International Journal of Enhanced Research in Management & Computer Applications
ISSN: 2319-7471, Vol. 11 Issue 11, November, 2022, Impact Factor: 7.751

An Investigation on Advanced Deep Learning Model for the Recognition of Agricultural Pests in Cloud Computing System

P. Bharathi[1], Dr. K. Dhanalakshmi[2]

[1]Ph.D Research Scholar, Department of Computer Science, Kongunadu Arts and Science College, Coimbatore-641029
[2]Associate Professor, Department of Computer Science, Kongunadu Arts and Science College, Coimbatore-641029

ABSTRACT

Agriculture is one among the primary sources of human food as far as the history of the human race goes. In several nations, agriculture forms the pillar of its economy, and over 90% of their population are dependent on it for their living. Agricultural pests are serious threats to crop developments or their storages. Insects/pests cause agricultural damages resulting in diminished crop outputs. Classifying insect is a major challenge owing to their complicated structures, species diversities and similarity of appearances. It is critical to identify and categorise these insects that damage early, especially to stop these insects from spreading and causing crop diseases with the use of efficient pesticides and natural control methods.A conventional manual classification of insects typically consumes lot of time, involves manual effort and inefficient owing to the manual choice of the useful feature sets. The last couple of years have witnessed the usage of the Learning mechanisms for classification and identification of insects to find a solution to these problems in the agricultural sector. Recently, DLTs (Deep learning techniques) have emerged as primary techniques to deal with the technical problems associated with pest identification. In this regard, this research introduces a systematic overview of the literature, whose objective is the recognition of the benchmarks involved in using DLTs and optimized model of DLTs during the procedure of identifying and classifying the plant diseases, defining trends, and specifying the disparities with the aim of finding the crop pests in a practical agricultural environment.

Keywords: Agriculture, pesticides, Deep learning classification and recognition

INTRODUCTION

In agricultural yield management, it is always a huge challenge to detect the insect pests [1]. Insect pests are behind 20% of crop loss esannually all over the world [2]. Hence, controlling insect pests has a critical part to play in agricultural yield, considerably impacting the agricultural progress, grain generation and rise in the farmers' revenue. Detection of insect pest is an important challenge faced in agricultural image processing [3]. Conventional pest identification techniques have their own drawbacks on accuracy when categorized by their physical characteristics.The focus on agricultural applications of intelligent technology has increased as computer science has developed [4]. The scientific and efficient management using intelligent algorithms is not just a technical means of replacing the conventional manual detection for improving the efficacy, but also prevents the insect pests being spread in a surrounding region, thereby making the quality of crop products to improve. Especially, DLTs are shifting the agriculture to gear forward From the conventional format to the smart one.

The detection of insect pests in agriculture is a significant precondition for the forecasting, prevention and management, so that the yield in prediction and control operations can be improved [5]. Image detection techniques offer the benefits of improved efficacy, reduced x penditure and simple functions for the detection of the insect pests. These technique retroactive and accurate in the detection of the kinds of insect pests and yield information required by the farmers to undertake suitable actions for the prevention and control the insect pests from spreading [6]. Therefore, image-based detection techniques have emerged to be hot topics for research in insect pest control in the last couple of years. In general, several conventional image detection approaches apt for insect pest detection, like the detection techniques on the basis of the threshold, edge, region test and graph theory are available. But, these conventional detection approaches are suitable for a less number of samples or reduced range of detection, and no stability is observed in the detection accuracies [7]. If the number of samples that needs detection is huge and the kinds of samples are complicated, there will be a sharp reduction in the accuracy rate.

Pesticides and other organic control mechanisms must be used for controlling the insect family and prevent them from spreading to dense areas. Furthermore, it guards against pest damage to the agricultural regions. Knowing the type of bug is crucial since different insect types require different ways to pest management. However, due to the commonalities between many insect species and their diverse organizational structures, classifying the insects is an important challenge [8]. Entomologists have performed the manual execution on the classification of insects, which consumes lot of time and is laborious too. Therefore, an expert knowledge of the domain is a prerequisite. In order to find a solution to these problems, specialists use several computer-aided classification mechanisms.

Conventional MLTs (Machine Learning techniques) are used in image classifications and have found consistency of application in various tasks such as insect classification and recognition [9]. However, the traditional MLTs face few disadvantages. One additional stage of data pre-processing in the form of feature engineering is required and it is quite important [10]. Moreover, their capability is not worth enough for the classification with different datasets. Moreover, their performance is highly dependent on the data considered, for example, the accuracy of the results of small dataset is low. Improving the dataset does not improve the performance once a specific accuracy is reached [11]. The same issues are encountered in the insect classification.

Presently, DLTs and specifically CNNs (Convolution Neural Networks) have found usage in image collections where for solving issues [12]. In the agricultural industry, Models based on DLTs are typically used for operations like plant identification, weed detection, and plant disease categorization. One particular type of ML is called DLTs, which employs multilayer neural networks to assist models in automatically learning and mining deep abstract characteristics. Different Models of DLTs have recently been used to classify pests, and they produce best-in-class results across a range of pest recognition applications. CNNs have been trained in a supervised approach and differentiating features are learned. CNNs makes use a couple of artificial neurons compared with rest of the conventional feed forward neural networks due to which its usage with image processing and identification is made easy. On the other side, CNNs require a massive number of samples for the training stage. Moreover, there are diverse hyperparameters in CNNs and various specific architectures that is regarded as a problem and expensive to decide the optimal values for these hyperparameters through manual means. Insect classification constitutes the prominent research domain. In this, DLT's performances outperformed traditional MLTs by wide margins [13]. It has been determined via analysis of the previous studies that feature selection based DLT models significantly enhance the performance of pest classification. Therefore, it is essential to create an intelligent expert system that can quickly and automatically recognize photographs of agricultural pests.

REVIEW OF LITERATURE

Thenmozhi& Reddy(2019) [14] studied about using three publicly accessible insect datasets, efficient models of DCNNs (deep CNNs) was developed for the categorization of insect species. NBAIR (National Bureau of Agricultural Insect Resources) dataset was the first dataset created using insects/pests and encompasses images of 40 different types of field crop insects while the datasets Xie1 and Xie2 contain images of 24 and 40 different insects, respectively. This study's suggested model was assessed in terms of its classifications using previously trained DLTs including AlexNets, ResNets, GoogleLeNets, and VGGNets. The study improved TL (transfer learning) to improve these pre-trained models. Data augmentation techniques like reflections, scaling, rotations, and translations were also used to reduce effects of data over fits. Accuracy and efficacy of hyperparameters the proposed model were evaluated. The study's proposed model based on CNNs achieved greatest classification accuracy of 96.75 NBAIR, 97.47 for Xie1, and 95.97% for Xie2 datasets. The study's findings show that their suggested CNNs outperformed other pre-trained models in classifications of field crop insects and thus could assist in saving crops.

Nanniet al (2020) [15] proposed a computerized classifier that relies on a mix of CNNs and saliency techniques. Popular image processing techniques known as saliency methods focus on the picture pixels with the greatest importance In this study, the preprocessing of the picture is done using three different saliency approaches, and three different images are produced for each saliency technique resulting in $3 \times 3 = 9$ new images for actual images which were then trained on several CNNs. The performances of pre-processes/network coupling were evaluated as collective performances. Their strategy was validated on both small and large datasets (IP102) where the smaller dataset's accuracy was 92.43% while for IP102 dataset, the accuracy was 61.93%. These results were found to be superior in evaluations taking them closer to human expert's performances.

Fan and J. Xu(2020) [16] examined local fuzzy based image processes based on DLTs to identify crop diseases and pests. It was evident from their results of the trials that their technique delivered greatest performances.

The analysis by Gauret al. (2020) [17] of crop illnesses and categories of illnesses and pests that harmed Cypress in southern India, as well as pests in New South India which were found useful for creation of preventative and control strategies.

The Inception-ResNet-v2 model was used by Ai et al. (2020) [18] to create integrated convolution operations for accurate detections of crop diseases/pests, though the actual model's parameter choices were complex and unsuitable for practical applications.

Despite the fact that Li et al. (2020) [19] established a video detection architecture based on DLTs to enable exact detection of plant diseases and insect pests, the recognition efficacy of various plant diseases and insect pests still needs to be improved.

Singh & Minj(2019) [20] suggested an image recognition method for identifying bacteria and fungus that relies on image processing technology. This method is effective in increasing the utility and accuracy of the detection, but it is very reliant on the real data.

For the categorization of pests in tomato plants, Pattnaiket al. (2020) [21] presented a transfer learning of a deep CNNs-based model that had previously been trained. 859 photos divided into 10 groups make up the dataset utilized for this evaluation, which was gathered from internet sources. This study was unique as it examined performances of 15 pre-trained DCNNs which classified tomato pests using a dataset of 10 tomato pest species. The results of their experiments show that their DenseNet169 model achieved maximum classification accuracy of 88.83%. Furthermore, the efficacy of TL based models in pest detections and classifications was particularly encouraging.

He et.al. (2019) [22] conducted research on a real-time model for Oilseed Rape pest identification. Twelve prevalent insect pests were included in the dataset the scientists created for oilseed rape. There are five different DLT architectures used. According to the findings of the mobile experimentation, a dropout layer and data augmentation were used to achieve an average accuracy (mAP) of 77.14%.

For the purpose of identifying nuisance insects, Dawei et al. (2019) [23] introduced a DLT that relied on transfer learning. The Alex Net-dependent system pre-trains the model for the categorization of 10 different types of insect pests. The accuracy of the suggested method is 93.84%.

Wu et al (2019) [24] studied about a novel dataset standard for insect pest known as IP102. The dataset includes over 75, 000 images that belong to 102 types of insect pest. Moreover, a baseline experiment is introduced that uses synthesized feature approaches and deep feature techniques dealing with the pest insect images. The authors gained the highest accuracy of 49.5% through ResNet. The results of the Experiments demonstrate that IP102 dataset faces the problems of classification and imbalanced dataset. The survey on many relevant studied using DLTs particularly in the classification of insect pests showed that there has been massive growth due to DLTs. Additionally, it was shown that applying the available benchmark DLTs in addition to pre-train models produces better outcomes and increases detection accuracy. In this research project, an effective pre-trained learning model to deal with insect pest photos is tried. End-to-end training of insect pest photos is possible using the pre-train learning model, making the training procedure very straightforward. The suggested transfer model with augmentation technique was evaluated on the IP102 dataset by Wu et al in 2019.

According to Enes Ayan et al. [25] in 2020, insects are a significant contributor to significant losses in a variety of crops, including wheat, rice, corn, sugarcane, soybeans, chickpeas, and potatoes. The D0 dataset containing 40 species, which was used to train seven distinct CNNs models, is corrected, and then re-training is carried out using the appropriate transfer learning and fine-tuning techniques. The best three CNNs models (Mobile Net, Xception, and InceptionV3) were then combined using maximum sum of probability approaches to improve classification performance. The procedure used two datasets, with the small dataset producing the highest accuracy (95.15%) and the IP102 dataset producing the lowest accuracy (67.13%).

A novel and straightforward design called the feature reuse residual block, which mixes features from the input signal of the residual block with the residual signal, was advocated by Fuji Ren et al. in 2020 [26]. Every feature is capable of reusing the residual block through the learning of 50% of a feature and then reusing the other 50% of it, improving representation capabilities. By stacking the feature reuse residual block, the feature reuse residual network (FR-ResNet) was created and verified using the IP102 benchmark dataset.

Nour Eldeen M.khalifa et al. [27] published an insect pest detection system based on deep transfer learning in 2020. This analysis used the IP102 insect pest dataset. The IP102 dataset, which contains 75000 photographs and only 27500 images of 102 insect pest classes and is one of the largest datasets for insect pests, was released in 2019. This study employs a number of DTLMs, including xNet, squeezNet, and GoogleNet. The augmentation method is used to create a robust model and alleviated the problem of over fits.The model was assessed using a number of criteria, including the F1 score, accuracy, and precision. With just the alexnet, a portion of the IP102 dataset may be used to get testing accuracy of 89.33%.

In 2020 Qi-Jin Wang et al. [28] recommended a massive dataset referred as Pest24, which includes more than 25000 annotated images obtained in a field using pest trap and imaging system. Pest24 consists of an overall 24 kinds of typical pests, a whole lot of it creating damage to field crops. The pests detection utilized diverse DL approaches, and encouraging results are achieved for real-time monitoring of the field crop pests.

Kararet al (2021) [29] presented an application that makes use of Faster R-CNNs (region-based CNNs) to complete insect pest detection operations based on cloud computing. In order to give farmers advice, a database of recommended pesticides is linked to the detected crop pests . This study was effective in examining five pest groups: aphids, cicadae, flax budworms, flea beetles, and red spiders. For all of the pest images considered, the proposed Faster R-CNNs had the highest correct identification rate of 99.0%. Furthermore, when compared to other identification methods such as SSD (Single Shot Multi-Box Detector), MobileNet, and classic BPNNs (back propagation neural networks), DLTs perform substantially better. The key achievement of this research is the implementation of the proposed application for online detection of agricultural pests in both large areas, such as large farms, and greenhouses for specific crops.

For vision-based automated pest detection and recognition using learning processes, Gutierrez et al. (2019) [30] proposed the development and comparison of two different techniques. A computer vision and MLTs-integrated system is contrasted with a DLTs-only solution. The research is largely concerned with selecting the best approach, which depends on the accuracy of pest detection and recognition. The study focuses on Bemisia tabaci and Trialeurodes vaporariorum, two of the most harmful pests that attack greenhouse tomato and pepper crops. In order to create and assess MLTs and other models, a dataset including a sizable number of photos of injured tomato plants was produced. The study's findings showed that DLTs produce better results, according to the study's findings, because they can detect and classify diseases in a single step, have improved accuracy, can distinguish between Bemisia tabaci and Trialeurodes vaporariorum with reasonable precision, and can balance speed and accuracy by using a variety of models.

Using a Faster R-CNNs model and image augmentation with an emphasis on performance accuracy is tested with a short dataset, Patel and Bhatt (2021) [31] discovered that multi-class pest identification may be accomplished. To address the issue of class imbalance, the augmentation parameters of 90 Degree Rotation and Horizontal Flip are used. It has been deduced that the trained pest detection model's performance with augmentation options is significantly enhanced, producing an accuracy of 91.02% when using the Faster R-CNNs model.

Buteraet al (2021) [32] analyzed the potentials of object detection frameworks based on CNNs for identifying beetle like pests with heterogeneous images captured outdoors using various sources. Also, differentiating a pest insect and identical innocuous species is focused. Not just the detection performance of various models is considered, but the computational resource is also taken into account The goal of this effort was to give a basic model for these types of jobs. Their results proved the appropriateness of existing SoA models for this application, emphasising that FasterRCNN with a MobileNetV3 backbone provides an extraordinarily strong foundation for accuracy and inference execution latency. This ensemble achieves an average accuracy score of 92.66%, which is considered qualitatively good and comparable to the score obtained by other authors using particular models.

To address this practical issue, Sourav, M. S. U., and Wang(2022) [33] introduced a smart model for jute pests identification based on transfer learning (TL) and DCNN (deep CNNs). The suggested DCNN model is capable of providing rapid and precise automated jute pest identification based on photographs. In particular, TL was used to train the VGG19 CNNs model on the ImageNet database. Additionally, a well-defined picture collection with four well-known jute pests is developed. The algorithm finally yields an accuracy of 95.86% for the four main jute pest groups. In terms of the accuracy, recall, F1-score, and confusion matrix results, the model's effectiveness is once again demonstrated. For real-world applications, the suggested paradigm has been integrated into Android and iOS applications.

Suneja et al (2022) [34] The humidity-temperature sensor detects humidity and temperature in the surrounding environment. The camera module has been used to detect diseases on tomato plants. The open-source platform Thing Speak is ideal for displaying accurate air temperature, humidity, soil temperature, soil moisture level, and so forth. To improve illness diagnosis accuracy, the Azure Custom Vision Model was deployed.

INFERENCE FROM THE EXISTING WORKS

One of the main factors affecting the output of agricultural goods is insect infestations. Accurate identification of insect pests permits proactive prevention measures to stop financial losses. To stop these insects from proliferating, farmers will greatly benefit from early detection of plant pests so they can select the most effective insecticides. As a result, past studies have heavily relied on computer vision systems and image processing using artificial intelligence techniques, such as MLTs and artificial neural networks, to discover answers to the aforementioned problems in the agricultural area. The progress made in MLTs and computer vision approaches has made in automated insect pest identifications have gained the research focus. Presently, DLTs empower reliable feature learning and yielded benchmark performances on different image classification tasks. But, till now, DLTs on insect pest detection are confined to small datasets, which has quite a less number of samples or pest species. At the same time, a majority of the available insect pest images in openly available datasets are gathered in managed lab environments, which is not suitable for the demands of insect pest identification in the practical field environment. Therefore, in this technical work, the improvement in the classification accuracy using feature selection models is highlighted.

Feature selection (or) extraction consists of mining the information out of the segmented image that could be helpful in accurately classifying the anomalies. Features whose extraction could be done include Shape, size, and colour are examples of texture (energy, contrast, homogeneity, and correlation). Statistical tools like LBPs (Local Binary Patterns), GLCMs (Grey Level Co-occurrence Matrices), CCMs (Colour Co-occurrence Matrices), and SGLDM can be used to extract textural information (Spatial Grey Level Dependence Matrix). Using model-based approaches such as Auto-Regressive (AR) and Markov Random Field (MRF) models, they may also be derived. Feature vectors are given to MLTs algorithms, and training is done to categorize the characteristics associated with each illness that has to be detected. The trained algorithm may then be used to detect the characteristics in fresh field-obtained photos. Matching a certain input feature vector with one of the several classes that are discovered during training is the goal of classification. To train, categorize, and aggregate the findings of the algorithms, the designer may use various learning algorithms [20].

CONCLUSION

Insect pest control is one among the important means of improving the crop yield and quality in agriculture and it can help in the accurate and timely detection of insect pests, which is very important for agricultural productivity. Earlier, a majority of insect pest detection tasks were dependent on the experience that agricultural specialists had, which involves a lot of time, huge lot of effort and subjectivity. Recently, different intelligent approaches have developed for detection process. Even though, it is possible to suggest the most appropriate deep network based on the image data conditions, few drawbacks still exists for the research. The setback of the suggested DLTs for insect pest detection is in the deficit of better adjustment to various image data conditions, leading to the critical performances in each case. Since the apt deep network has to be chosen automatically or must be selected manually to fit the real situation of the sample data, the way the technique will be applicable is quite restricted for the sample data having varying complexity and modifiable scale. In order to deal with it, in the future, the current work will incorporate the design of an enhanced DLTs that depends on optimization based future selection techniques. This approach will combine the advantages of the three DLTs into one model and it can be hoped that it is adaptive to various image data complexities and scales so that insect pest detection in agricultural sector is accurate and quick.

REFERENCES

[1] Amiri, A.N. and Bakhsh, A, 2019. “An effective pest management approach in potato to combat insect pests and herbicide”, 3 Biotech, vol. 9, no. 1, pp. 1-12.

[2] Fernández, R, Petek, M, Gerasymenko, I, Juterek, M, Patron, N.J, 2021. “Insect Pest Management in The Age of Synthetic Biology”, Plant Biotechnol. J, vol. 20, pp. 25–36.

[3] Süt″o, J, 2021. “Embedded System-Based Sticky Paper Trap with Deep Learning-Based Insect-Counting Algorithm”, Electronics, vol. 10, pp. 1754.

[4] Amarathunga, D.C.K, Grundy, J, Parry, H and Dorin, A, 2021. “Methods of insect image capture and classification: A Systematic literature review”, Smart Agricultural Technology, vol. 1, pp. 100023.

[5] Ngugi, L.C, Abelwahab, M and Abo-Zahhad, M, 2021. “Recent advances in image processing techniques for automated leaf pest and disease recognition–A review”, Information processing in agriculture, vol. 8, no. 1, pp. 27-51.

[6] Gayathri, A.G and AS, R.A, 2021. “Vlsi implementation of improved sobel edge detection algorithm”, In 2021 International Conference on Communication, Control and Information Sciences (ICCISc) (Vol. 1, pp. 1-6). IEEE.

[7] Arshad, T, Jia, M, Guo, Q, Gu, X and Liu, X, 2019. “Fruit Classification Through Deep Learning: A Convolutional Neural Network Approach”, In International Conference in Communications, Signal Processing, and Systems (pp. 2671-2677). Springer, Singapore.

[8] Lu, F, Xie, F, Shen, S, Yang, J, Zhao, J, Sun, R and Huang, L, 2020. “The One-Stage Detector Algorithm Based on Background Prediction and Group Normalization for Vehicle Detection”, Applied Sciences, vol. 10, no. 17, pp. 5883.

[9] Zelazo, D, Mesbahi, M and Belabbas, M.A, 2018. “Graph theory in systems and controls”, In 2018 IEEE Conference on Decision and Control (CDC) (pp. 6168-6179). IEEE.

[10] Junyan, B, 2020. "Research on the technology of artificial intelligence in computer network under the background of big data", In 2020 International Conference on Computer Communication and Network Security (CCNS) (pp. 51-54). IEEE

[11] Arshad, T, Jia, M, Guo, Q, Gu, X and Liu, X, 2019. "Fruit Classification Through Deep Learning: A Convolutional Neural Network Approach", In International Conference in Communications, Signal Processing, and Systems (pp. 2671-2677). Springer, Singapore.

[12] Tetila, E.C, Machado, B.B, Astolfi, G, de Souza Belete, N.A, Amorim, W.P, Roel, A.R and Pistori, H, 2020. "Detection and classification of soybean pests using deep learning with UAV images", Computers and Electronics in Agriculture, vol. 179, pp. 105836.

[13] Panchbhaiyye, V and Ogunfunmi, T, 2018. "Experimental results on using deep learning to identify agricultural pests", In 2018 IEEE Global Humanitarian Technology Conference (GHTC) (pp. 1-2). IEEE.

[14] Thenmozhi, K and Reddy, U.S, 2019. "Crop pest classification based on deep convolutional neural network and transfer learning", Computers and Electronics in Agriculture, vol. 164, pp. 104906.

[15] Nanni, L, Maguolo, G, and Pancino, F. (2020). "Insect pest image detection and recognition based on bio-inspired methods", Ecological Informatics, vol. 57, pp. 101089.

[16] Fan, T. and Xu, J, 2020. "Image classification of crop diseases and pests based on deep learning and fuzzy system", International Journal of Data Warehousing and Mining (IJDWM), vol. 16, no. 2, pp. 34-47.

[17] R. K. Gaur, M. Kumar, S. Sharma, and B. S. Yadav, "Survey studies on insects and non insect pest associated with ber crop in South West Haryana," Journal of Entomology And Zoology Studies, vol. 8, no. 2, pp. 856–863, 2020.

[18] Y. Ai, C. Sun, J. Tie, and X. Cai, "Research on recognition model of crop diseases and insect pests based on deep learning in harsh environments," IEEE Access, vol. 8, no. 3, pp. 171686–171693, 2020.

[19] Li, R. Wang, C. Xie et al., "A recognition method for rice plant diseases and pests video detection based on deep convolutional neural network," Sensors, vol. 20, no. 3, pp. 578–591, 2020.

[20] R. K. Singh and J. Minj, "Detection of bacterial and fungal leaf diseases using image processing and machine learning techniques," International Journal of Computer Science and Engineering, vol. 7, no. 3, pp. 1126–1129, 2019.

[21] Pattnaik, G., Shrivastava, V. K., and Parvathi, K. (2020). "Transfer learning-based framework for classification of pest in tomato plants", Applied Artificial Intelligence, vol. 34, no. 13, pp. 981-993.

[22] Y. He, H. Zeng, Y. Fan, S. Ji, and J. Wu, 2019. "Application of Deep Learning in Integrated Pest Management: A Real-Time System for Detection and Diagnosis of Oilseed Rape Pests," Mobile Information Systems, vol. 2019.

[23] W. Dawei, D. Limiao, N. Jiangong, G. Jiyue, Z. Hongfei, and H. Zhongzhi, "Recognition pest by image-based transfer learning", Journal of the Science of Food and Agriculture, vol. 99, no. 10, 2019, pp. 4524– 4531.

[24] X. Wu, C. Zhan, Y. Lai, M.-M. Cheng, and J. Yang, "IP102: A Large-Scale Benchmark Dataset for Insect Pest Recognition", in IEEE CVPR, 2019.

[25] Ayan, H. Erbay, F. J. C. Varçın, and E. i. Agriculture, 2020. "Crop pest classification with a genetic algorithm-based weighted ensemble of deep convolutional neural network", vol. 179, pp. 105809.

[26] Ren, W. Liu, and G. J. I. A. Wu, 2019. "Feature reuse residual networks for insect pest recognition", vol. 7, pp. 122758- 122768.

[27] N. E. M. Khalifa, M. Loey, and M. H. N. J. J. T. A. I. T. Taha, 2020. "Insect pests recognition based on deep transfer learning models", vol. 98, no. 1, pp. 60-68,

[28] Wang, Q.J, Zhang, S.Y, Dong, S.F, Zhang, G.C, Yang, J, Li, R and Wang, H.Q, 2020. "A large-scale very small object data set of agricultural pests for multi-target detection", Computers and Electronics in Agriculture, vol. 175, pp. 105585.

[29] Karar, M. E, Alsunaydi, F, Albusaymi, S and Alotaibi, S, (2021). A new mobile application of agricultural pests recognition using deep learning in cloud computing system. Alexandria Engineering Journal, vol. 60, no. 5, pp. 4423-4432.

[30] Gutierrez, A, Ansuategi, A, Susperregi, L, Tubío, C, Rankić, I, and Lenža, L. (2019). A benchmarking of learning strategies for pest detection and identification on tomato plants for autonomous scouting robots using internal databases. Journal of Sensors, 2019.

[31] Patel, D and Bhatt, N. (2021). Improved accuracy of pest detection using augmentation approach with Faster R-CNN. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1042, No. 1, p. 012020). IOP Publishing.

[32] Butera, L, Ferrante, A, Jermini, M, Prevostini, M and Alippi, C. (2021). "Precise Agriculture: Effective Deep Learning Strategies to Detect Pest Insects", IEEE/CAA Journal of Automatica Sinica, vol. 9, no. 2, pp. 246-258.

[33] Sourav, M. S. U and Wang, H. (2022). "Intelligent Identification of Jute Pests Based on Transfer Learning and Deep Convolutional Neural Networks", Neural Processing Letters, pp. 1-18.

[34] Suneja, B, Negi, A, Kumar, N and Bhardwaj, R. (2022). "Cloud-based Tomato Plant Growth and Health Monitoring System using IoT", In 2022 3rd International Conference on Intelligent Engineering and Management (ICIEM) (pp. 237-243). IEEE.