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An Expert Model Using Deep Learning for Image-based Pest Identification with the TSLM Approach for Enhancing Precision Farming

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Abstract

The rise of digital agriculture has sparked considerable interest in its potential to revolutionize farming practices by integrating of advanced technologies. Unmanned aerial vehicles (UAVs), commonly known as drones, have emerged as a crucial tool in precision agriculture, offering diverse applications for real-world scenarios. This research focuses on harnessing the power of drones in the context of digital agriculture support, particularly in addressing the challenges of crop protection and pest management. The objective is to develop an innovative approach for crop-disease diagnosis using an upgraded Transfer-Driven Self-Adaptive Learning Model (TSLM) that leverages multispectral remote sensing data of drone-captured images to improve pest classification and streamline pesticide application. The study explores nine potent deep neural network models' capabilities for identifying plant diseases using various approaches within the digital agriculture framework. Transfer learning and advanced feature extraction techniques are employed to tailor these deep neural networks to the specific crop protection context. Using of pre-trained deep learning models for feature extraction and fine-tuning enhances the effectiveness of the proposed model. Evaluating the model's performance, precision, sensitivity, specificity, and F1-score metrics are assessed, leading to the discovery that deep feature extraction and Self-Adaptive Learning Model (SLM) classification outperform traditional transfer learning methods. The novelty of this work lies in its application of communication protocols to coordinate a fleet of drones for crop protection within the digital agriculture framework. By combining deep learning techniques with transfer-driven self-adaptive learning, the proposed approach significantly enhances the accuracy and efficiency of pest classification in precision agriculture. The study's findings offer valuable insights into optimizing drone-based technologies to combat plant disease epidemics, thereby contributing to the advancement of digital agriculture and its role in supporting sustainable farming practices.

Keywords: Drones, Precision Farming, Deep Neural Networks, Transfer Learning, Deep Feature Ex-traction, Pest Classification and Crop-disease Diagnosis.

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1 Introduction

One of the major challenges faced in the agricultural industry is the presence of insect pests. According to the Food and Agricultural Organisation of the United Nations (FAO), these pests cause a global reduction in crop yield every year, ranging from 20 to 40 per cent (Ullah et al., 2022; Radhika & Masood, 2022). In the United States alone, invading insects result in approximately $70 billion in economic losses annually, with pest infestations causing around $220 billion in damages worldwide. To enhance the quality and storage life of crops, farmers rely on a wide array of pesticides (Kalyani & Collier, 2021). However, prolonged use of these chemicals has led to environmental contamination and the emergence of potentially fatal diseases, including cancer, severe respiratory and genetic conditions, and even fetal demise (Shukla et al., 2022). As a result, it has become crucial to adopt innovative technical solutions in agriculture to prevent unnecessary pesticide use and detect plant pests earlier (Srinivasa Rao et al., 2023).

To accomplish the exact management of crop diseases, fertilization, irrigation, and plant pests in the field, smart agriculture has just been introduced (Angin et al., 2020). This approach involves the use of artificial intelligence (AI) techniques, information, and technology for wireless communication, such as the Internet of Things (IoT), across all aspects of agriculture (Wilkinson et al., 2011; Srinivasa Rao et al., 2023; Rehman et al., 2022; Singh et al., 2021). Among the various applications of innovative agriculture, crop health monitoring, which assesses the presence of plant pests, is considered the primary focus (Kavipriya & Kumar, 2021). Nevertheless, because of their intricate structures and close resemblances, categorizing insect pests is a difficult task for farmers (Albattah et al., 2022). The major ten most common pest varieties are shown in Figure 1. In addition to being costly and time-consuming, the conventional way of manually identifying bug infestations is also unsuccessful (Wilkinson et al., 2011). Detecting insect pests in their early stages of infection, however, can help farmers choose the appropriate insecticides to halt their spread (Albattah et al., 2022).

Figure 1: Ten Common Pest Varieties

As a result, past research has extensively utilized computer vision and image processing systems employing AI techniques like machine learning and neural networks to address the aforementioned challenges in the agricultural sector (Paul et al., 2020). Entomologists have recommended the use of image-based recognition for pest insects to serve various purposes, including insect monitoring as a measure of biodiversity (Lu et al., 2021). Recently, in agriculture, convolutional neural networks (CNNs), a type of deep learning technique, have been successfully applied to automatically classify agricultural pests (Wang et al., 2021; Salih, 2020; Maddikunta et al., 2021). Unlike conventional image processing techniques and machine learning, CNNs work directly on raw visuals and possess their feature generator, making them more effective. Moreover, in several applications like medical imaging analysis (Singh et al., 2022; Ahmed et al., 2021), intelligent defect diagnosis (Beriya, 2021) and infrastructural fracture identification in construction (Garrett et al., 2022), CNNs have demonstrated their ability to handle picture noise and changes in illumination. A comprehensive deep CNN called Faster R-CNN (Convolutional neural network with regional focus) (Hanif et al., 2022) has been developed for target recognition and identification in pictures, involving feature detection, candidate region generation, regional image categorization, and location refining.

A drone is used to scan the area and record an aerial image to examine the issue. To identify an environment of parasites in crops, the photos must be analyzed after being captured using GPS-tagged data. Instead of processing photos in the cloud, edge computing-based evaluation may be done in the field. In the realm of edge computing, processing happens close to where information is being collected by detectors (O'Grady et al., 2019). By doing this, the algorithm built into the system will be able to make decisions more quickly, which will decrease the time it takes to transfer data to the cloud for computing. Edge computing, as used informally, is the process of globalizing the training of an AI model before using it locally. Edge computing has a location understanding of the illness's impacted region, the ability to move in ranging applying pesticide techniques translation in making decisions, a lower reaction time, knowledge of the illnesses disseminating in the environment, and an inconsistent position (Javadzadeh & Rahmani, 2020). Incorporating cutting-edge computing technology into unmanned aircraft to create a variable insecticide application approach requires the ability to make quick decisions on the development of pathogens in crops (Kalyani & Collier, 2021). An AI model is being created by fine-tuning CNNs and building a Deeper Learning-based illness recognition method (Camgözlü & Kutlu, 2023). The illness in the Village plants database has already been identified using a ResNet-based method by us (Murugan et al., 2021).

This AI-based edge design will produce a drone for agricultural testing. In this regard, object identification algorithms employing deep learning are created and used to localize and categorize plant diseases. Although these techniques may pinpoint the precise site and illness kind, they function less well when used in a challenging natural setting (Saleem et al., 2020). Although algorithms using DL have been used to categorize a variety of crops and illnesses affecting plants, much work has to be performed to increase their accuracy and resilience to extension. This is particularly true for cutting-edge deep-learning systems used to classify agricultural plant diseases. Many diseases of plants continue to be challenging to diagnose because the diseased regions exhibit a variety of physical traits, including size, shape, colour, and position.

This work will create crop-disease diagnosis capabilities using a drone-based up-graded Transfer-driven Self-adaptive Learning Model (TSLM). To significantly advance the pest classification, the proposed model gets the input from drone captured images and the categorization methodology Self Adaptive Learning Model might be a potent tool in streamlining pesticide application. Evaluating this approach will help us determine how precise and effective the proposed drone-based technology is, enabling us to better combat diseases of plant epidemics.

1) The Major Contribution of the Proposed Model

The primary benefits of the proposed TSLM model are presented in this section to highlight the originality of the proposed research.

- Suggested a drone-based Transfer-driven Self Adaptive Learning Model (TSLM) as the foundation for a drone system AI framework with little complexity. This framework involved deep feature extraction using transfer learning knowledge.
- Introduced an efficient computational approach for accurate detection of insect pests, leveraging TSLM's capabilities as a framework for one-stage object detection.
- Enhanced the precision of insect pest classification by utilizing the Self-adaptive Learning Model's ability to compute deep key points and the Transfer approach to handle over-fitted training data.
- To illustrate the efficacy of our approach, we carried out a thorough quantitative and qualitative evaluation of the proposed procedure using a difficult benchmark dataset that was made publicly available.

2 Related Works

Due to a lot of progress in the field of computer vision, researchers are now thinking about how to find and classify pests. This is possible with many standard datasets. Such datasets, however, contain just a handful of sample information comparable to the usual data required by the most recent DL-based architectures. To identify and classify pests from plants automatically, this part carefully reviewed earlier research in the field.

CNNs and importance techniques were used (Nanni et al., 2020) to automatically identify and categorize crop pests. Five alternative ShuffleNet (SN), MobileNetv2 (MN), GoogLeNet (GL), and CNN models—AN, DenseNet201,)—were trained to categorize the insects after the importance approach was first used to enrich the information. This method enhances pest categorization. However, the performance suffers when trying to identify species of pests that differ significantly within their class. The authors of (Thenmozhi & Reddy, 2019). introduced a unique CNN architecture and contrasted it with the models DL, AN, RN, GL, and VGG that were already in use. The model was kept from excessive fitting and its precision for classification was increased by using machine learning along with information replenishment.

Similar to this, a technique for automatically classifying and recognizing agricultural insects was suggested. After converting the input sample to a binary picture with the adaptable thresholds (AT) approach, morphological methods and the water-shed technique were used to find the ROIs. Following the removal of the backdrop using the GrabCut approach, the insect population from the input specimens were categorized using several DL models, including VGG, GL, and RN. Although it takes more time to compute, these approaches show improved insect categorization accuracy. DeepPest, a portable DL technology (Li et al., 2020), recognizes and categorizes insects. Contextual data was used to teach the technique (Li et al., 2020) to locate tiny insects. The technique (Li et al., 2020) is unsuitable for diverse handheld devices owing to computational restrictions.

Wang et al., (2020) presented AF-RCNNs for automatic agricultural insect localization and classification. A key location fusing unit was created at first for calculating an accurate collection of characteristics, especially for tiny pests. Finally, the AFRPN and Fast R-CNN were combined into one system and taught to recognize 24 types of insects. Small insects can be located effectively using this approach (Wang et al., 2020). The result, however, is dependent on several hyper-parameter selections made during the period of training.

An approach to identifying pests was put out (Jiao et al., 2020). Then, Sangwine's approach was used to the processing data to generate the two coloured keypoint maps as well as horizontally and vertically. ROIs were created by merging and binarizing the maps. This method (Jiao et al., 2020) is impervious to recognizing pest variations in colour and size.

This work's generality should be improved. A DL-based strategy for agriculture pest recognition and classification was put out (Rodríguez et al., 2021). The SSD determined the supplied data's in-depth properties. The structure which was then utilized to categorize the insects into the appropriate groups. The method (Rodríguez et al., 2021) produced more precision than earlier established techniques. Small insects couldn't be detected, though. Diverse training samples are required for CNN-based methods to demonstrate improved accuracy. But databases don't have this feature. Nam & Hung, (2018) offered an information augmenting-based solution.

By moving the initial information to different positions and performing a cropped procedure throughout the training phase, information enhancement was used. This approach helped collect different multi-scale specimens for developing a multi-scale insect recognition paradigm. CNN simulations received training to show the strategy's efficacy. Despite notable positional differences, this method (Nam & Hung, 2018) still finds insects. It is, nevertheless, computationally expensive. Crop pests may be located and categorized using a 2 phase CNN structure, according to (Li et al., 2019). The GaFPNs were used to calculate the input pictures represented characteristics. The LaRPNs utilized its vector characteristics to detect and categorize pests in the following step. The approach (Li et al., 2019) performs better in terms of pest categorization. But it is susceptible to excessive fitting problems, which leads to poor performance on unobserved information.

1) Research Gaps Identified

This section describes the research gaps identified through the related works section.

- Many of the proposed methods use deep learning models, which need large amounts of labelled data for training. However, the standard datasets available for insect pest classification often contain just a handful of samples, which may limit the performance of these models.
- Several methods mentioned in the text, especially those utilizing deep learning models, are computationally expensive, which may restrict their deployment on resource-constrained devices such as drones.
- Certain approaches rely on hyper-parameter selections during training, which can impact the final results. A thorough exploration of hyper-parameter settings to achieve optimal performance is needed.
- Detecting small insects is a recurring issue in some approaches, highlighting the need for techniques that can effectively identify and categorize small pests.
- The proposed techniques need to be further tested and integrated into real-world agricultural systems to assess their practicality and scalability in addressing pest-related challenges.

Addressing these research gaps can lead to the development of more effective and practical solutions for automated pest recognition and classification in agriculture.

3 Proposed Taxonomy

This research utilizes an IoT application to implement precise pest control in agriculture. The main objective is to employ unmanned aerial vehicles (UAVs) for pest regulation in the context of precision agriculture. The study begins by providing a comprehensive explanation of precision farming and then applies a pre-trained deep neural network along with a transfer algorithm for pest classification. After categorizing the pests, the researchers utilize drone communication and a pest search technique to effectively eliminate the pests in three different scenarios. The effectiveness of the suggested method is then assessed in each of these scenarios.

1) Precision Farming

Precision agriculture and smart farming have gained significant attention in recent times. The utilization of novel communication and information technologies has opened up new possibilities for actively monitoring agriculture, livestock, and water infrastructure to ultimately minimize living organisms. Resource management plays a crucial role in precision farming, with improved performance resulting from more efficient resource utilization. To acquire more data and better understand the challenges, image-based measurements and intelligent data mining are essential. Drones can be employed to capture aerial images of farms and agricultural fields, enabling effective and productive utilization of limited resources and significantly impacting the final agricultural output. Precision farming is an innovative approach that leverages digital technologies to enlarge agricultural practices.

The terrain and characteristics of smart farming are changing due to numerous technological advancements. Key trends in the field include the Internet of Things (IoT), meteorology, and cutting-edge analytics technologies. The impact of the World Wide Web and the Internet of Things spans across various industries, and researchers creatively apply these technologies to improve operational efficiency, productivity, and decision-making in farming practices. The use of precision agriculture has allowed for the gathering of accurate field data on factors like atmospheric conditions and soil temperature through the use of drones, spacecraft, and aerial imagery. Researchers have employed learning algorithms and statistical analysis techniques to positively influence decisions and enhance the viability, reliability, optimization, and efficiency of precision farming. Another crucial area of research and application lies in identifying pests in agricultural areas, which can significantly impact plant growth. Currently, precise identification of these pests is a work in process. The most popular way to use cannabis infestation control is the use of herbicides.

In precision agriculture, drones are extensively used to monitor crops, detect diseases, parasites, and infections, and collect data on plant growth, soil moisture, and fertilization levels in the field. UAVs are frequently utilized for crop insurance surveys, dusting, and surveillance purposes. High-resolution cameras mounted on UAVs are commonly used for aerial photography of areas of interest.

2) Deep Learning Model

DL is a kind of AI that analyzes information attributes utilizing mathematical representations with many processing units. The rise of significant accomplishments regarding fields like detection and categorization using artificial intelligence has been facilitated by attention to this problem. Recognition of objects, visual object identification, and recognizing speech are only some of the most recent uses that have used these methods. The generation of large information and the growth of strong computers with enormous storage capacities are the main factors for deep learning's present growth. Once again, this study investigates different approaches on 9 more potent models using DL for the issue of crop-identified diseases. Deep learning algorithms are trained on a section of ImageNet. The AlexNet architecture is an artificial intelligence system with 25 layers and criteria, just 8 of which can be taught. The VGG system, which is a consistent framework and was created from the Oxford VGGs was used to verify the results of the ILSVRC - 2014 competition. To train more sophisticated networks, they invented ResNet.

VGGNet and AlexNet differ from this micro-architecture-based structure. The remaining linkages and the network architecture of Inception's Res system were built on the foundation network developed by Perception. Even while InceptionResNetV2 functions essentially the same as earlier Insomnia designs, it is faster for training thanks to the layers of convolution. A clever framework called SqueezeNet was created via research to offer AlexNet-level precision on Image Net with fifty times fewer parameters. The data consumption characteristics of different designs are summarized in Table 1.

Classification Phase

This study uses the typical classifying methodology of the Self-adaptive Learning Model for deep categorization to create profound characteristics from a particular layer of the previously trained deeper system.

SLM is a research-oriented learning method designed for Single Hidden Layer Feedforward Networks (SLFN). In the SLM approach, the hidden state values are randomly generated, while the output of the least-squares approach is used to rescale values. Equation (1) can be utilized to formulate the description of SLM. In the incoming and the outgoing channels, J is the total amount of simulated samples, ?? is the weight input, and?? is the layer that is concealed. If the outcome of the computation network suggests that the converging of the actual value with 0 error has occurred, Z = T? is represented in the matrix. The outcome of ELM is denoted by Z. The secret layer of the outputting matrices is represented by Equation (2-4).

∑_µ$1^Na_(u) a(x_(u)*y_(v)+g_(u))=z_(v) v=1,2,..J (1)

T =a(x1 * y1 + g1)...a (xN * y1 + gN) (2)

a > x1 * yJ + g1?...a > xN * yJ+ gN? (3)

α = T'Z (4)

Table 1: Configurations of the Utilized Pre-trained Models

System	Deepness	Size of File	Values	Data capacity
Inceptionv3	46s	87MB	24.9	299*299
AlexNet	16	228MB	63	228*228
VGG19	19	535MB	145	224*244
InceptionResNetv2	165	209MB	56.9	299*299
VGG16	17	515MB	139	224*224
ResNet101	102	167MB	45.7	224*224
SqueezeNet	17	4.6MB	1.26	228*228
GoogleNet	23	27MB	8	224*224

Data Collection Phase

In this study, we used the IP102 insect pest classification database to assess how well the suggested model performed. The 75,222 photos in this collection span 102 popular insect pest classifications. FCs and ECs which are additionally separated into subdivisions that correspond to the specific crop kinds harmed by pest insects, make up the two super-classes in the systematically arranged IP102 database. The EC has three subclasses namely Citrus, Vitis, and mangoes, but the FC has five, namely Rice, Corn, Wheat, Beet, and Alfalfa. All of these subcategories are further divided into 102 pest classes, which outline the kinds of organisms connected to the particular crop. The IP102 collection contains a variety of photos, including creatures with a wide range of ages, sizes, colours, and forms. The dataset is extremely difficult to work with because of the fluctuations in luminance, magnification level, and position, in addition to the complexity of real-life scenarios. Examples of pest photos from multiple species are shown in the following figure from the IP102 database. The collection's instances are challenging because of the complexity of several ecological aspects, such as shifting lighting settings or insects lurking in the origins. Each item in this image collection is a three-channel (RGB) coloured image with a resolution of 4000-6000 pixels. Table 1 provides details of the pests and plant pests present in the collection.

According to Table 1, there are 1965 images in the collection, depicting seven different phyto-pests. These images were taken at different times of the day. Additionally, images of diseases were captured from various types of trees. In this study, deep feature extraction was performed using multiple fully connected layers, and classification methods were based on pre-trained models of neural network architectures. The taxonomies are depicted in Figures 2 and 3. Subsequent steps in the study involved domain modification and further deep feature extraction.

Transfer Learning Phase

An approach called transfers controlled machine learning makes use of model data created to address a specific problem as a springboard for addressing other problems. Convolution models of neural networks that have already been trained to enhance the approach, the current study incorporated theories on transfer learning. Pre-trained convolution layers have a faster learning curve than convolutional networks with initialization of random values, which is an advantage (Nanni et al., 2020). Furthermore, the fine-tuning procedure is based on the transfer additional layer, as can be seen in Figure 2, and it appears in Algorithm 1, as opposed to moving the last three layers of the trained model networks to their classification job.

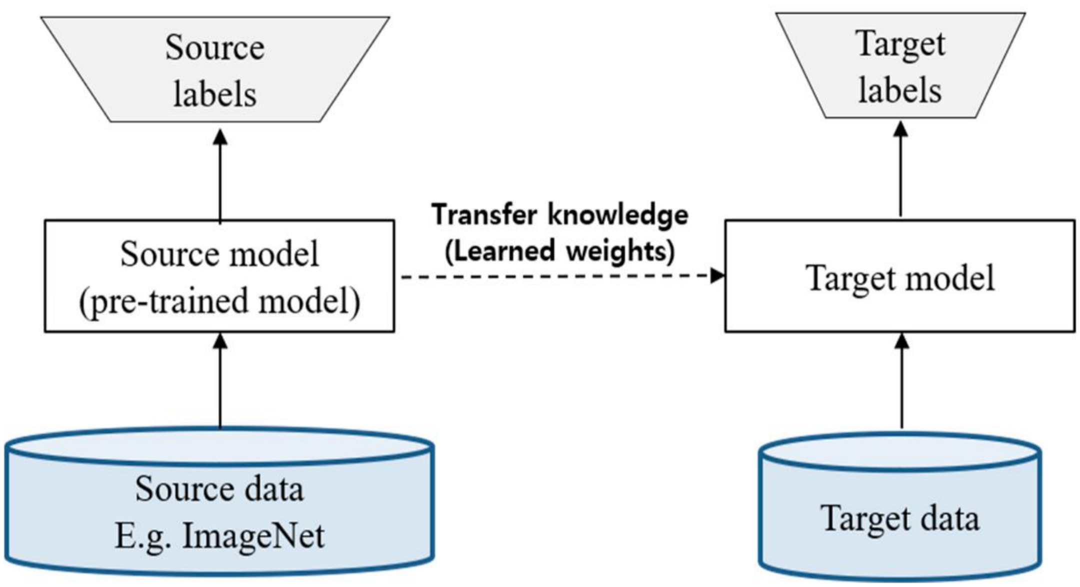

Figure 2: Transfer Learning Flow

Feature Extraction Phase

The primary focus of deep extracted features lies in utilizing features obtained from a pre-trained deep learning model. These parameters are employed for categorization through machine learning. In other words, this approach extracts that have representations from the fully connected layers of pre-trained models. An individual layer of deep learning models provided effective deep characteristics, including ResNet50, Res-Net101, InceptionRNetV2, InceptionV3, GoogleNet, and SqueezeNet, as well as fc1000, fc1000, forecast, predictions, and pool10 (Li et al., 2020). Figure 3 demonstrates how common models like SVM and ELM are employed in the categorization stage, utilizing the extracted deep features as described in Algorithm 2.

Strategy for Pest Movement

The parasite can be transported through various methods, either by random route selection or by searching for crops. The pest is guided by the presence of vegetation during its movement, regardless of the behaviour of other insects. Its visual range is limited to the immediate surroundings (Wang et al., 2020). Once the pest attaches itself to a host, it will continue feeding until the plant dies. Conversely, if it finds itself in an area without any plants, it actively seeks out a suitable one. Three primary scenarios are considered to identify pests during their mobility:

- The pest will target a nearby plant if it is visible;
- If it detects multiple plants, it will choose which one to attack.
- If the insect being attacked can see more than one plant's surface, it can also choose which one to attack. Alternatively, if there are no plants in the immediate vicinity, the pest will continue moving until it finds one.

Drones use a distributed approach to look for pests, managed through message passing. Each drone has a storage area where information about previously visited locations is stored. This information is encrypted and maintained in the storage, and the drone updates its mapping at each pass, adding new details like the presence of healthy or sick crops and removing incorrect information. Based on this mapping, the UAV can decide the next action and avoid areas that have already been inspected and treated to save time and resources. To choose the next step, a non-visited location is randomly selected, and the drone determines the distance and travel orientation (Jiao et al., 2020). Priority is given to areas closest to the drone that have not yet been surveyed, considering its initial orientation to avoid unnecessary turns. UAVs transmit local map views to reconstruct the entire map. As illustrated in Figure 4, the information mapping of a grid of locations with the drones at its centre can be used to symbolise the drones.

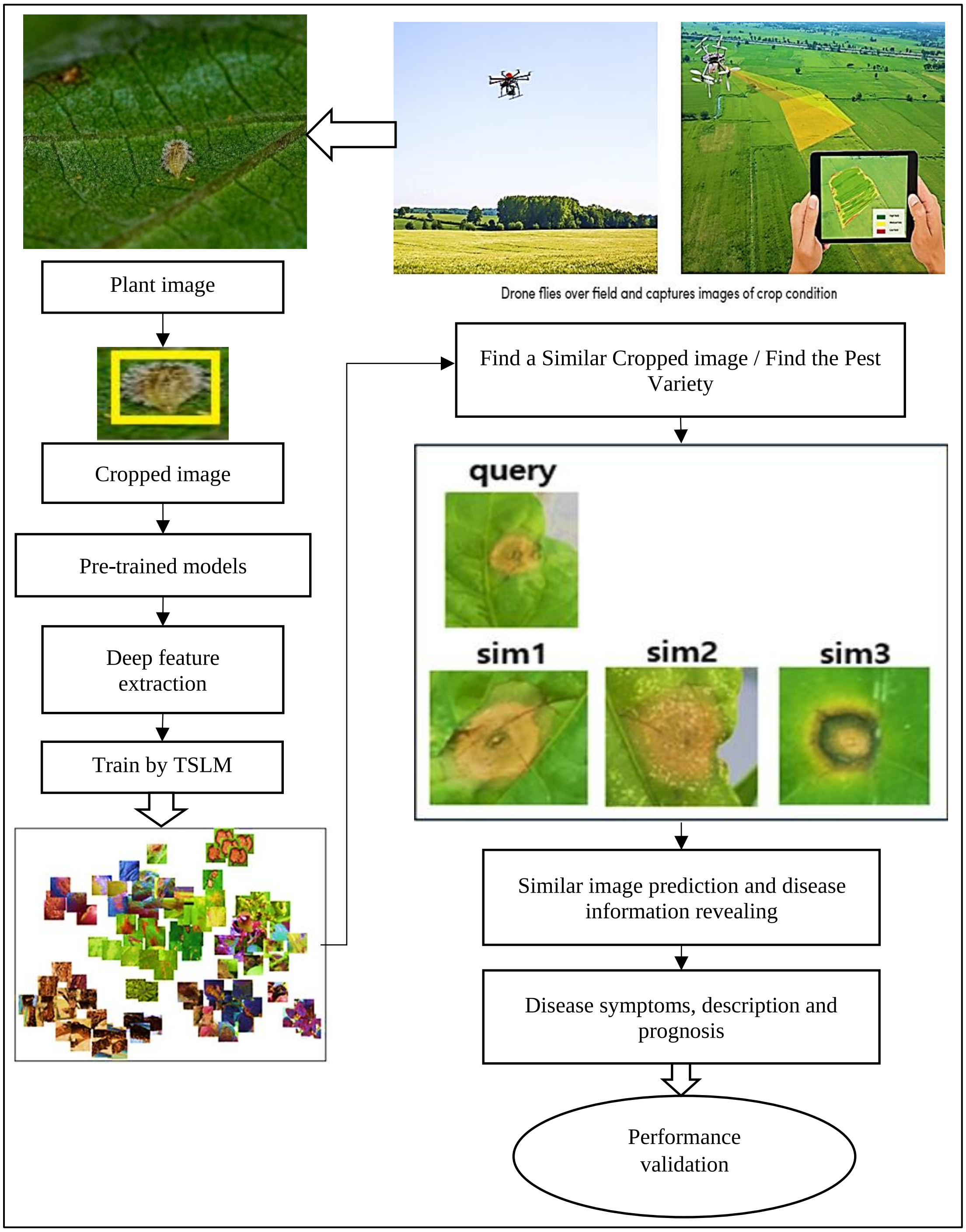

Figure 3: Overall Taxonomy of the Proposed Work

The UAV's change in position during each movement is determined by the distance it has travelled. Each drone's database is shared with adjacent drones within the Wi-Fi range, enabling them to learn about the places other UAVs have explored without actually going there. This reduces time complexity and eliminates unnecessary duplication of efforts. The transfer of images may take place regularly or in response to adjustments made to the maps. A UAV updates its database whenever it receives fresh mapping data from another drone (Rodríguez et al., 2021). This distributed method utilizes a dispersed search message (DSM) to provide details about a portion of the original search area. Each drone needs to memorize information from new locations to keep knowledge associated with those areas in its memory, as indicated by the distributed searching message. Consequently, drones exchange DSMs to update their current mappings. The size of a distributed search message is twenty-five bytes, and the A and B fields represent the location of each section within the square, where each section is represented by 10 square meters in the northwest orientation of the square. The data's expiration time is displayed in milliseconds in the Timer to Live section (Table 2) (Nam & Hung, 2018). The "State field" designates the area that has been thought of as:

1. No vegetation and no pests: "0000000".
2. The plant's health is present: "0000001".
3. The presence of a plant treated with pesticides: "0000010".
4. The presence of a plant that is infected: "0000011".
5. With the absence of a plant, the rest of the permutations will be utilized for the next task: "000000100".

Algorithm 1: Transfer Learning Procedure
Phase 1: Data Collection: Gather a dataset of crops present in the field. Phase 2: Data Resizing: Resize the data size using bilinear interpolation based on the deep network. Phase 3: Pretrained Model Adaptation: Replace the final three layers of deep networks with layers that are fully connected, a SoftMax surface, and classification output units to solve the issue. Phase 4: Classification: Utilize the TSLM to perform the classification process.

Algorithm 2: Feature Extraction Procedure
Stage 1: Data Collection: In this initial phase, a comprehensive dataset containing information about crops in the field is gathered. The dataset comprises relevant attributes and characteristics of the crops, which will be utilized for subsequent stages of the algorithm. Stage 2: Data Resizing: The acquired data is subjected to resizing using a deep network with bilinear interpolation. This process ensures that the data is appropriately standardized and adjusted to meet the requirements of the subsequent processing steps. Stage 3: Feature Extraction: Employing a fully connected layer of a deep learning algorithm, the data undergoes feature extraction. This layer efficiently extracts essential and relevant features from the resized data, aiming to capture the most discriminative and informative patterns for further analysis. Stage 4: Classification: The extracted features from the previous stage are utilized for the classification task. Prominent classification technique, namely Self-adaptive learning model (SLM), are applied to categorize the crops based on the extracted features. This classification process yields the final categorization results, facilitating decision-making and further analysis in agricultural applications.

3) Communication Phase

Either the intended drone or all drones will receive the package, depending on which drone created it. A drone's implementation of a particular process depends on the type of packet it receives (Li et al., 2019). Drones communicate with one another for three basic reasons.

Enrollments: A UAV transmits a request for help via the Internet if it discovers a pest and one or more of the following situations apply. A low pest container and inadequate battery power, excluding reserves, prevent the device from returning to the base for recharging.

Sharing Information from Previous Identifications: The drones can relay critical information regarding their current condition, like how much insecticide is still present and how much energy they have left.

Sending Status Information on Specific UAVs: To prevent repeatedly visiting the same places, the drones relay messages regarding the areas they have already visited at regular intervals. The search for and elimination of pests is sped up by this coordinated UAV effort.

(a) (b)

Figure 4: Drone DSM Application in Precision Agriculture (a) Mapping the Field (b) Drone Capturing Pictures and Monitoring Crops

Table 2: DSM Configurations

Direct of A	Direct of B	TTL	Phase
Bytes in 8	Bytes in 8	Bytes in 8	Bytes in 1

4 Experimental Results

This part includes the execution specifics and experiments that were done to assess the effectiveness of the proposed model. By assessing its pest identification and categorization capabilities and contrasting them with those of other existing models, the objective is to provide a thorough demonstration of the performance of the unique TSLM model.

The Keras library was used to implement the suggested framework in TensorFlow. Table 2 presents the Custom TSLM model's final training parameters. We adjusted the model's hyperparameters during the study by adjusting the number of epochs, number of batches, and learning rate to get the optimised model. In the studies, the Stochastic Gradient Descent (SGD) training optimizer was utilised with learning rates of 0.01, 0.001, and 0.0001. The number of epochs was set to 16, 32, and 64, while the size of the mini-batch was set to 15, 25, 35, and 45, respectively.0.3 was chosen as the dropout value to avoid overfitting. The data were split into training, verification, and test sets at random, with the input photo size set at 224 224. 30% of the data was utilised for testing, 10% was used for validation, and 60% was used for training.

1) Parameters for Evaluation

To determine the suggested technique, we employed various quantitative metrics for evaluation. Table 3 depicts the simulation parameters of the proposed model. These metrics include precision (P), recall (R), accuracy (Acc), Intersection over Union (IoU), and mean average precision (mAP). The computation of these metrics is carried out as follows and the equation (5-10) is given as,

$$P=TPs/((TPs+FPs)) \quad (5)$$
$$R=TPs/((TPs+FNs)) \quad (6)$$
$$ACC=((TPs+TNs))/((TPs+FNs+TNs+FPs)) \quad (7)$$
$$IoU=TPs/((FNs+TPs+FPs))*2 \quad (8)$$

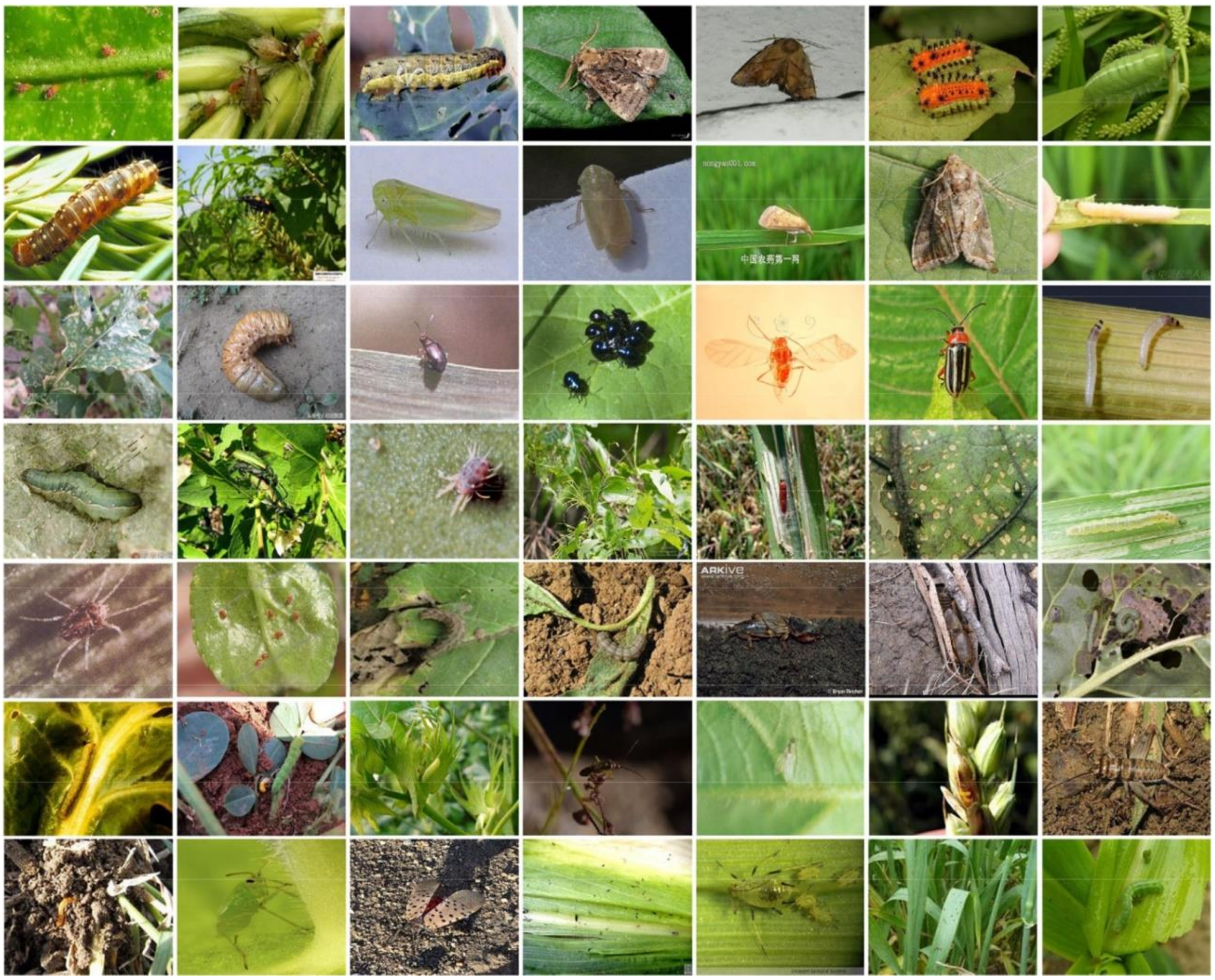

Figure 5: Sample Images of the Dataset IP102

Table 3: Simulation Parameters Considered

Factors	Ranges
Epochs	36
Rate of learning	0.01
Size of the batch	65
Threshold Confidence score level	0.51
Threshold unmatched	0.51

$$mAP = \sum_{(i=1)}^{t} (AP(t_i))/T \quad (9)$$
$$F1score = (2 * p * R)/((P + R)) \quad (10)$$

The letters TP, TN, FP, and FN. The bug in the image is treated as TP if it is accurately identified; otherwise, it is treated as FN. If the insect's categorization is incorrect, it is categorized as TN; otherwise, it is categorized as FP. Where T stands for the overall amount of images tested, and AP is the median correctness of every class.

2) Localization Outcomes: Insect Pests

To create a successful automatic pest-identifying approach, precise localization of insects is crucial. As a result, we created a trial to evaluate the suggested framework's efficiency for localization. We used all of the test photos from the IP102 collection for evaluation, and the graphical findings are given in Figure 5. We may infer from the published findings that the suggested technique is effective at finding pests of a variety of shapes, sizes, and colours. In addition, despite challenging backdrop conditions, lighting shifts, direction shifts, and varied acquiring angles, our method can successfully find pests. The suggested framework's capacity of localizing by using keypoint determinination permits it to distinguish and detect pests of different types accurately and efficiently.

To formally assess the effectiveness of localization, we calculated the mAP or IOU. These measurements demonstrate how effectively the suggested methodology recognizes and finds various pest types. The overlapping score within the anticipated region and the actual location must be less than this number to be perceived as foreground; alternatively, it is regarded as an issue.

Table 4: Efficiency of the Suggested Approach for Classifying Insects based on Crops

Species	**Recall**	**F1-score**	**Precision**
Rice	36.48	33.9	33.8%
Corn	56.7	55.76	55.75
Beet	44.7	49.50	56.89
Wheat	53.56	56.7	59.88
Alfalfa	76.84	57.6	80.96
Mango	72.89	78.9	76.88
Cirtus	76.83	74.5	84.26
Vitis	78.90	77.43	81.23

These findings suggest that the suggested method may locate insects exactly and successfully even in environments with a variety of backgrounds.

3) Consequences of Identifying Insects as Pests

To show that a model is reliable, it is crucial to accurately classify different pests. According to a particular kind of crop production region is likely to have a variety of bug species. To complete this assignment, all test pictures extracted from the IP102 database have been added to the learned TSLM classifier. Table 4 displays the recall, accuracy, and F1 score results for the suggested method's crop-based insect classification The findings show that the suggested design has achieved accuracy, recall, and F1 scores of 61.89%, 58.56%, and 60.40% for all bug classes that are particular to different plants.

Figure 6: Detection Outcome: Insect Pests

Strong pest categorization is an outcome of the applied important points calculation technique's accuracy, which consistently and accurately reflects every pest category. As a consequence, the performance of the distinctive TSLM in crop-wise insect recognition shows the potency of the suggested strategy.

Additionally, we have included a boxplot in Figure 7 exhibiting the reliability of eight crop-wise pest categorizations. The distribution of categorization accuracy across several classes is shown by the boxplot. To be more precise, we demonstrated the effectiveness of the suggested method by achieving a median classification precision of 0.6874 and minimal errors in every category. Figure 6 shows that our strategy has produced relatively favourable outcomes for crops including mangoes, vitis, and orange because of visual parallels with the backdrop and substantial intra-class variations, the suggested scheme obtains low proficiency in classification across multiple classes, including wheat and alfalfa. We have included multiple instances of similar-looking photos taken from the IP102 database in Figure 8. Although the specimen in the identical column contains pests from multiple genera, they are visually comparable.

Furthermore, Figure 8 displays the normalization confused matrix plot of the proposed approach, which summarizes the results of field stage insect identification as a function of expected and real categories. The acquired scores for accuracy in Figure 9 demonstrate the recommended algorithm's ability to recognize every among the 102 pest species. These findings confirm the strong efficacy of the suggested method across 102 insects or crop-wise insect categories.

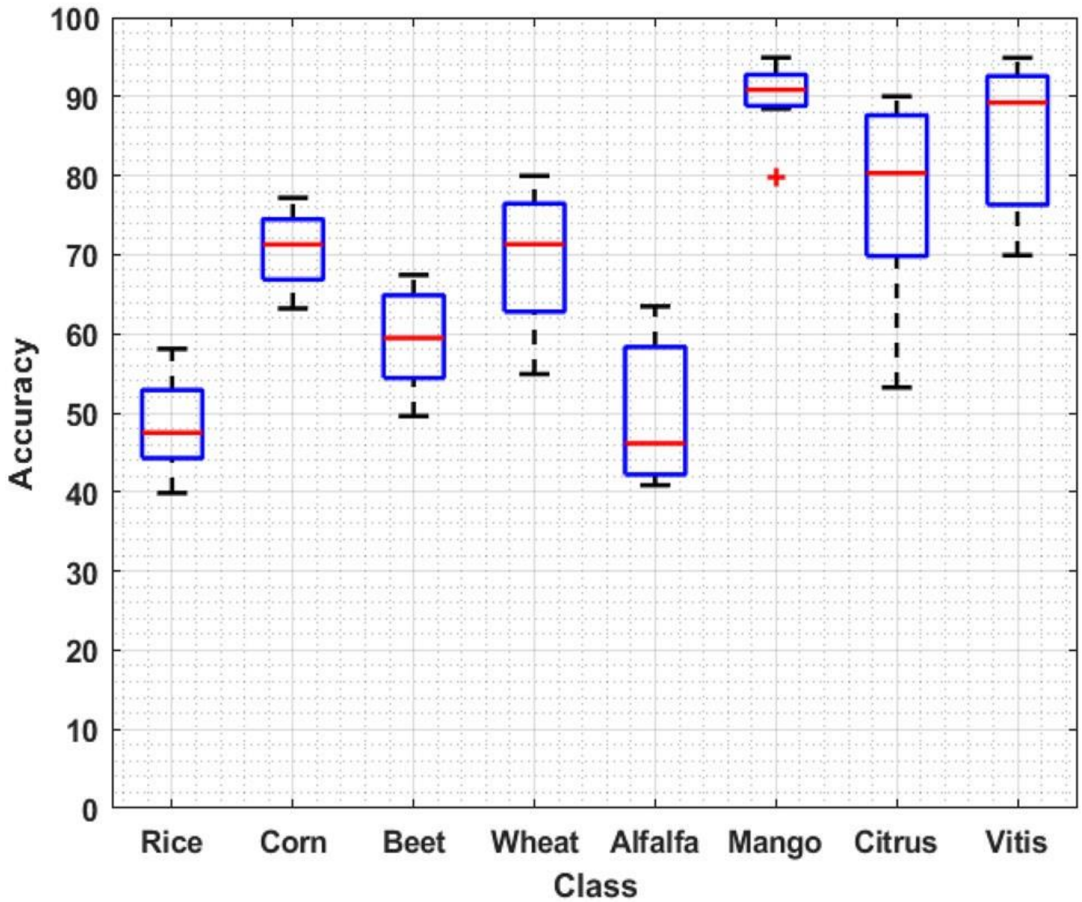

Figure 7: Reliability of the Suggested Approach for Crop-specific Pest Categories

4) Analysis of the DenseNet-100 Models

We evaluated the attributes-based learn capabilities on the DenseNets 100 framework for additional deeper analysis algorithms for insect identification as well as classification. Due to this, the detection efficiency of the suggested Customized TSLM is evaluated in comparison to several basic models, including ResNet-50, EfficientNet, Alexnet, GoogleNet, Inception V4, Hour-Glass104 VGGNet, ResNet-101, DenseNet-121

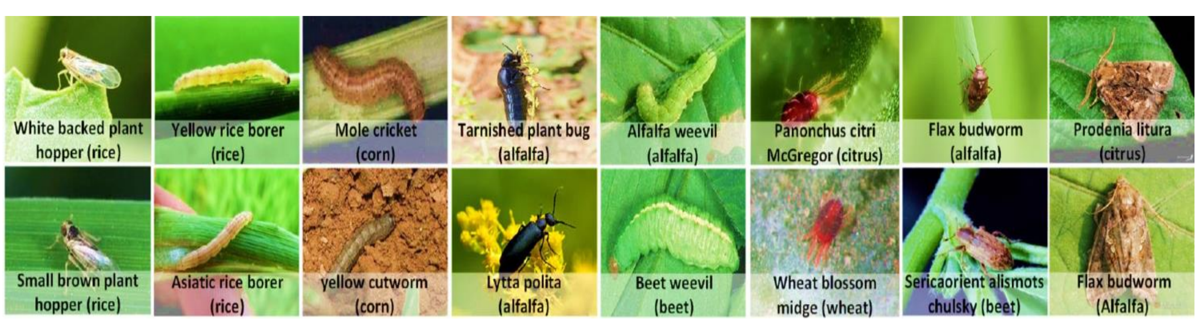

Figure 8: Examples of Insect Pests with Comparable Appearance, Labelled with the Pest Category and Related Crop Subcategory

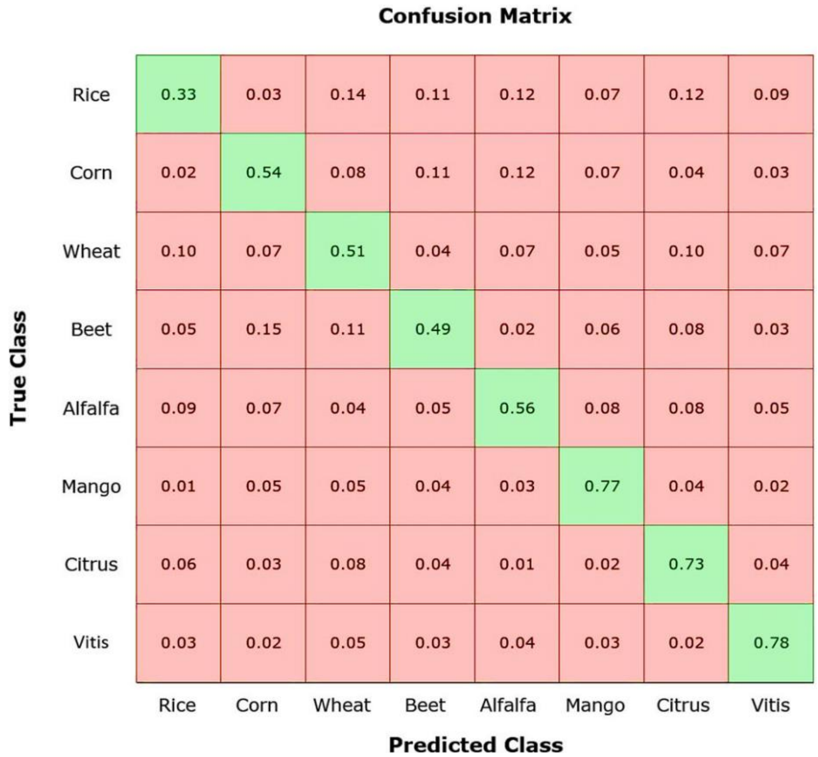

Figure 9: Confusion Matrices for Suggested Approach Over Cropping Insect Categories

Table 5: Evaluation of the Suggested Method's Effectiveness with Different Extraction of Features Methods

Approach	Factors	Precision ±STD
AlexNet	64.5	42.9±2.52
GoogleNet	8.9	44.5±2.02
VGGNet	139	49.7±3.09
ResNet-50	24.75	58.10±2.56
ResNet-101	43.64	48.9±2.65
Inception v4	42.4	55.64±2.48
Hourglass 104	188	62.34±2.20
EfficientNet	19.4	55.72±2.46
DenseNet-121	9.08	55.76±2.56
DenseNet-100	8.09	73.45±9.02

Transfer learning was used to provide a more accurate expanding ability on the unobserved data. The last layer of each of these basic networks was fine-tuned using the IP102 information after receiving training on ImageNet. For the present study, neural networks were conditioned for a period of 30 with mini-batch sizes of 16 and 64. SGDs changed the processing speed to 0.0010 with a motivation score of 0.09. The IP102 statistics systems setting was used to evaluate the algorithms' categorization findings.

Table 5 compared our approach to various methods for extracting features algorithms. There is a presentation of the categorization accuracy and STDs. The STDs demonstrate the repeatability method outputs for categorization. This superior importance of STDs demonstrates the unreliable actions of the framework for the outcome of insect detection and categorization. The findings show that customized

TSLM operates superior to alternatives when DenseNet-100 serves as the backbone connection. This is brought about by efficient deep characteristic computing utilizing the DenseNet framework, which offers an improved and varied description of many harmful insect genera. The basic platforms, including ResNet, Inception v4, AlexNet, HourGlass, and VGGNet, produce poor results for pest detection, as shown in Table 6. This may occur to understand the subtle differences between different kinds of pests in an intricate setting, leading to a high percentage of misunderstanding. AlexNet has the smallest precision of 41.8% in forecasting insects across all 102 groups as in Figure 10.

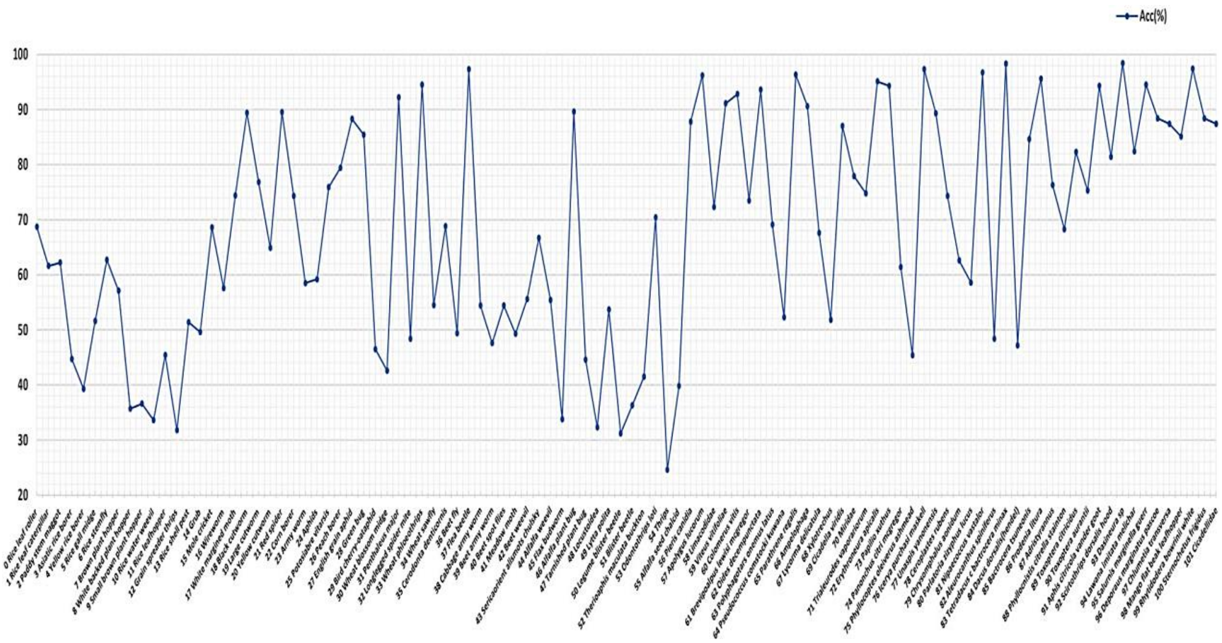

Figure 10: Reliability of the Suggested Strategy throughout 102 Types of Pests

The deeper systems, such as DenseNet-121, ResNet-101, and HourGlass, however, can learn extra detailed distinctions between several similar species of insects. However, they still do poorly when it comes to classifying different pests. This suggests that such methods are more probable to overfit insect classifications on IP102 information within fewer initial materials due to network characteristics. Contrarily, the customized TSLM built using DenseNet-100 worked very well (70.79% reliability) classifying every kind of sort of pest.

The second-highest reliability is attained by the EfficientNet algorithm (60.6%). On the other hand, the DenseNet-100 has the fewest number of parameters—7.08 million—of all the DL models that are that have been used. Our strategy's enhanced network design enables efficient reuse of all model parameters, resulting in increased pest identification accuracy. For the basic theories, which possess an extremely intricate structural design and therefore are difficult to extract their trustworthy characteristics, we utilized their initial solutions. By utilizing a successful system for discriminatory key points computation and recycling characteristics from the first levels in every succeeding level, our technique addresses the drawbacks of comparison models. The outcome is enhanced productivity as an outcome of appropriately handling complicated conversions. According to this investigation, the suggested custom TSLM using DenseNet-100 backbone outperforms existing extracted features algorithms in terms of precision and effectiveness.

5) Evaluation of Accuracy with ML-based Classifications

We crashed a test to illustrate our classification efficiency evaluation using additional ML-based algorithms to further establish the usefulness of our suggested strategy. For this study, we utilized using IP102 a database, splitting it into training, verification, and testing establishes, as well, as 61%, 11%, & 30%.

The three different feature mining algorithms listed in Table 4 that performed the best were used for extracting deep characteristics. The ML machine learning algorithms, SVM then KNN as the model undergo training using deep characteristics using EfficientNet, ResNet-50, and DenseNet-100 and their classification outcomes with averages are shown in Table 6. It also shows that, compared to other arrangements, utilizing the DenseNet-100-based advanced attributes with the pair of SVMs & KNNs algorithms produced superior outcomes. Nevertheless, our Customized Corners Nets approach continued to produce the greatest outcomes. DenseNet 100 using SVMs and KNNs as the back-end classifications obtained 53.6% and 51.4%. The suggested Customized TSLM approach, however, only managed to reach a precision of 69.75%. This demonstrates that, in comparison to ML-based classification techniques, the model suggested delivers an improved representation of features of the insects and handles over-fit information from training better.

Table 6: Evaluation of the Suggested Method's Effectiveness with ML-based Detectors

Techniques	**Precision ±STD**	
	SVMs	**KNNs**
ResNet-50	50.6 ± 2.70	50.5±3.39
EfficientNet	52.8±2.09	52.9±2.87
DenseNet-100	53.8 ± 0.99	51.5 ±2.20
Proposed	69.8 ±0.99	-

6) Evaluation of Performance on Alternate Item Detecting Methods

We evaluated how well the suggested model performed against other cutting-edge object identification techniques. Since background noise might fool the algorithm when the intended insect is not obvious, proper pest translation is crucial. The presence of many pests might make the detecting procedure much more difficult. Correct localization can increase classification precision even more by eliminating unnecessary contextual data. Compared multiple one-stage object recognition models such as SSD, YOLOv3, RefineDet & TSLM that have shown accurate results on the COCO set of images as well as many detectors with both stages are faster R-CNNs, Fast R-CNNs. To evaluate those algorithms' capacity to locate pests in a variety of difficult environments, including those with complicated backgrounds, vibration, brightness changes, and variations in their colour, size, & influence, we evaluated how well they performed across the IP102 database.

Table 7: Performance Assessment of the Suggested Technique against Various Techniques of Identifying Items

Techniques 2 phase Detector	**Back Bone**	**Map**	**Time of Test**
Fast R-CNNs	VGGs-16	47.13	3
Fast R-CNNs	DenseNets-100	48.36	2.74
Faster R-CNNs	VGGs-16	48.89	0.46
Faster R-CNNs	DenseNets-100	49.13	0.43
1 phase detector			
Refinedets	VGGs-16	50.02	0.32
Refinedets	DenseNets-100	51.26	0.30
SSDs	VGGs-16	48.18	0.39
SSDs	DenseNets-100	51.65	0.35
YOLOv3s	DarkNets-53	51.90	0.32
YOLOv3s	DenseNets-100	54.27	0.29
PROPOSEDs	DenseNets-100	55.76	0.25

Figure 11: An Example of a Graphical Outcome based on the TSLM approach, SSDs, RefineDets, & YOLOv3s

In addition, we estimated testing intervals for every approach to evaluate the computational demands of every model. Table 8 compares the map and time to of several object recognition strategies with various foundations for identifying pestsOutcomes Table 8 indicates that the suggested approach for identifying pests performs better than the alternative. Table 8 demonstrates significantly distinct detectors for objects work for more effectively when combined with DenseNet, a robust vertebral column, to identify insects. Fast R-CNN and Faster R-CNN, 2 phase event detecting devices, exhibit poorer results. Since these methods employ anchor boxes to pinpoint the possible region that is relevant before doing categorization and regression in finding the appropriate box, they are rumoured to be costly.

RefineDets, SSDs & YOLOv3s are one-stage systems that directly determine the location and classification of an item while functioning better in comparisons. The original formulations of those algorithms, which are examined in this study, do not do exceptionally well in identifying and detecting bugs in environments with extreme fluctuations in illumination. The graphical outcomes of one-stage detection procedures on the experimental material are shown in Figure 11.

Additionally, it is demonstrated that one-stage detectors are quicker to compute than two-stage recognition algorithms. The DenseNet backbone lets the TSLM acquire more accurate characteristics, which aid in improved insect localization and categorization into distinct groups, allowing for higher efficiency. In addition, the TSLM approach has a computation advantage over other approaches owing to its one-stage recognition structure and requires simply 0.23 s to analyse an observation.

7) Evaluation of Performance for Recent Methods

In this part, we compare the categorization efficiency of our technique to findings from other studies using the same database, IP102. Table 7 compared noxious bug categorization findings to previous methodologies of overall precision. They transferred learn to train VGG-19, inceptionNetV3, as well as ResNet-50 artificial intelligence architectures for the categorization of insect pests, and they found that inception NetV3 has the greatest general mean efficiency (57.08%). However, the training framework, dataset chopping and augmentation procedures have been utilized. CCNs (Inception-V3, Xception, and MobileNet) were combined using ensemble strategy, including GA Ensemble, to enhance the performance of classification. However, due to the lengthy computation of an ensembles measurements, these approaches only achieved a precision of 61.93% & 67.13%, respectively. The EquisiteNet model, which consists of double merging with squeeze or excitation and max-feature expansion blocks was employed the preciseness of the simulation was 52.32%. For practical usage in the actual world, the resulting reliability is significantly reduced.

These approaches acquired reliability of 56.34% and 55.53% by integrating the reuse of characteristics and a combination of feature mechanisms within the redesigned Resnet blocks. ResNet-based structure proves more operationally costly than Dense Net. These findings unambiguously demonstrate that the suggested TSLM system using Dense-Net-100 beats the previous experiments by obtaining a median reliability of 69.84%. The DenseNet essentially calculates the characteristic maps by linking results from prior layers as inputs to all succeeding layers, thus providing a contributor to better performance. The TSLM framework uses the calculated characteristics to locate and identify bugs.

Table 8: Compares the Map and Time to of Several Object Recognition Strategies

Techniques	Precision
InceptionNetV3	58.09
GAEnsemble	68.15
EquisiteNet	54.32
FR-ResNet-50	56.27
DFF-ResNet-82	57.89
FusionSum-Densenet201	63.45
Proposed	69.78

5 Conclusions

In this study, we introduced a deep learning (DL) based system for the drone-assisted automatic detection and classification of crop pests in the field. This system is both cost-effective and efficient. The proposed approach that we have developed is founded on a Transfer-driven Self-adaptive Learning Model (TSLM), which makes use of pre-trained neural network architectures as a basis for the extraction of features. To be more specific, we extracted important key points from the input data by using the Transfer Learning (TL) network. Following that, the TSLM model was educated to accurately recognize a wide variety of different kinds of pests. We conducted experiments on the IP102 dataset, which is a challenging benchmark database featuring in-field collected photos of pests. The purpose of these studies was to determine how effective our approach is against this database. We have shown that our methodology is applicable for use in pest monitoring applications that take place in the real world through the use of thorough testing. The findings that were obtained demonstrated that our method can exactly localize and categorize pests across different categories, even with varied pest characteristics like shape and complex origins, colour, size, orientation, and luminosity. This was demonstrated by the fact that our method was able to accurately localise and categories pests.

In the course of our future work, we plan to build a more sophisticated approach to feature fusion to significantly improve the efficiency of our method, in particular when it comes to the classification of finer-grained pests.

Declarations

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Conflicts of Interest: The authors declare no conflict of interest.

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