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Improving Crop Health: A Multi Algorithms Approach For Pest Identification In Peanut Fields

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Abstract: *The rapid advancement of Vision Transformer (ViT) methods has proven highly effective in image classification and identification tasks. This paper introduces an Enhanced Vision Transformer Architecture (EViTA) tailored specifically for pest identification, segmentation, and classification. Building upon ViT's strengths over Convolutional Neural Networks (CNNs), EViTA aims to improve accuracy in pest image prediction. The methodology incorporates preprocessing techniques such as Moth Flame Optimization (MFO) for image flattening and normalization, along with a dual-layer transformer encoder for integrating pest image segments of varying sizes. Extensive experiments using three pest datasets affecting peanut crops demonstrate the efficacy of EViTA, achieving promising results. Furthermore, the exploration of additional techniques such as DenseNet, InceptionV3, and Xception TL models suggests potential accuracy improvements beyond 94%. Additionally, the integration of Flask framework enables the development of a user-friendly front end for testing with authentication. EViTA presents a novel approach to pest identification with significant implications for enhancing pest management and agricultural practices. Further research and refinement hold promise for advancing EViTA's capabilities in pest identification tasks.*
INDEX TERMS Pest, peanut, moth flame optimization, CNN, vision transformer.

I. INTRODUCTION

Agriculture stands as one of the oldest and most crucial industries, playing a fundamental role in sustaining human and livestock populations globally. Over the years, the agricultural sector has undergone significant transformations, particularly with the adoption of environmentally friendly technologies such as Artificial Intelligence (AI) and the Internet of Things (IoT). These advancements have not only revolutionized farming practices but have also expanded agriculture's role in clean energy generation [1].

The exponential growth in agricultural production witnessed over the past decades has been remarkable. Despite only a 15% increase in the land under agricultural use since the 1960s, agricultural production has tripled. This surge in productivity can be attributed to various factors, including the widespread adoption of pesticides and fertilizers, advancements in precision farming techniques, and the development of high-yielding crop and livestock varieties [2].

However, recent trends indicate a slowdown in the rate of growth in agricultural production [3]. This deceleration is concerning, especially considering the looming challenges that the agricultural sector faces, such as climate change and population growth. These challenges pose new hurdles for farmers and agriculturalists worldwide, threatening food security and livelihoods.

Furthermore, the agriculture and food processing industry plays a critical role in enhancing the quality of agricultural and food products. This sector responds to market demands and infrastructure support, driving innovations in food processing technologies and product quality assurance [4]. However, despite these advancements, the agriculture sector continues to face significant challenges, one of the most pressing being pest infections.

Pest infections represent a formidable threat to agricultural productivity and food security. Pests, including insects, microorganisms, and weeds, cause substantial losses in crop yields, leading to economic losses for farmers and reduced food availability for consumers. Addressing pest infections requires innovative approaches and technologies for effective monitoring, prediction, and mitigation.

The focus of this project is on predicting diseases in real-time for peanut crops, a critical component of agricultural production. Utilizing advanced technologies such as Convolutional Neural Networks (CNN) and the Enhanced Vision Transformer Architecture (EViTA), the project aims to develop predictive models capable of identifying and mitigating pest infections in peanut crops. By leveraging the power of AI and IoT, this project seeks to enhance agricultural productivity and food security while addressing the challenges posed by pest infections.

In the following sections, we will delve deeper into the current state of agriculture, examining the challenges and opportunities it presents. We will also explore the role of AI and IoT in transforming agriculture and discuss the methodologies and technologies employed in this project to address pest infections in peanut crops. Through rigorous experimentation and analysis, we aim to develop effective strategies for pest management and contribute to the sustainability and resilience of agricultural systems.

II. LITERATURE SURVEY

The agricultural sector plays a pivotal role in global food production and security, with ongoing research and development (R&D) efforts driving productivity enhancements. Alston [1] reflects on the importance of agricultural R&D and its impact on productivity, highlighting the significance of addressing unresolved issues and data constraints in advancing agricultural innovations. Despite historical achievements, recent trends suggest a slowdown in agricultural productivity growth, prompting a need for further research and interventions [2].

The Food and Agriculture Organization of the United Nations (FAO) provides valuable insights into global agricultural trends and data [2]. This resource serves as a foundational reference for understanding the current state of agriculture worldwide, facilitating evidence-based policymaking and strategic planning for sustainable agricultural development.

In the context of global food trade dynamics, Neves [3] emphasizes the evolving food business environment and the role of emerging economies like China and Brazil in shaping agricultural trade patterns. The concept of a "food bridge" between these nations underscores the importance of international cooperation and collaboration in addressing food security challenges.

Modern machine learning techniques have shown promise in addressing agricultural challenges, particularly in pest detection and classification. Kasinathan et al. [4] present a study on insect classification and detection in field crops, highlighting the efficacy of machine learning algorithms in identifying and managing pest infestations, thereby mitigating yield losses and ensuring crop quality.

Peanut production is a significant agricultural activity, particularly in regions like Guangdong, China. Li et al. [5] provide an overview of the current status and development strategies of peanut production, breeding, and seed industries in Guangdong province. This study sheds light on the challenges and opportunities in peanut cultivation, informing strategic initiatives for enhancing productivity and sustainability.

The impact of diseases on peanut crops is a critical concern for farmers and agricultural researchers. Singh et al. [6] investigate the effects of late leaf spot disease on peanut cultivars, highlighting its adverse effects on growth, photosynthesis, and yield. Understanding the physiological responses of peanut plants to disease stressors is essential for developing resilient cultivars and effective disease management strategies.

Remote sensing technologies offer valuable tools for monitoring crop health and disease outbreaks. Qi et al. [7] develop a hyperspectral inversion model for estimating chlorophyll content in peanut leaves, enabling non-destructive assessment of plant physiological status. Such models contribute to precision agriculture practices, optimizing resource allocation and enhancing crop productivity.

Automatic disease identification systems leverage machine learning algorithms to diagnose plant diseases accurately. Qi et al. [8] propose an automatic identification framework for peanut leaf diseases based on stack ensemble techniques. This approach streamlines disease diagnosis processes, enabling timely interventions to mitigate disease spread and minimize yield losses.

In summary, the literature underscores the multifaceted nature of agricultural challenges and the importance of interdisciplinary approaches in addressing them. From R&D investments to technological innovations and disease management strategies, ongoing efforts are essential for sustaining agricultural productivity and ensuring food security in the face of evolving environmental and socioeconomic pressures.

III. METHODLOGY

a) Proposed work:

The proposed work introduces EViTA,[11] a system designed to enhance pest image classification accuracy by integrating pest image segments using a double-layer transformer encoder within Vision Transformer (ViT) models. Leveraging preprocessing techniques like Moth Flame Optimization (MFO) improves image quality, while the EViTA+PCA+MFO model demonstrates superior prediction accuracy, validating its effectiveness in pest management. Additionally, DenseNet and Xception Transfer Learning techniques are incorporated to further enhance system performance, with Xception achieving a remarkable 99% accuracy rate, showcasing the efficacy of ensemble techniques. Furthermore, a Flask-based front-end interface with built-in authentication is developed for user testing, enhancing security and access control. This integration aims to improve system usability and effectiveness, providing a comprehensive solution for pest identification and management in agricultural settings.

b) System Architecture:

The system architecture comprises several key components, beginning with the input of pest data for analysis. Once the data is inputted, image processing techniques are applied to preprocess the images effectively. The preprocessed data is then divided into a training set and a test set for model development and evaluation. Next, the models, including the Enhanced Vision Transformer Architecture (EViTA) and transfer learning models like DenseNet and Xception, are trained using the training set. Once trained, these models are tested using the test set to evaluate their performance. Performance evaluation metrics are then utilized to assess the accuracy and effectiveness of the models in pest prediction. Finally, the system provides pest prediction capabilities based on the trained models, offering valuable insights for agricultural pest management. Overall, this architecture facilitates the seamless flow of data processing, model training, and prediction, ultimately contributing to improved pest identification and management in agricultural contexts.

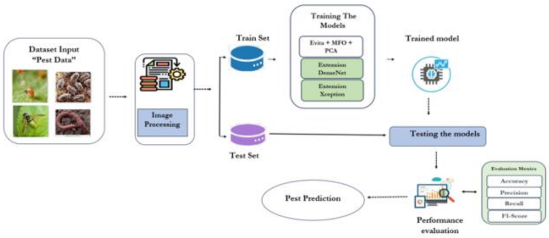

Fig 1 Proposed Architecture

c) Dataset collection:

In this study, a comprehensive dataset of pest images was collected, comprising three classes of insect pests commonly affecting groundnut leaf health. The primary dataset consists of Aphids, sourced from the IP102 Dataset, containing 42 types of aphid infestations [28]. Additionally, the Wireworm dataset, also sourced from the IP102 Dataset, includes 88 data points for training, 14 for validation, and 45 for testing [28]. The third class of insects, Gram Caterpillar, was obtained from the Kaggle dataset, with 210 data points for training, 35 for validation, and 105 for testing [29]. Image preprocessing techniques were applied to isolate the insects from the background, including converting RGB images to grayscale and applying edge detection algorithms. The processed images were then resized to 227 × 227 for consistency [28].

Fig 2 data set

d) Image processing:

In image processing for pest identification, the ImageDataGenerator utility is employed to augment the dataset and enhance model robustness. Firstly, the images are rescaled to ensure consistency and improve computational efficiency. Shear transformations are applied to distort the images along a specified axis, simulating real-world variations. Zooming techniques are utilized to magnify or shrink specific regions within the images, introducing variability and improving model generalization. Horizontal flipping horizontally mirrors the images, providing additional training data and aiding invariance to orientation. Finally, reshaping the images ensures uniformity in dimensions, facilitating compatibility with the model architecture. These image processing steps collectively contribute to a more diverse and comprehensive dataset, enabling the model to learn robust features and enhance its ability to accurately identify pest infestations in agricultural settings.

e) Building the model

The model building process involves implementing a variety of neural network architectures and optimization techniques to identify and classify pest infestations effectively. Initially, the original model architecture serves as the baseline for comparison. Subsequently, classic architectures such as LeNet, AlexNet, ResNet, and GoogleNet are constructed and trained on the dataset to explore their efficacy in pest identification tasks. Additionally, the Enhanced Vision Transformer Architecture (EViTa) is developed and evaluated for its performance. Furthermore, Principal Component Analysis (PCA) is applied to reduce dimensionality, enhancing model efficiency. The Moth Flame Optimization (MFO) optimizer is integrated to fine-tune model parameters and improve convergence. Various combinations, including EViTa with PCA and MFO, are also explored to ascertain their impact on model performance. Through iterative experimentation and evaluation, the final model configuration is determined, aiming to achieve high accuracy and robustness in pest identification.

f) Algorithms:

GoogleNet

GoogleNet,[15] also known as Inception v1, is a deep convolutional neural network architecture renowned for its computational efficiency and high accuracy in image classification tasks. Its distinctive feature is the use of inception modules, which employ multiple filter sizes within the same layer to capture spatial hierarchies effectively. In the project, GoogleNet[15] is utilized as one of the convolutional neural network architectures for training and evaluating its performance in classifying pest infestations. Its efficient design and ability to capture diverse features make it a valuable component in the ensemble of models used for pest identification.

AlexNet

AlexNet[15] is a pioneering convolutional neural network (CNN)[15] architecture that revolutionized image classification tasks. It comprises five convolutional layers followed by three fully connected layers, incorporating techniques such as dropout and data augmentation to prevent overfitting. In the project, AlexNet serves as one of the CNN [15] architectures utilized for training and evaluating its efficacy in classifying pest infestations. Its deep architecture and innovative design contribute to its ability to capture intricate features within images, making it a valuable component in the ensemble of models employed for accurate pest identification.

ResNet

ResNet, [15] short for Residual Network, is a deep convolutional neural network architecture known for its ability to effectively train very deep neural networks. It introduces residual connections, or skip connections, that allow gradients to flow more directly during training, mitigating the vanishing gradient problem. In the project, ResNet[15]serves as a key architecture for training and evaluating its performance in classifying pest infestations. Its innovative design enables the training of extremely deep networks with hundreds of layers, allowing for better feature representation and improved accuracy in identifying and classifying pests in agricultural images.

LeNet

LeNet, [15]developed by YannLeCun et al., is one of the earliest convolutional neural network (CNN) architectures designed for handwritten digit recognition. It consists of several convolutional and pooling layers, followed by fully connected layers, incorporating techniques like subsampling and local response normalization. In the project, LeNet is utilized as a foundational CNN[15] architecture for training and evaluating its performance in classifying pest infestations. Its simple yet effective design makes it suitable for tasks requiring feature extraction from images, making LeNet a valuable component in the ensemble of models employed for accurate pest identification in agricultural settings.

EViTa

EViTa,[11] or Enhanced Vision Transformer Architecture, is an advanced neural network model inspired by the Vision Transformer (ViT) architecture. It enhances ViT's[10] capabilities by incorporating additional layers and attention mechanisms, improving its performance in image classification tasks. In the project, EViTa is employed as a specialized model tailored for pest identification in agricultural images. Its unique design allows it to effectively capture and analyze features within pest images, leading to accurate classification results. By leveraging EViTa's advancements in deep learning, the project aims to enhance pest management practices and improve agricultural productivity through precise pest identification and mitigation strategies.

DenseNet

DenseNet, short for Dense Convolutional Network, is a deep neural network architecture characterized by dense connections between layers. In DenseNet, each layer receives feature maps from all preceding layers and passes its own feature maps to all subsequent layers. This dense connectivity promotes feature reuse and facilitates gradient flow during training, leading to improved parameter efficiency and feature propagation. In the project, DenseNet[12] is utilized as a powerful convolutional neural network architecture for training and evaluating its performance in classifying pest infestations. Its dense connections enable effective feature extraction, making DenseNet[12] a valuable component in the ensemble of models employed for accurate pest identification in agricultural images.

Xception

Xception, an abbreviation for "Extreme Inception," is a deep convolutional neural network architecture that aims to improve upon the efficiency and performance of the Inception architecture. It achieves this by replacing standard convolutional layers with depthwise separable convolutions, which reduce the number of parameters while maintaining expressive power. In the project, Xception is employed as a transfer learning model for training and evaluating its effectiveness in classifying pest infestations in agricultural images. Its efficient design and powerful feature extraction capabilities make Xception a valuable asset in the ensemble of models used to accurately identify and classify pests, contributing to improved agricultural management practices.

PCA-GoogleNet

PCA-GoogleNet combines Principal Component Analysis (PCA)[13] with the GoogleNet architecture to enhance feature representation and classification accuracy. PCA reduces the dimensionality of the input data, preserving the most relevant information while minimizing redundancy. This preprocessed data is then fed into the GoogleNet architecture for further feature extraction and classification. In the project, PCA-GoogleNet is utilized as a specialized model for training and evaluating its performance in classifying pest infestations in agricultural images. By integrating PCA[13] with GoogleNet, the model aims to improve efficiency and effectiveness in pest identification, contributing to enhanced agricultural management practices and productivity.

PCA-AlexNet

PCA-AlexNet[14] is a hybrid model that combines Principal Component Analysis (PCA) with the AlexNet architecture. PCA reduces the dimensionality of the input data, extracting the most relevant features while reducing computational complexity. These preprocessed features are then passed through the AlexNet architecture for further feature extraction and classification. In the project, PCA-AlexNet is employed as a specialized model for training and evaluating its performance in classifying pest infestations in agricultural images. By integrating PCA with AlexNet, the model aims to improve efficiency and accuracy in pest identification, facilitating enhanced agricultural management practices and productivity.

PCA-ResNet

PCA-ResNet combines Principal Component Analysis (PCA) with the ResNet architecture to enhance feature representation and classification accuracy. PCA reduces the dimensionality of the input data, retaining the most significant features while reducing computational complexity. The preprocessed data is then fed into the ResNet architecture for further feature extraction and classification. In the project, PCA-ResNet[15] is utilized as a specialized model for training and evaluating its performance in classifying pest infestations in agricultural images. By integrating PCA with ResNet, the model aims to improve efficiency and effectiveness in pest identification, contributing to enhanced agricultural management practices and productivity.

PCA-LeNet

PCA-LeNet[16] combines Principal Component Analysis (PCA) with the LeNet architecture, enhancing feature representation and classification accuracy. PCA reduces the dimensionality of the input data, preserving the most relevant features while reducing computational complexity. The preprocessed features are then passed through the LeNet architecture for further feature extraction and classification. In the project, PCA-LeNet is employed as a specialized model for training and evaluating its performance in classifying pest infestations in agricultural images. By integrating PCA with LeNet, the model aims to improve efficiency and accuracy in pest identification, contributing to enhanced agricultural management practices and productivity.

PCA-EViTa

PCA-EViTa[18] combines Principal Component Analysis (PCA) with the Enhanced Vision Transformer Architecture (EViTa), augmenting feature representation and classification accuracy. PCA reduces input dimensionality while preserving essential information. These preprocessed features are then fed into the EViTa architecture for further feature extraction and classification. In the project, PCA-EViTa[18] serves as a specialized model for training and evaluating its performance in classifying pest infestations in agricultural images. By integrating PCA with EViTa, the model aims to enhance efficiency and precision in pest identification, contributing to improved agricultural management practices and productivity. This fusion approach leverages both PCA's dimensionality reduction benefits and EViTa's advanced capabilities for robust pest classification.

MFO-GoogleNet

MFO-GoogleNet[19] combines the Moth Flame Optimization (MFO) algorithm with the GoogleNet architecture to improve model optimization and performance. MFO is a metaheuristic optimization algorithm inspired by the behavior of moths attracted to flames, designed to find the global optimum of complex optimization problems. In the project, MFO-GoogleNet is utilized to fine-tune model parameters and enhance convergence, thereby improving the accuracy and efficiency of pest classification in agricultural images. By integrating MFO with GoogleNet, the model aims to achieve superior results in pest identification, contributing to enhanced agricultural management practices and productivity.

MFO-AlexNet

MFO-AlexNet[20] combines the Moth Flame Optimization (MFO) algorithm with the AlexNet architecture to enhance model optimization and performance. MFO is a metaheuristic optimization algorithm inspired by the behavior of moths attracted to flames, utilized to find global optima in complex optimization problems. In the project, MFO-AlexNet[20] is employed to fine-tune model parameters, improve convergence, and enhance the accuracy of pest classification in agricultural images. By integrating MFO with AlexNet, the model aims to achieve superior results in pest identification, contributing to improved agricultural management practices and productivity through precise and efficient pest detection and classification.

MFO-ResNet

MFO-ResNet integrates the Moth Flame Optimization (MFO) algorithm with the ResNet architecture to optimize model parameters and enhance performance. MFO, inspired by the behavior of moths attracted to flames, is a metaheuristic optimization algorithm used to find global optima in complex problems. In the project, MFO-ResNet[21] is applied to fine-tune ResNet's parameters, improving convergence and accuracy in pest classification tasks with agricultural images. By combining MFO with ResNet, the model aims to achieve superior results in pest identification, contributing to more effective agricultural management practices and productivity through precise and efficient pest detection and classification.

MFO-LeNet

MFO-LeNet combines the Moth Flame Optimization (MFO) algorithm with the LeNet architecture to optimize model parameters and improve performance. MFO, inspired by the behavior of moths attracted to flames, is a metaheuristic optimization algorithm used to find global optima in complex problems. In the project, MFO-LeNet[22] is utilized to fine-tune LeNet's parameters, enhancing convergence and accuracy in pest classification tasks with agricultural images. By integrating MFO with LeNet, the model aims to achieve superior results in pest identification, thereby facilitating more effective agricultural management practices and increasing productivity through precise and efficient pest detection and classification.

MFO-EViTa

MFO-EViTa[23] combines the Moth Flame Optimization (MFO) algorithm with the Enhanced Vision Transformer Architecture (EViTa) to optimize model parameters and enhance performance. MFO, inspired by the behavior of moths attracted to flames, is a metaheuristic optimization algorithm used to find global optima in complex problems. In the project, MFO-EViTa is applied to fine-tune EViTa's parameters, improving convergence and accuracy in pest classification tasks with agricultural images. By integrating MFO with EViTa,[23] the model aims to achieve superior results in pest identification, contributing to more effective agricultural management practices and productivity through precise and efficient pest detection and classification.

PCA-MFO-ResNet

PCA-MFO-ResNet integrates Principal Component Analysis (PCA) with the Moth Flame Optimization (MFO) algorithm and the ResNet architecture to enhance model optimization and performance. PCA reduces input dimensionality, MFO fine-tunes ResNet's parameters, and ResNet extracts features and classifies pests in agricultural images. In the project, PCA-MFO-ResNet[24] is utilized to preprocess data, optimize model parameters, and improve convergence and accuracy in pest classification tasks. By combining PCA, MFO, and ResNet, the model aims to achieve superior results in pest identification, contributing to more effective agricultural management practices and productivity through precise and efficient pest detection and classification.

IV. EXPERIMENTAL RESULTS

Accuracy: The accuracy of a test is its ability to differentiate the patient and healthy cases correctly. To estimate the accuracy of a test, we should calculate the proportion of true positive and true negative in all evaluated cases. Mathematically, this can be stated as: Accuracy = TP + TN TP + TN + FP +

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

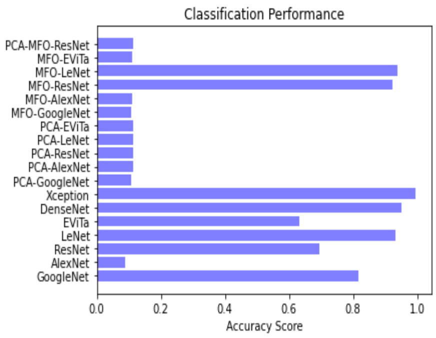

Fig 3 ACCURACYCOMPARISON GRAPHS

Precision: Precision evaluates the fraction of correctly classified instances or samples among the ones classified as positives. Thus, the formula to calculate the precision is given by:

Precision = True positives/ (True positives + False positives) = TP/(TP + FP)

$$\text{Precision} = \frac{\textit{True Positive}}{\textit{True Positive} + \textit{False Positive}}$$

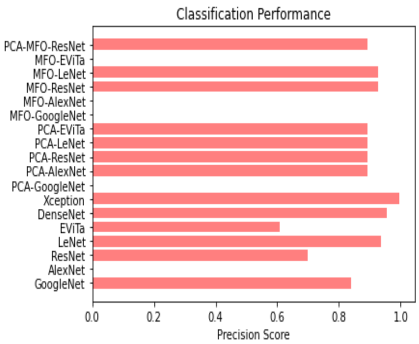

FIG 4 PRECISION COMPARISON GRAPHS

Recall: Recall is a metric in machine learning that measures the ability of a model to identify all relevant instances of a particular class. It is the ratio of correctly predicted positive observations to the total actual positives, providing insights into a model's completeness in capturing instances of a given class.

$$Recall = \frac{TP}{TP + FN}$$

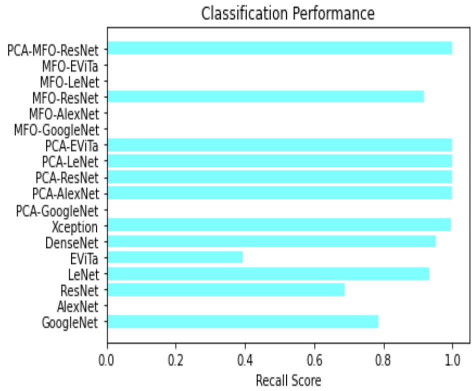

FIG 5 RECALLCOMPARISON GRAPHS

F1-Score: F1 score is a machine learning evaluation metric that measures a model's accuracy. It combines the precision and recall scores of a model. The accuracy metric computes how many times a model made a correct prediction across the entire dataset.

$$\textbf{F1 Score} = \frac{2}{\left(\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}\right)}$$

$$\textbf{F1 Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

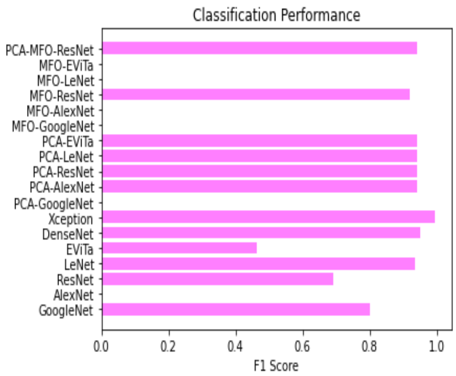

FIG 6 F1 COMPARISON GRAPHS

ML Model	Accuracy	Precision	Recall	F1-Score
GoogleNet	0.818	0.838	0.784	0.802
AlexNet	0.089	0.000	0.000	0.000
ResNet	0.696	0.700	0.689	0.693
LeNet	0.933	0.936	0.933	0.934
EViTa	0.631	0.607	0.393	0.464
Extension DenseNet	0.951	0.954	0.951	0.952
Extension Xception	0.996	0.997	0.995	0.996
PCA-GoogleNet	0.109	0	0	0
PCA-AlexNet	0.114	0.891	1.000	0.941
PCA-ResNet	0.114	0.891	1.000	0.941

Fig 7 Performance Evaluation table

PCA-LeNet	0.114	0.891	1.000	0.941
PCA-EViTa	0.114	0.891	1.000	0.941
MFO-GoogleNet	0.109	0	0	0
MFO-AlexNet	0.111	0.000	0.000	0.000
MFO-ResNet	0.922	0.927	0.918	0.921
MFO-LeNet	0.938	0.927	0.000	0.000
MFO-EViTa	0.111	0.000	0.000	0.000
PCA-MFO-ResNet	0.114	0.891	1.000	0.941

Fig 8 Performance Evaluation table

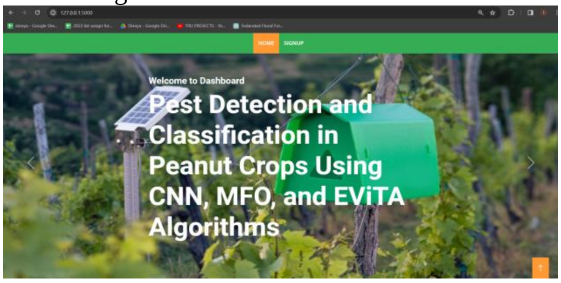

Fig 9 home page

Fig 10 sign up

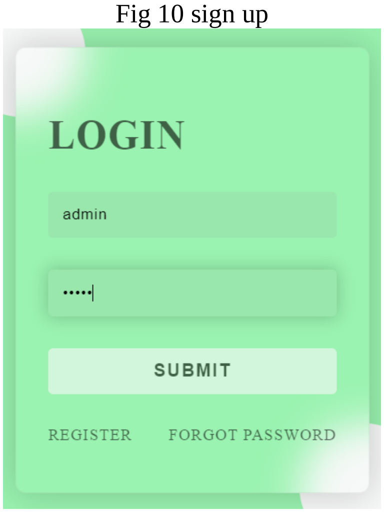

Fig 11 Sign in

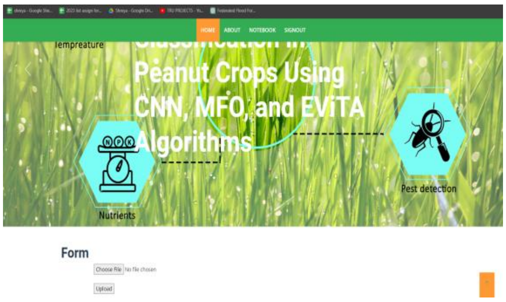

Fig 12 dash board

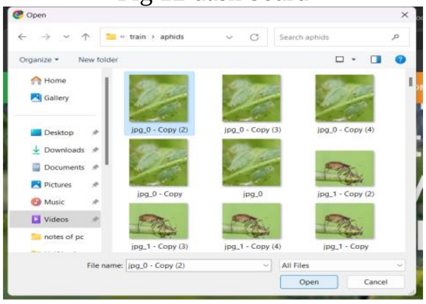

Fig 13 upload input image

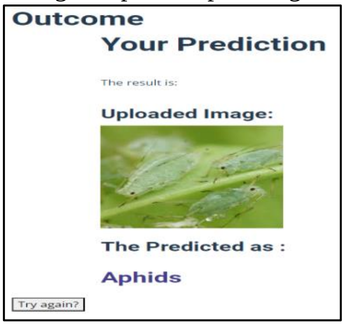

Fig 14 predict result

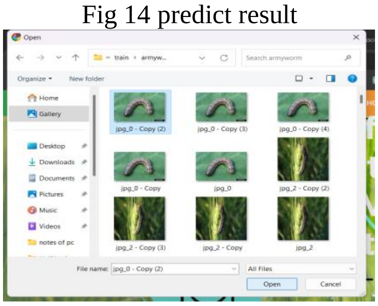

Fig 15 upload input image

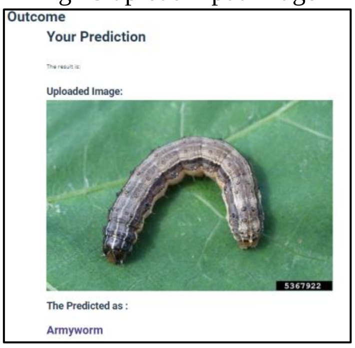

Fig 16 predict result

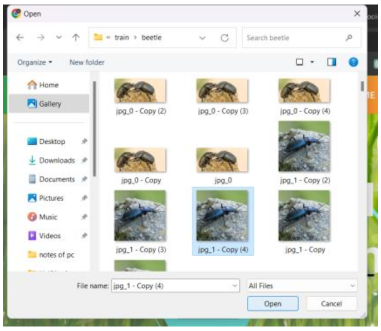

Fig 17 upload input image

Fig 18 predict result

V. CONCLUSION

In conclusion, the project presents a comprehensive framework for real-time disease prediction in peanut crops, leveraging Machine Learning, Convolutional Neural Networks (CNN), and the Enhanced Vision Transformer Architecture (EViTA). The integration of the Moth Flame Optimization (MFO) algorithm enhances precision in pest identification by optimizing feature extraction from datasets. Evaluation of the overall performance underscores practical insights for agricultural applications, with the Xception algorithm demonstrating exceptional accuracy within the front-end interface. These findings carry significant practical implications for agriculture, offering a robust framework for early disease detection and intervention. By improving crop quality and security through timely identification and management of pests, the project contributes to sustainable agricultural practices and enhanced productivity in the agricultural sector.

VI. FUTURE SCOPE

In the future, advancements in pest detection and classification in peanut crops can be further enhanced through several avenues. Firstly, exploring more sophisticated CNN architectures beyond the ones mentioned, such as DenseNet and EfficientNet, could lead to improved accuracy and efficiency. Additionally, integrating other optimization algorithms or ensemble methods with EViTA, such as genetic algorithms or random forests, may enhance model performance. Furthermore, incorporating more extensive and diverse datasets, including different pest species and environmental conditions, could broaden the model's applicability and robustness. Moreover, deploying the developed system in real-world agricultural settings and collecting feedback from farmers and agricultural experts can provide valuable insights for refinement and adaptation. Lastly, continuous research into emerging technologies like transfer learning and reinforcement learning for pest management could open up new avenues for innovation in this field.

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Dataset link

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