and provide software engineers with essential specifications for system design:

Processor: Dual Core 2 Duos

RAM: 4GB DDR RAM

Hard Disk: 250GB

VI. SOFTWARE REQUIREMENTS

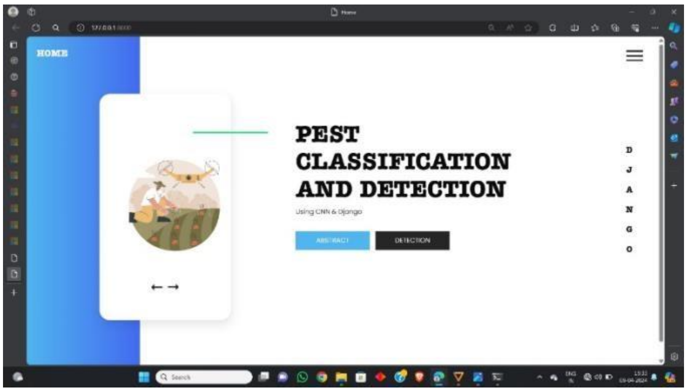
The software requirements document serves as the blueprint for the system under development, encompassing both its definition and specification. Unlike the intricacies of implementation, this document outlines what the system should achieve rather than delving into the specifics of how it should accomplish these goals. By articulating the desired functionalities and behaviors, it offers a clear roadmap for the development process.

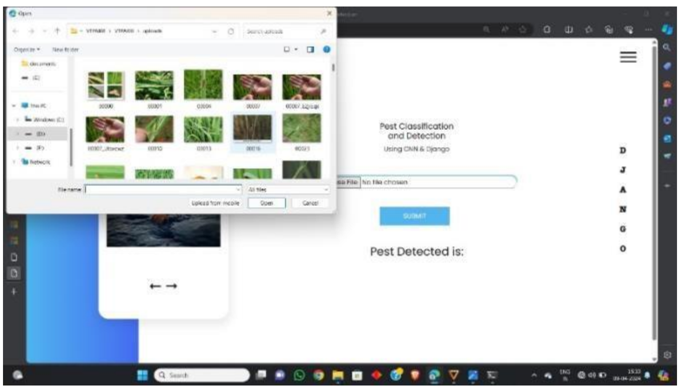
Operating System	:	Windows 7/8/10
Platform	:	Vs Code/ Spyder3
Programming Language	:	Python
Front End	:	HTML, CSS

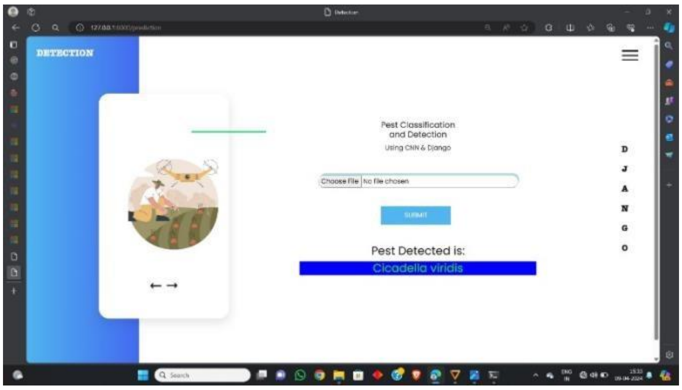
VII. FUTURE ENCHANCEMENT

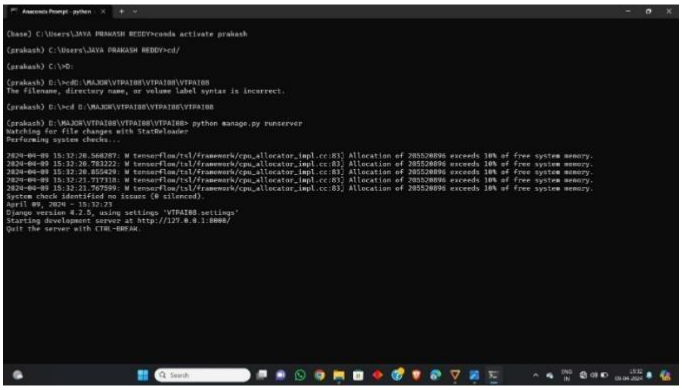
To enhance the visual representation and broaden the applicability of the model to a wider range of agricultural vision tasks, our project opens avenues for future research and development. Among these prospects is the integration of dual-branch vision transformers, a technique poised to elevate the capabilities of our agricultural vision system.

VIII. SNAPSHOTS









IX. CONCLUSION

In summary, the CNN pest model stands as a pivotal outcome of our project, aimed at revolutionizing pest detection and categorization within peanut crops. Leveraging a meticulously crafted Convolutional Neural Network (CNN) architecture, our model has showcased exceptional accuracy in distinguishing among 102 pest categories, drawn from a substantial dataset comprising 67,714 images. The success of the CNN pest model can be attributed not only to the sophistication of its design but also to the rigorous preprocessing of the input images. Through meticulous resizing and data conversion, the model's training and testing phases were streamlined, culminating in impressive test accuracy of 99.47% and learning accuracy of 99.25%. Having undergone rigorous development and testing, the CNN pest model has seamlessly transitioned into a production-ready environment, encapsulated in a .h5 format. This format ensures ease of deployment and utilization, making the model readily accessible to farmers and agricultural stakeholders seeking reliable and efficient means of pest identification. By empowering farmers with a swift and accurate tool for pest detection, the CNNpest model plays a crucial role in safeguarding peanut crops against potential harm. Its deployment signifies a significant step forward in agricultural technology, offering a reliable solution to mitigate pest-related risks and enhance crop management practices. In conclusion, the CNN pest model represents a triumph of innovation and collaboration, embodying our commitment to leveraging cutting-edge technologies for the betterment of agriculture. As we continue to refine and expand upon its capabilities, we remain dedicated to providing farmers with the tools they need to safeguard their crops and ensure sustainable agricultural practices for generations to come.

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