Real-Time Classifications of Pests from Agriculture Industry Based on Their Color and Texture Features by Using Machine Learning Models

Athithya Elumalai[1], Vijayakumar Jeganathan[2]
[1]*Student, Department of Electronics and Instrumentation, Bharathiar University, Coimbatore, Tamil Nadu, India*
[2]*Professor, Department of Electronics and Instrumentation, Bharathiar University, Coimbatore, Tamil Nadu, India*
Corresponding Author: athithya20021@gmail.com

Abstract— Insects and pests are major sources for causes of agricultural damage. Earlier identification and resistance of pest insects is the only solution to this real-time problem. The combination of computer vision made possible by Machine Learning (ML) has paved the way for smart devices assisted crop insect pest identification. The proposed work aims to develop a classification system for pests using machine learning algorithms. Implementing color and textural features extracted from K-Means clustering and GLCM provides an explicit and comprehensive representation of pest color and texture, enabling the model to classify the pests. Incorporating K-means clustering and GLCM algorithms further enhances the proposed model's ability to differentiate between pests based on their unique features and patterns. This study introduces a novel supervised ML approach for classifying agricultural affecting pests that integrate K-means clustering with color and textural features extracted through the Gray-Level Co-occurrence Matrix GLCM algorithm. Using these advanced techniques, the model achieved an impressive accuracy rate of 98.5% for ten classes of pest classification work. Overall, this study highlights the significance of integrating supervised ML methods with specialized image analysis techniques for precise pest classification in agricultural sectors. The obtained results underscore the potential impact of these advanced technologies on improving pest control and overall agricultural productivity.

Index Terms— **K-means clustering, GLCM, Pest Classification, Supervised Machine Learning models, F-KNN.**

1. Introduction

A wide range of aspects of the economy, society, and environment are impacted by the agricultural department, which is the backbone and wealth of the global economy and also the major source of food.

Manuscript revised March 29, 2024; accepted March 30, 2024. Date of publication April 02, 2024.
This paper available online at www.ijprse.com
ISSN (Online): 2582-7898; SJIF: 5.59

The quality and quantity of agricultural products are severely impacted due to the reasons of different kinds of pests. So, protection from pests will impact the yields, in recent years agriculture sector has seen a rise in the need for practical and effective pest management strategies. Both beneficial and harmful insects play a major role in the ecosystem, affecting crop output and the long-term viability of the agricultural sector as an entire sector. Identifying and classifying insects is a crucial starting point in developing specific pest management methods (Jin Wang et al., 2020). Traditionally, the manual identification and classification techniques are mostly followed by the farmers, but this can be a time-consuming task for the farmers in large-scale production and prone to human mistakes leads the spread of pests in the entire farm and also creating an impact on economic losses to the farmers. In recent years, researchers proposed different techniques in the agricultural sector for pest monitoring and control (Zhankui Yang et al., 2023). Among these, Artificial Intelligence (AI) is one of the most advanced techniques, which plays an important role in all sectors, including agriculture, Machine Learning (ML) and Deep Learning (DL) are the sub-fields of AI technology (Weiguang Ding et al., 2016). This proposed work utilized the ML model for classifying the ten categories of pests that most commonly affect the agriculture industry these pests negatively impact the food sources from the beginning of crop cultivation to the end of the harvest and storage processes. So, the identification of pests earlier, the farmers will avoid economic losses and also help to obtain quality products (Ayad Saad Almryad et al., 2020). This pest identification and classification work utilized the texture and color-based feature for pest identification which features are extracted from the pest images by using K-means clustering and Gray Level Co-Occurrence Matrix (GLCM) algorithm and the supervised ML models for classifying the types of pests (Yu Sun et al., 2018).

2. Literature Survey

Our proposed system tries to classify the different types of pests which creates a negative impact on the agriculture industry. The main objective of this work is to automatically identify and classify the pest in real-time, the accurate prediction will minimize the human resource in the farming and production industry. In recent years was large number of research works have been proposed by the researchers to resolve the major problem.

Using supervised machine learning methods and shape-based features to identify 33 different insect types, researchers developed a model for crop pest identification. To increase accuracy, image-enhancing and preprocessing techniques were applied [1]. Applying machine learning techniques (LMT, SVM, Random Forest) in conjunction with object- and pixel-based characteristics, insect species, and gender classification were applied to 600 photos. 100% accuracy was reached by SVM and Random Forest, with feature extraction being improved by image pre-processing [2]. A model that uses machine learning techniques on 4500 pest images combined with manually developed features like SIFT and HOG to automatically classify field crop pests. KSVD was one of the classifiers that produced the highest accuracy, at 98.6% [3]. Machine Learning algorithms on 307,719 images and several citizen science platforms for biodiversity monitoring make use of pest, user, observation, time, and environment variables. For the SPIPOLL dataset, the classifiers with the highest classification accuracies, SGD and DT, were 81% and 82% [4]. Mean pixel values, morphologies, and wing patterns were used in conjunction with Machine Learning, Image Processing, and Data Mining methods for 35 UK species in the automated identification of live moths [5]. Eight insect classes' worth of global and local features were examined utilizing Image Processing algorithms for image-based automated insect identification. A Deep Learning algorithm was used in conjunction with k-means features on 2200 aphid images in a study that evaluated the identification and detection of aphids in agricultural settings [6]. 1800 planthopper images have been subjected to Image Programming algorithms and HOG features automatically identify the rice planthoppers. Three classifiers—SVM, DR, and FDR—were used; SVM had the best accuracy, at 85.2%. Similarly, RGB and CMYK features were used with the Digital Image Processing method to count the whiteflies on soybean leaves [7]. ANN characteristics and the Digital image processing method were used in the neural identification of particular apple pests. Machine Learning was successful in the identification process, attaining the greatest accuracy timing of 23:19:1 [8]. K-fold cross-validation and Region of Interest features were used in 48 models to automatically detect insect predation using leaf segmentation. Insect predation segmentation achieved a 90% precision accuracy and an 86% recall accuracy using classifiers such as Template Matching learning and Line Segmentation [9]. 9401 pest images were used to pre-train ResNet with SNE features and perform 5-fold cross-validation in the model for bug microhabitat identification via image background evaluation [10]. Five thousand images were evaluated using Deep Learning algorithms and SLSI segmentation features in a model for identifying and classifying soybean pests. In this detection and classification effort, classifiers Inception-v3, Resnet-50, VGG-16, VGG-19, and Xception were used [11]. Machine Learning algorithms along with 10-fold cross-validation features were applied to 1426 images to create a model for detecting and classifying rice illnesses. In this rice illness diagnosis and recognition test [12]. 563 insect images have been evaluated to SIFT-HMAX, LCP characteristics, and Image Processing algorithms for the identification and detection of insect pests for food security. Classifiers NIMBLE, MatConvNet, Sparse coding, and our approach HMAX were applied; MatConvNet obtained the maximum accuracy of 86.9% in this classification and identification work [13]. RGB HIS features and Image Processing algorithms were applied to 678 photos for vision-based pest detection. Several classifiers were used, such as MSE, RMSE, MAE, and MPE [14]. Machine Learning and Image Processing algorithms were applied to 30 classes of flying insects using SE, CBAM, ECA, and CA features for automatic monitoring and hierarchical classification. In this extensive classification work, PCNet achieved the greatest accuracy of 98.4% by using classifiers like AlexNet, VGG16, ResNet101, and others [15].

3. Material And Methods

The materials and methods of the proposed work for identifying and classifying the pest classes based on their color and texture features were discussed here. This section included the following subsections which detailed and explained the proposed work, such as the architecture of the proposed work, dataset preparation process, image pre-processing, K-means clustering based color feature extraction, GLCM for texture feature extraction, and supervised classification model (F-KNN) classes of pest classification.

A. Proposed system architecture

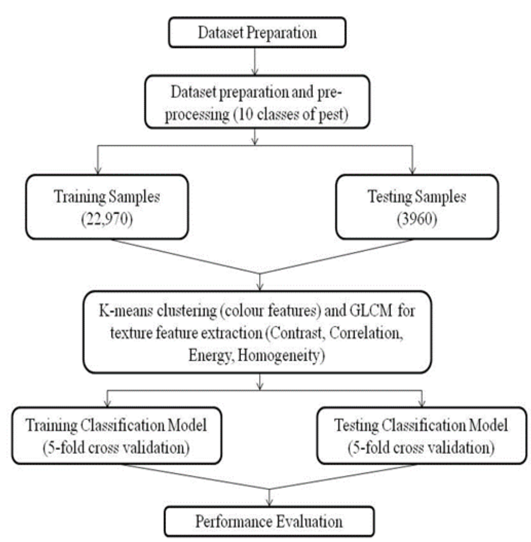

Fig.1. Shows the proposed system architecture

B. Insect dataset

This proposed work used a dataset including a variety of agricultural crop pests to classify and detect insects. My dataset was gathered from internet resources. 22,970 images in all from 10 different types made up the collection. 2400 pest images were used to represent each class, ensuring a balanced distribution among them. In particular, there were 22,970 insect images in the training set and 3960 in the testing set. This is mentioned in Table 1. There were 22,970 insect images in the training set and 3960 in the testing set. As a result, accurate classification and detection tasks were made possible by ensuring that each class was completely represented for model training and evaluation.

Table.1. Describes the number of observations for training and testing samples in each class.

Name of the pest	Number of observations	Training samples	Testing samples
Black Sting Bug	1400	1200	200
Brown Harvester Termite	1400	1200	200
Citrus Leaf Miner	1400	1200	200
Citrus Red Spider Mite	1400	1200	200
Diamond Back Moth	1200	1000	200
Dried Fruit Beetle	1200	1000	200
Field Cricket	1400	1200	200
Flower Trips	1400	1200	200
Green Leaf Hopper	1200	1000	200
Green Sting Bug	1400	1200	200
Leaf Cutting Ant	1400	1200	200
Leaf Hopper	1380	1200	180
Lygus	1200	1000	200
Mediterranean Fruit Fly	1400	1200	200
Melon Fly	1400	1200	200
Mole Cricket	1400	1200	200
Saw-thoothed Grain Beetle	1350	1170	180
Termite	1400	1200	200
Trips	1400	1200	200
Wasps	1400	1200	200

C. Image pre-processing

Image pre-processing is an essential and initial process of insect detection and categorization, image pre-processing involves applying a variety of approaches to improve the quality of images (Yuanjia Zhang et al., 2022; Lin Jiao et al., 2020). Removing noise and sharpening details in images is a crucial step in this process since it improves accuracy for the work that follows. Reducing noise minimizes unwanted artifacts or disturbances in the image, which improves the extraction of the necessary information from the dataset (Morteza Khanramaki et al., 2021). The clarity of edges and fine details is improved by sharpening the image, which is especially useful for identifying and categorizing complex elements like insect morphology (Fangyuan Wang et al., 2021). To make sure the data is ready for analysis, pre-processing frequently involves processes like noise removal, contrast enhancement, and normalization (V. Malathi and M. P. Gopinath et al., 2021). In contrast, segmentation involves separating the image into meaningful parts, which is essential for identifying certain insects or important structures in the image. Researchers can concentrate more on the particular goals of insect identification and classification by using pre-processed and segmented datasets, as this allows them to avoid being impeded by issues like noise or unnecessary background information (Shifeng Dong et al., 2021). This proposed work used color-based features of pest classification, so RGB to L*a*b color conversion was applied for converting the dataset from RGB to grayscale images.

D. K-means clustering for color feature segmentation

The unsupervised machine learning technique called K-means clustering is used to divide data into clusters. By repeatedly allocating data points to clusters depending on the closest central point, it optimizes the center of the cluster and reduces the sum of squares inside a cluster. In the data space, the k factors of the centers are initially assigned at random. The centers are then recalculated as the mean of the points in each cluster, and data points are assigned to the closest centroid. Until centroids stabilize or an established number of iterations is reached, this process is repeated (Shifeng Dong et al., 2021; Yanfen Li et al., 2020). Because of its ease of use and effectiveness, K-means is frequently used for cluster analysis, pattern identification, and image segmentation. (Shuli Xing, Hyo Jong Lee et al., 2022). In this work the K-means clustering algorithm is used to extract the color features from the given inputs, the K-means for color image segmentation which measures the ab, colors, distance, sqEuclidean, and Replicates information from an image, and finally which creates a final cluster based on the selection for next level of processing.

E. Texture Feature Extraction by using the GLCM Algorithm

An image processing approach called GLCM which approach is used to identify texture patterns in an image. Through the calculation of sets of values for pixels at given spatial offsets, it measures the spatial connection between pixel intensities.

These pairs come together to form a matrix, in which each member denotes how frequently a specific pair of pixels occurs Everton Castelão Tetila et al., 2020).

Several statistical metrics that characterize texture attributes, including contrast, homogeneity, entropy, and correlation, can be calculated from this matrix. In particular, GLCM features are useful for tasks like object detection, segmentation, and picture classification in the fields of medical imaging and remote sensing. By describing the spatial correlations of pixel intensities in image data, the GLCM texture feature extraction is essential for pest categorization. In this study, the frequencies of occurrence pixel intensity combinations at specific spatial relationships within an image are computed to construct GLCM matrices. To measure the texture attributes from the image, a set of texture features are retrieved, including contrast, correlation, energy, and homogeneity. These characteristics help with automated pest identification and classification operations in agricultural and environmental settings by offering useful information for differentiating between pest kinds based on their distinctive textural patterns (Yang Li et al., 2020; Fangyuan Wang et al., 2020).

F. Machine Learning Classification Models

ML and DL are the subfields of AI technology, in which models help the computer systems learn from their previous work and advance without direct programming. It centers on creating algorithms that can see patterns on their own, make choices, and get better with time as they process more information. Supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, and self-supervised learning are the different types of machine learning methods (Zhankui Yang et al., 2023; Loris Nanni et al., 2020). Among these, supervised machine learning works with labeled datasets, in which every input data point has a matching objective label. When new, unknown data is supplied, the model uses the labeled examples to learn from them to generalize patterns and make predictions. To improve the prediction or classification accuracy of the actual labels, the algorithm iteratively modifies its parameters during training (Thenmozhi Kasinathan et al., 2021). After training, the model applies the patterns it has learned from the training set to new data to predict results. Because supervised learning can learn complicated associations and produce accurate predictions when given labeled data, it is widely utilized in many applications, including image recognition, spam detection, medical diagnosis, and financial forecasting (Yu Sun et al., 2018; Shundong Fang et al., 2022).

The systematic division of insects into groups according to their morphological, ecological, behavioral, and genetic characteristics is known as insect classification. Using a variety of hierarchical levels—kingdom, phylum, class, order, family, genus, and species—taxonomists categorize insects into groups based on shared evolutionary characteristics. For preliminary identification, morphological characteristics like size, shape, wing structure, antennae, mouthparts, texture, and colors are frequently utilized (Chengjun Xie et al., 2018). Furthermore, ecological aspects including preferred habitat, eating habits, and life cycle are important categorization considerations. Genetic information, like as gene sequences, is being used more and more for more exact and accurate insect classification as a result of advances in molecular techniques.

This all-encompassing method makes it easier to control pests, promote conservation efforts, conduct scientific studies in a variety of environments, and understand the biodiversity, ecology, and evolution of insects (Madhur Devi Chodey et al., 2020).

G. Supervised Machine Learning Classifiers

An artificial intelligence technique called "supervised machine learning" uses labeled data inputs with related outputs to provide the algorithm with new skills. This method involves training the model on a dataset that has suitable target labels in addition to input characteristics. The algorithm finds patterns in the data and builds a mapping function that connects input characteristics to the desired result through iterative changes (M. Chithambarathanu et al., 2020). Next, new data can be accurately identified or classified using this trained model. Because supervised learning can produce accurate predictions based on labeled examples, it is widely used in many fields, including recommendation systems, medical diagnosis, image identification, and speech recognition (Yuanhong Zhong et al., 2020).

In supervised machine learning, a model is trained to accurately identify and classify pests using features generated from input data, such as images and written descriptions. Usually, this approach starts with a labeled dataset that includes classifications and instances of different pests (J Manoj Balaji Chinmaya et al., 2020). The model uses techniques like Fine-KNN (Fine-K-Nearest Neighbors) models for text data to learn to identify patterns and features predictive of various insect species. Optimizing parameters during model training reduces classification errors and boosts accuracy. After being trained, the model can accurately identify invisible pest cases, supporting pest management plans in the forestry, public health, and agricultural sectors by facilitating prompt and focused responses to reduce hazards associated with pests. Evaluation criteria that help determine how well the model performs in correctly identifying pests include accuracy, and precision (Gayatri Pattnaik et al., 2020).

H. Fine KNN classifier

An improvement to the K-Nearest Neighbors (KNN) algorithm's performance in classification tasks is the Fine-KNN classifier. Fine KNN gives different weights to related points depending on the distance removed they are from the request point, in contrast to regular KNN, which uses all data points equally to determine the class of a given input. The classifier can favor nearest neighbors by using this weighting system, which gives their class labels greater weight when predicting (Javeria Amin et al., 2020). The Fine-KNN classifier is an effective tool in machine learning applications because it improves reliability and precision by modifying the KNN method, especially in situations with noisy or unbalanced data distributions (Sunil G C et al., 2022). Particularly in agricultural settings, Fine K-nearest neighbors (KNN) classification is a reliable method for classifying pests.

Based on the majority class among its Fine-K closest neighbors in the feature space, Fine-KNN classifies a target pest according to its attributes, which include pest morphology, behavior, and environmental factors. KNN efficiently determines the most predicted categorization for the target species by measuring the distance between feature vectors, which helps to identify similarities between pests (Chowdhury R. Rahman et al., 2020). This method is a useful tool in pest management for timely and accurate classification, assisting in the implementation of targeted control measures while minimizing ecological impact and optimizing resource allocation. Its simplicity, flexibility, and ability to handle non-linear decision boundaries are its main advantages (Limiao Deng et al., 2018).

4. Results And Discussion

In this study, we used a dataset of 22,970 images and supervised machine-learning algorithms to categorize the pests and their classes. Figure 2. Shows the confusion matrix of the number of pest observations. The proposed work used 5-fold cross-validation for classifying the ten classes of pests to tune a set of parameter values for the fine-KNN method. The Principal Component Analysis (PCA) model used for individual feature selection was shown to be significant contributions to classification accuracy through feature selection, and correlation was the distance metric employed. In Figure 3. Shows the ROC for proposed models which shows the TPR and FPR of F-KNN classifiers and Figure 4. Shows the parallel coordination of the proposed model. With a total cost validation of 30 and an accuracy of 99.9%, the model produced important validation results. With a training time of 58.524 seconds, the model also showed a quick prediction speed of around 3000 observations per second. The model showed excellent performance without sacrificing size it was just about 1MB implementing various computing platforms simply. This work demonstrates how well-supervised machine learning can classify insect species, with potential applications in public health, ecology, and agriculture. The model's efficiency and accuracy were increased by utilizing a correlation-based distance metric in conjunction with feature selection. All things considered, this method offers a strong solution for classifying insect species, with excellent accuracy, little computing cost, and small model sizes. Figure 5. Shown in F-KNN TPR (True Positive Rate) and FNR (False Negative Rate) and Figure 6. Mentioned the F-KNN PPV (Positive Predictive Values) and FDR (False Discovery Rates) of the proposed work. A system like this could be useful for entomology, agriculture, ecology, and other fields by enabling quick and precise identification of insect species from images. Black Sting Bug, Brown Harvester Termite, Citrus Leaf Miner, Citrus Red Spider Mite, Diamond Back Moth, Dried Fruit Beetle, Field Cricket, Flower Trips, Green Leaf Hopper, Green Sting Bug, Leaf Cutting Ant, Leaf Hopper, Lygus, Mediterranean Fruit Fly, Melon Fly, Mole Cricket, Termite, Trips and Wasps this all species achieved 100% of training and testing accuracy respectively, and the identification and classifications of Saw-toothed grain beetle achieved comparatively low accuracy of training and testing accuracy of 75%, and this proposed system achieved 99.9% and 98.5% of training and testing accuracy respectively for prediction and classification of pest in the agricultural sectors, the classifications results of ten classes of pest were mentioned in Table 2. Figures 7 and 8 show the Local Explanation for F-KNN and Local Sharply Explanations for F-KNN respectively.

Table.2. Shows The Overall Accuracy of Both Training and Testing

Classification Results of the F-KNN Model		
Name of the pest	Training Accuracy	Testing Accuracy
Black Sting Bug	100%	100%
Brown Harvester Termite	100%	100%
Citrus Leaf Miner	100%	100%
Citrus Red Spider Mite	100%	100%
Diamond Back Moth	100%	100%
Dried Fruit Beetle	100%	100%
Field Cricket	100%	100%
Flower Trips	100%	100%
Green Leaf Hopper	100%	100%
Green Sting Bug	100%	100%
Leaf Cutting Ant	100%	100%
Leaf Hopper	100%	90.9%
Lygus	100%	100%
Mediterranean Fruit Fly	100%	100%
Melon Fly	100%	100%
Mole Cricket	100%	100%
Saw-thoothed Grain Beetle	75%	90.9%
Termite	100%	100%
Trips	100%	100%
Wasps	100%	100%
Overall Accuracy	99.9%	98.5%

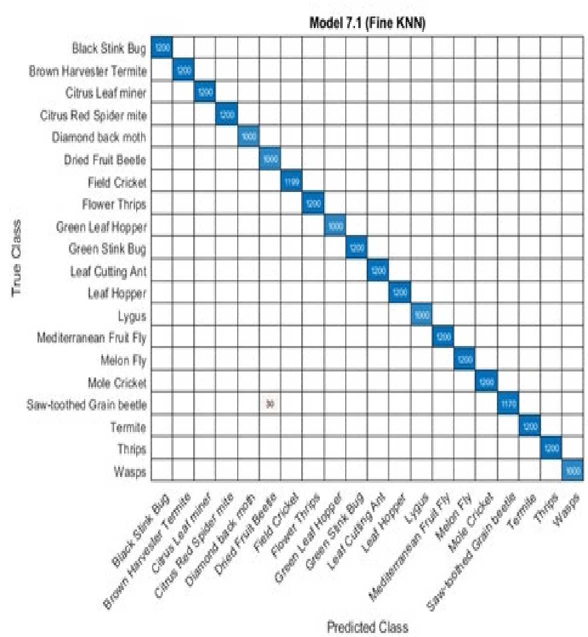

Fig.2. Shows the number of observations for ten classes of pest classification work.

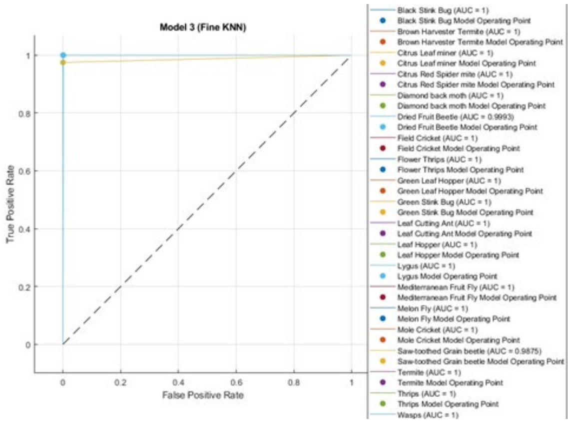

Fig.3. Shows the ROC for proposed models which shows the TPR and FPR of F-KNN classifiers.

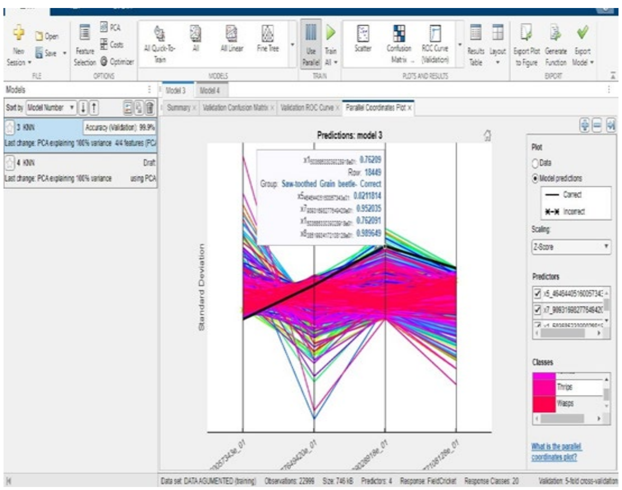

Fig.4. Parallel Coordination diagram of F-KNN classifier.

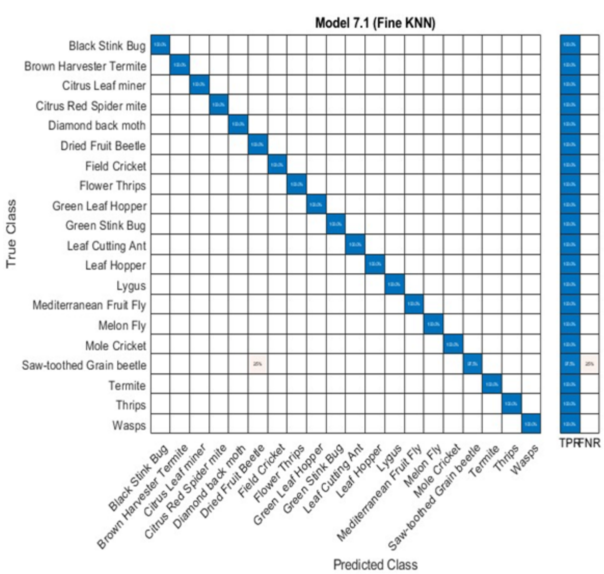

Fig.5. Shown in F-KNN TPR (True Positive Rate) and FNR (False Negative Rate)

A. Testing Results

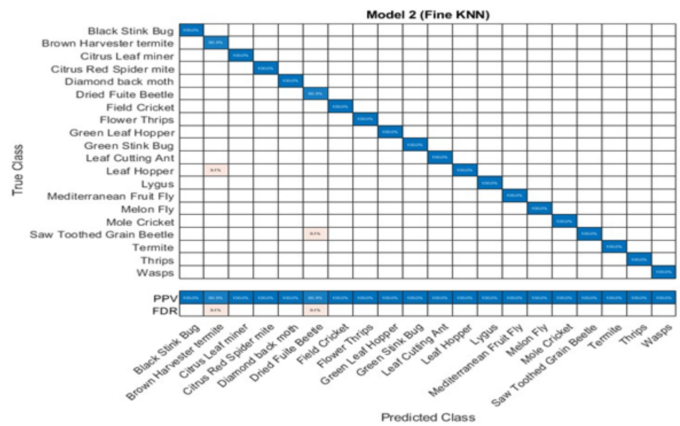

Fig.6. Shown in F-KNN PPV (Positive Predictive Values) and FDR (False Discovery Rates

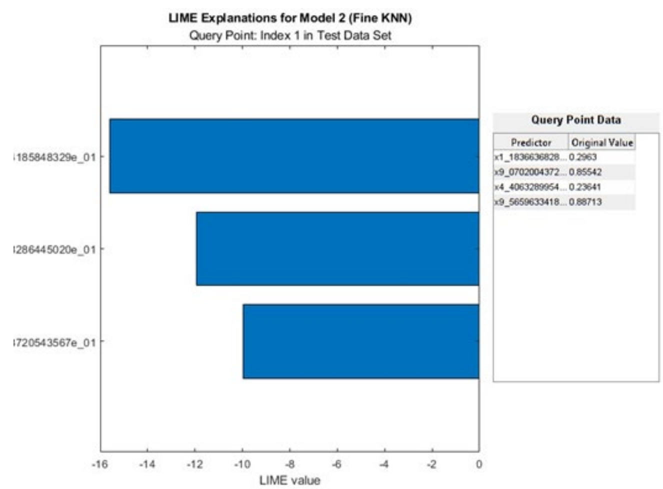

Fig.7. Shown in Lime Local Explanation for F-KNN

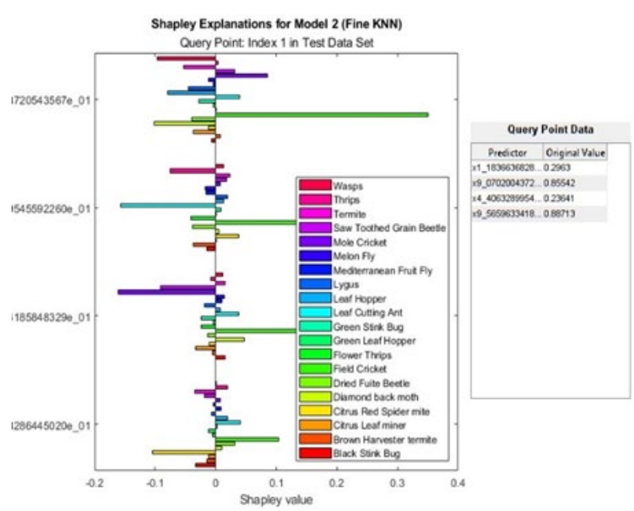

Fig.8. Shown in Local Sharply Explanations for F-KNN

B. Proposed model performance evaluation

The results of the performance test showed an amazing 99.9% accuracy validation, indicating that the model is capable of reliably guessing the species of insects from the given images. Additionally, the low score of 30 for the overall cost validation indicates that there were few misclassifications or related expenses. The prediction speed, which processed about 3000 observations per second, remained excellent despite the large dataset and complex feature set. This shows how effective the model is in large-scale or real-time deployment scenarios when quick processing is essential. The model could be trained in a comparatively short amount of time (58.524 seconds), demonstrating the method's computational efficiency. In this proposed system accuracy was calculated by using the following equations 1 and 2 which are calculated from the confusion matrix of both training and testing samples.

Accuracy

$$\frac{True\ Positive + True\ Negative}{False\ Positive + True\ Positive + True\ Negative + False\ Negative} X100\% \quad (1)$$

Precision

$$\frac{True\ Positive}{False\ Positive + True\ Positive} X100\% \quad (2)$$

5. Conclusion

The integration of computer vision through Machine Learning algorithms has significantly enhanced the identification and classification of agricultural pests, providing a practical solution to combat agricultural damage. The supervised machine learning model incorporating K-means clustering and GLCM-based color and textural features for pest classification in agricultural settings yielded exceptional results. The utilization of K-means clustering allowed for the grouping of similar data points, aiding in the segmentation and classification of pests based on their visual characteristics. Additionally, the extraction of color and textural features using GLCM provided valuable information for distinguishing between different types of pests based on their unique visual patterns and textures. By utilizing color and textural features extracted from K-Means clustering and GLCM algorithms, a classification system for pests has been developed, achieving an impressive accuracy rate of 98.5% across ten classes of pests. This innovative approach highlights the potential of supervised ML methods combined with specialized image analysis techniques to revolutionize pest control in agriculture. In conclusion, this study underscores the importance of leveraging advanced technologies to address agricultural challenges effectively. The successful implementation of ML algorithms in pest identification demonstrates a promising path toward more efficient pest management strategies, ultimately leading to improved agricultural productivity and sustainability. By continuously integrating cutting-edge technologies, the agricultural sector can further enhance pest control practices and mitigate the detrimental impact of pests on crops.

References

[1]. Jin Wang, Yane Li, Hailin Feng, Lijin Ren, Xiaochen Du, Jian Wu, Common pests image recognition based on deep convolutional neural network, Computers and Electronics in Agriculture, Volume 179, 2020.

[2]. Zhankui Yang, Xinting Yang, Ming Li, Wenyong Li, Automated garden-insect recognition using improved lightweight convolution network, Information Processing in Agriculture, Volume 10, Issue 2, 2023, Pages 256-266.

[3]. Weiguang Ding, Graham Taylor, Automatic moth detection from trap images for pest management, Computers and Electronics in Agriculture, Volume 123, 2016, Pages 17-28.

[4]. Ayad Saad Almryad, Hakan Kutucu, Automatic identification for field butterflies by convolutional neural networks, Engineering Science and Technology, an International Journal, Volume 23, Issue 1, 2020, Pages 189-195.

[5]. Yu Sun, Xuanxin Liu, Mingshuai Yuan, Lili Ren, Jianxin Wang, Zhibo Chen, Automatic in-trap pest detection using deep learning for pheromone-based Dendroctonus valens monitoring, Biosystems Engineering, Volume 176, 2018, Pages 140-150.

[6]. Yuanjia Zhang, Benxue Ma, Yating Hu, Cong Li, Yujie Li, Accurate cotton diseases and pests' detection in the complex background based on an improved YOLOX model, Computers and Electronics in Agriculture, Volume 203, 2022, 107484.

[7]. Lin Jiao, Shifeng Dong, Shengyu Zhang, Chengjun Xie, Hongqiang Wang, AF-RCNN: An anchor-free convolutional neural network for multi-categories agricultural pest detection, Computers and Electronics in Agriculture, Volume 174, 2020.

[8]. Morteza Khanramaki, Ezzatollah Askari Asli-Ardeh, Ehsan Kozegar, Citrus pests' classification using an ensemble of deep learning models, Computers and Electronics in Agriculture, Volume 186, 2021.

[9]. Fangyuan Wang, Rujing Wang, Chengjun Xie, Jie Zhang, Rui Li, Liu Liu, Convolutional neural network based automatic pest monitoring system using hand-held mobile image analysis towards the non-site-specific wild environment, Computers, and Electronics in Agriculture, Volume 187, 2021.

[10]. V. Malathi and M. P. Gopinath, Classification of pest detection in paddy crop based on transfer learning approach, Computers and Electronics in Agriculture, Volume 187, 2021.

[11]. Shifeng Dong, Rujing Wang, Kang Liu, Lin Jiao, Rui Li, Jianming Du, Yue Teng, Fenmei Wang, CRA-Net: A channel recalibration feature pyramid network for detecting small pests, Computers and Electronics in Agriculture, Volume 191, 2021.

[12]. Yanfen Li, Hanxiang Wang, L. Minh Dang, Abolghasem Sadeghi-Niaraki, Hyeonjoon Moon, Crop pest recognition in natural scenes using convolutional neural networks, Computers and Electronics in Agriculture, Volume 169, 2020.

[13]. Shuli Xing, Hyo Jong Lee, Crop pests and diseases recognition using DANet with TLDP, Computers and Electronics in Agriculture, Volume 199, 2022.

[14]. Everton Castelão Tetila, Bruno Brandoli Machado, Gilberto Astolfi, Nícolas Alessandro de Souza Belete, Willian Paraguassu Amorim, Antonia Railda Roel, Hemerson Pistori, Detection and classification of soybean pests using deep learning with UAV images, Computers and Electronics in Agriculture, Volume 179, 2020.

[15]. Yang Li, Jiachen Yang, Few-shot cotton pest recognition and terminal realization, Computers and Electronics in Agriculture, Volume 169, 2020.

[16]. Fangyuan Wang, Rujing Wang, Chengjun Xie, Po Yang, Liu Liu, Fusing multi-scale context-aware information representation for automatic in-field pest detection and recognition, Computers and Electronics in Agriculture, Volume 169, 2020.

[17]. Loris Nanni, Gianluca Maguolo, Fabio Pancino, Insect pest image detection and recognition based on bio-inspired methods, Ecological Informatics, Volume 57, 2020.

[18]. Thenmozhi Kasinathan, Dakshayani Singaraju, Srinivasulu Reddy Uyyala, Insect classification and detection in field crops using modern machine learning techniques, Information Processing in Agriculture, Volume 8, Issue 3, 2021, Pages 446-457.

[19]. Shundong Fang, Yanfeng Wang, Guoxiong Zhou, Aibin Chen, Weiwei Cai, Qifan Wang, Yahui Hu, Liujun Li, Multi-channel feature fusion networks with hard coordinate attention mechanism for maize disease identification under complex backgrounds, Computers and Electronics in Agriculture, Volume 203, 2022.

[20]. Chengjun Xie, Rujing Wang, Jie Zhang, Peng Chen, Wei Dong, Rui Li, Tianjiao Chen, Hongbo Chen, Multi-level learning features for automatic classification of field crop pests, Computers and Electronics in Agriculture, Volume 152, 2018.

[21]. Madhur Devi Chodey, Dr.Noorullah Shariff, Pest detection and identification using Optimised Neural Network Techniques, , Computers and Electronics in Agriculture, Volume 169, 2020.

[22]. M. Chithambarathanu, M. K. Jeyakumar, Survey on crop pest detection using deep learning and machine learning approaches, Computers and Electronics in Agriculture, Volume 169, 2020.

[23]. Yuanhong Zhong, Junyuan Gao, Qilun Lei and Yao Zhou, A Vision-Based Counting and Recognition System for Flying Insects in Intelligent Agriculture, Computers and Electronics in Agriculture, Volume 169, 2020.

[24]. J Manoj Balaji Chinmaya H S Ganesh N Sharma Nithish Divakar, A Comprehensive Survey on Vision-Based Insect Species Identification and Classification, Computers and Electronics in Agriculture, Volume 169, 2020.

[25]. Gayatri Pattnaik, Vimal K. Shrivastava, and K. Parvathi, Transfer Learning-Based Framework for Classification of Pest in Tomato Plants, Computers and Electronics in Agriculture, Volume 169, 2020.

[26]. Javeria Amin, Muhammad Almas Anjum, Rida Zahra, Muhammad Imran Sharif, Seifedine Kadry, and Lukas Sevcik, Pest Localization Using YOLOv5 and Classification Based on Quantum Convolutional Network, Computers and Electronics in Agriculture, Volume 169, 2020.

[27]. Sunil G C, Yu Zhang, Cengiz Koparan, Mohammed Raju Ahmed, Kirk Howatt, Xin Sun, Weed and crop species classification using computer vision and deep learning technologies in greenhouse conditions, Journal of Agriculture and Food Research, Volume 9, 2022.

[28]. Chowdhury R. Rahman, Preetom S. Arko, Mohammed E. Ali, Mohammad A. Iqbal Khan, Sajid H. Apon, Farzana Nowrin, Abu Wasif, Identification and recognition of rice diseases and pests using convolutional neural networks, Biosystems Engineering, Volume 194, 2020.

[29]. Limiao Deng, Yanjiang Wang, Zhongzhi Han, Renshi Yu, Research on insect pest image detection and recognition based on bio-inspired methods,Biosystems Engineering, Volume 169, 2018.