Available online at www.sciencedirect.com

ScienceDirect

Procedia Computer Science 252 (2025) 1–6

Procedia Computer Science

www.elsevier.com/locate/procedia

4th International Conference on Evolutionary Computing and Mobile Sustainable Networks

Evolutionary Computation in Early Detection and Classification of Plant Diseases from Aerial View of Agricultural lands

K. Sujatha[a,*], R.S. Ponmagal[b], Prameeladevi Chillakuru[c], U. Jayalatsumi[d], N. Janaki[e], NPG. Bhavani[f]

[a]*Professor, EEE Department, Dr. MGR Educational and Research Institute, Chennai-600095, India.*
[b]*Professor, CSE Department, SRM Institute of Science and Technology, Chennai, India.*
[c]*Asso. Professor, Artificial Intelligence and Data Science, Velammal Institute of Technology, Chennai, India.*
[d]*Associate Professor, ECE Department, Dr. MGR Educational and Research Institute, Chennai-600095, India.*
[e] *Assistant Professor, EEE Department, Vels Institute of Science, Technology & Advanced Studies, Chennai, India.*
[f]*Associate Professor, ECE Department, Saveetha Institute of Medical and Technical Sciences, Chennai, India.*

Abstract

This research presents a new combined deep learning system for effective and reliable identification of plant diseases in complicated agricultural environments. One of the most difficult jobs in agriculture is identifying plant diseases early on. Early disease detection in plants is crucial for increasing agricultural yield. With the application of machine learning and deep learning techniques, this issue has been resolved. Large crop farms can now detect plant illnesses automatically, which is advantageous as it reduces the monitoring time. The suggested approach consists of multiple important stages. To begin with, image quality of the agricultural lands is improved through preprocessing techniques like noise reduction, gamma correction and white balancing. Data augmentation is incorporated to expand the dataset and improve the generalization capacity of the model. Efficient methods such as EfficientDet and Squeeze Net, as well as color and shape based features, are included in feature extraction. The most relevant features are selected by a Hybrid Optimization Algorithm (HOA), which integrates Mother Optimization Algorithm (MOA), Teaching learning-based optimization (TLBO) and Improved Wild Horse Optimization to detect the various plant diseases like Bacterial Blight, Tungro, Blast and Brown spot. At last, a deep learning detector, which may include Recurrent Convolutional Neural Networks (R-CNNs) and Recurrent Neural Network (RNN), identifies the location and type of objects. The use of hyper parameter tuning techniques is also implemented to avoid over fitting and improve the overall generalization. This comprehensive approach depicts encouraging results in overcoming challenges in plant disease detection.

Keywords: EfficientDet, Squeeze Net; Plant diseases, Mother Optimization Algorithm, Teaching learning-based optimization *and Improved Wild Horse Optimization; R-CNNs and recurrent neural networks*

This is an open access article under the CC BY-NC-ND license (https://creativecommons.org/licenses/by-nc-nd/4.0)
Peer-review under responsibility of the scientific committee of the 4th International Conference on Evolutionary Computing and Mobile Sustainable Networks
10.1016/j.procs.2024.12.001

1. Introduction

The need for efficient analysis arises due to the daily accumulation of large amounts of aerial and satellite imagery; and presenting a new method in the proposed work that uses content-based techniques to automatically identify and annotate objects or areas in high-resolution aerial images [1] and innovate Convolutional Neural Network (CNN) models for detecting important ground features in aerial disaster images, such as buildings, vehicles, vegetation, debris, and floods [2].The identification of objects in aerial images is difficult due to differences in size and direction, as well as a shortage of comprehensive standards, leading to limited advancements in this area [3].Presents a rapid, accurate vehicle detection system employing Adaptive Virtual Private Network (AVPN) to achieve precision for small objects, and a combined R-CNN for simultaneous identification of vehicle location and characteristics [4]. Identifying various objects in remote sensing images is difficult, and deep learning methods such as Full Resolution Convolutional Network (FRCN) are showing potential despite facing application challenges [5].

When using Earth Vision, accurately identifying, and classifying objects in aerial photos typically involves the use of OBBs. However, this can lead to problems with uncertainty in defining the target, which can impact the efficiency and accuracy of the process [6]. CNN is used to examine aerial images captured by high definition cameras fixed in the Unmanned Aerial Vehicle (UAV) and is divided into tiles, for the classification of multiple labels using radial basis function network [7]. Presenting YOLO, designed specifically for analysing multiple types of remote sensing imagery, providing a range of detection capabilities at different scales, the ability to detect small targets, predicting orientations, and featuring a unique mid-level fusion architecture [8] and presenting "Focus-and-Detect," a two-stage approach to addressing the detection of small objects. This framework includes a clustering object detector guided by Gaussian distribution and specific prediction for focal regions. Additionally, it incorporates Incomplete Box Suppression to handle challenges related to object truncation [9]. Presenting a point-based estimator design that utilizes spatial data through point representation and a convolutional network to improve localization precision and differentiate recognition by aligning instances to achieve feature-to-region congruence [10].

Feature Fusion Deep Networks (FFDN), improves the detection of aerial images by using a combination of structural learning layer to enhance the spatial relationship between the objects. This has shown significant progress on UAV123 and UAVDT datasets [11]. A Network for Multi-Scale Object Detection in Aerial images (mSODANet) is a network specifically created for the purpose of identifying objects within aerial images. Hierarchical dilated convolutions are utilized to analyse context from various perspectives and scales, ultimately enhancing the ability to capture and detect visual data effectively [12] and suggested the use of Adaptive Saliency Biased Loss to improve DNN object detectors.

2. Literature Survey

In 2024, Ge et al. [9] suggested an adaptable dynamic labelling method to enhance the detection of small objects by adjusting the allocation thresholds for samples according to the specific characteristics of each ground truth. This method, using dynamic IoU, improved training by adjusting sample sets, leading to a significant improvement in performance on various standard agricultural datasets without increasing computational expenses. Our approach has exceeded the current standards in both efficiency and accuracy.

In 2024, Weng et al. [10] presented the Selective Frequency Interaction network, which is a new method for detecting aerial objects. It includes two main components: Selective Frequency-domain Features Interaction and Selective Frequency-domain Feature Extraction (SFFE). The SFFE module excelled in extracting important frequency-domain information and it significantly improved the richness of feature maps at various frequencies.

In 2022, Wang et al. [6] proposed the Adaptive Recursive Feature Pyramid, which encompasses a recursive structure, an Efficient Global Context bottleneck, and a Discriminative Feature Fusion module. This design allowed for efficient utilization of semantic and location information across pyramid levels by using dense connections and adaptive weighting. Extensive testing on VisDrone2019 and DIOR datasets showed that ARFP outperformed existing models, with average performance gains of 2.7% and 2.8% respectively.

In 2022, Xu et al. [3] created a new evaluation method known as Normalized Wasserstein Distance, combined with a Ranking-based Assigning approach, in order to enhance the identification of small objects. The NWD-RKA approach, which can be used with various anchor-based detectors, has replaced traditional IoU threshold-based methods, leading to substantial enhancements in label assignment and offering extensive training supervision. After conducting tests on four separate datasets, it was evident that NWD-RKA significantly improved the detection of small objects.

In 2022, Hu et al. [4] suggested a training method called Correction Maximization Training, which focuses on removing incorrect annotations from datasets before training a model. We developed a new noise filter called the Probability Differential as part of our strategy to accurately identify and correct errors in labels. After being cleaned, the detector was trained using the revised dataset. This method showed that it works well with popular object detectors like Faster RCNN and Retina Net, requiring few changes to hyper-parameters when used with different datasets and models.

In 2021, Han et al. [8] presented the Single-shot Alignment Network comprising a Feature Alignment Module and an Oriented Detection Module (ODM). The FAM utilized a new Alignment Convolution method to improve anchoring and adjust features, while the ODM employed rotating filters to encode orientation, thereby enhancing the alignment between classification and localization. This approach also enhanced the identification of objects in extensive images, finding a more favorable balance between quickness and precision.

In 2021, Xu et al. [12] tackled the issue of feature misalignment by introducing a streamlined single-shot detector that incorporates a pseudo anchor proposal module and a context-based feature alignment module. The PAPM enhanced the primary anchors for aligned positions, addressing spatial misalignment and imbalance issues. Following this, CFAM adjusted the sampling points of the convolution kernel using the main anchors, effectively resolving any misalignment between the kernel and the object and extracting powerful, aligned features.

In 2020, Wang et al. [7] created a new method for training and making inferences, significantly improving the accuracy of detecting objects in high-resolution aerial photographs. This method, different from straightforwardly regressing object orientations, used segmentation tasks to make more accurate predictions of rotated bounding boxes. Paired with a strategy that synthesizes images for data augmentation, it effectively tackled the challenges of data imbalance and achieved remarkable performance on the Dataset of Object detection in Aerial images (DOTA) dataset through extensive experimentation.

In 2020, Wang et al. [5] suggested to change the method of regression by instead predicting center-probability maps. This would help to minimize uncertainties related to identifying targets and background pixels. The use of the forecasted center maps helped in creating regression models. The center maps based regression models are known for its simplicity and effectiveness. Additionally, weighted pseudo segmentation-guided attention network was used to enhance the distinction between the desired objects and the densely populated background.

In 2018, Xu et al. [11] presented a new framework for detecting moving objects, which improves accuracy by extracting selected feature points and predicting registration accuracy. Drawing on input from previous iterations, we removed inaccuracies and incorporated a measurement to anticipate registration precision, providing guidance for incorporating supplementary indicators. Our study on feature extractors for registering aerial infrared images found that SURF and LDB are highly effective.

3. Proposed Method

To enhance the initial quality and feature extraction from the images of the agricultural lands, a series of preprocessing steps are incorporated, including Bilateral Filtering for diminishing noise without blurring edges, Gamma Correction for optimizing contrast, and Grey Card Reference-based White Balancing for achieving accurate color representation. To reduce the risk of over fitting and bolster the algorithm's ability to generalize across diverse data, the research work applied data augmentation techniques such as rotations, mirroring, and scaling. In the feature extraction phase, a dual approach is utilized by combining EfficientDet and SqueezeNet for capturing complicated features like Color Correlograms and Color Coherence Vectors for color attributes, and geometric metrics like Area, Perimeter, and Eccentricity for shape attributes. To ensure the selection of the most impactful features, a novel hybrid optimization algorithm is introduced by merging the MOA with an Enhanced Wild Horse Optimization (EWHO) integrated with TLBO, fine-tuning the feature selection process for optimal performance. For the object detection mechanism, integrated an advanceddeep learning framework that combines the strengths of region-based CNN, BiLSTM and Recurrent Neural Networks. This ensemble is carefully designed to localize and categorize objects with high precision. Additionally, to optimize the model's accuracy and robustness, a unique combination of hybrid deep learning methodologies for hyperparameter optimization, effectively minimizing over fitting while maximizing generalization is employed across unseen plant images as depicted in Figure 1. During the initial processing stage, improve the quality of the image by employing various enhancement techniques such as utilizing Bilateral Filtering to suppress noise, implementing Gamma Correction to optimize contrast, and enhancing color accuracy with the use of a Grey Card Reference for white balancing. Furthermore, enhance the dataset and the model's flexibility by utilizing data augmentation techniques.

Fig. 1. Images of the plants affected by various diseases

4. Results and Discussion

This study utilizes PYTHON to execute the proposed model, employing performance indicators such as NPV, MCC, FNR, FPR, precision, F-measure, sensitivity, specificity, and accuracy. A hybrid optimization model enhances accuracy. It also explores accuracy loss and density variations at learning rates of 70% and 75%. Table 1 delineates the comparative performance metrics for various models, each set at a learning rate of 70%. In Table 2, the assessment of various models at a learning rate of 75% is displayed.

Table 1. Performance measures of proposed model with learning rate 70%

	Bacterial Blight		Tungro		Blast		Brown spot	
	Algorithm used for training and testing							
Metrics	**RNN**	**R-CNN**	**RNN**	**R-CNN**	**RNN**	**R-CNN**	**RNN**	**R-CNN**
Accuracy	00.974	00.972	00.973	00.972	00.974	00.932	00.964	00.972
Precision	00.817	00.843	00.826	00.842	00.817	00.843	00.827	00.843
Sensitivity	00.984	00.984	00.963	00.934	00.984	00.944	00.974	00.984
Specificity	00.978	00.976	00.954	00.926	00.978	00.956	00.968	00.976
F-Measure	00.898	00.917	00.875	00.907	00.898	00.927	00.888	00.917
MCC	00.884	00.902	00.877	00.912	00.884	00.922	00.894	00.902
NPV	00.988	00.992	00.986	00.942	00.988	00.932	00.978	00.992
FPR	00.029	00.021	00.028	00.027	00.028	00.021	00.028	00.0219
FNR	00.015	00.013	00.017	00.014	00.018	00.016	00.019	00.012

Table 2. Performance measures of proposed model with learning rate 75%

	Bacterial Blight		Tungro		Blast		Brown spot	
	Algorithm used for training and testing							
Metrics	**RNN**	**R-CNN**	**RNN**	**R-CNN**	**RNN**	**R-CNN**	**RNN**	**R-CNN**
Accuracy	00.971	00.986	00.963	00.971	00.977	00.952	00.964	00.972
Precision	00.853	00.888	00.726	00.843	00.937	00.893	00.877	00.843
Sensitivity	00.984	00.985	00.863	00.932	00.978	00.944	00.977	00.984
Specificity	00.971	00.986	00.854	00.924	00.976	00.956	00.988	00.976
F-Measure	00.927	00.946	00.875	00.905	00.998	00.927	00.868	00.917
MCC	00.915	00.938	00.877	00.916	00.984	00.922	00.899	00.902
NPV	00.987	00.975	00.886	00.947	00.988	00.932	00.977	00.992
FPR	00.0239	00.027	00.028	00.026	00.037	00.032	00.028	00.029
FNR	00.021	00.025	00.027	00.026	00.025	00.026	00.029	00.022

5. Conclusion

This study presents a cutting-edge hybrid deep learning strategy designed to overcome the challenges presented by traditional monitoring methods, especially in complex and computationally limited scenarios. By incorporating advanced image enhancement techniques like Bilateral Filtering, Gamma Correction, and White Balancing, along with extensive data augmentation, the approach substantially improves image quality and increases the dataset size, enabling more precise feature extraction for accurate plant disease detection. This is the major strength of this work. The methodology leverages EfficientDet and Squeeze Net to extract robust features, and introduces innovative descriptors such as the Color Coherence Vector and shape-based metrics to form an extensive feature set. The integration of complex deep learning architectures, including region-based RNN and R-CNN, with strategic hyper-parameter optimization, ensures not only high accuracy but also effective generalization to new scenarios. The future potential for this technology is significant. Prospective studies could investigate its application to real-time scenarios in dynamic environments like autonomous driving and surveillance, where fast and dependable object detection is essential. One drawback of this work is that the computational complexity increases because of the usage of various machine learning algorithms. Further, advancements could include exploring more complex deep learning models and additional optimization strategies to further improve both the precision and the speed of the object detection system, extending the frontiers of current capabilities in the field.

References

[1]. Ševo, I. and Avramović, A., (2016). "Convolutional neural network based automatic object detection on aerial images". IEEE geoscience and remote sensing letters, 13(5), pp.740-744.

[2]. Pi, Y., Nath, N.D. and Behzadan, A.H., (2020). Convolutional neural networks for object detection in aerial imagery for disaster response and recovery. Advanced Engineering Informatics, 43, p.101009.

[3]. Ding, J., Xue, N., Xia, G.S., Bai, X., Yang, W., Yang, M.Y., Belongie, S., Luo, J., Datcu, M., Pelillo, M. and Zhang, L., (2021). Object detection in aerial images: A large-scale benchmark and challenges. IEEE transactions on pattern analysis and machine intelligence, 44(11), pp.7778-7796.

[4]. Deng, Z., Sun, H., Zhou, S., Zhao, J. and Zou, H., (2017). Toward fast and accurate vehicle detection in aerial images using coupled region-based convolutional neural networks. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 10(8), pp.3652-3664.

[5]. Deng, Z., Sun, H., Zhou, S., Zhao, J., Lei, L. and Zou, H., (2018). Multi-scale object detection in remote sensing imagery with convolutional neural networks. ISPRS journal of photogrammetry and remote sensing, 145, pp.3-22.

[6]. Wang, J., Yang, W., Li, H.C., Zhang, H. and Xia, G.S., (2020). Learning center probability map for detecting objects in aerial images. IEEE Transactions on Geoscience and Remote Sensing, 59(5), pp.4307-4323.

[7]. Zeggada, A., Melgani, F. and Bazi, Y., 2017. A deep learning approach to UAV image multilabeling. IEEE Geoscience and Remote Sensing Letters, 14(5), pp.694-698.

[8]. Sharma, M., Dhanaraj, M., Karnam, S., Chachlakis, D.G., Ptucha, R., Markopoulos, P.P. and Saber, E., (2020). YOLOrs: Object detection in multimodal remote sensing imagery. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14, pp.1497-1508.

[9]. Koyun, O.C., Keser, R.K., Akkaya, I.B. and Töreyin, B.U., (2022). Focus-and-Detect: A small object detection framework for aerial images. Signal Processing: Image Communication, 104, p.116675.
[10]. Fu, K., Chang, Z., Zhang, Y. and Sun, X., (2020). Point-based estimator for arbitrary-oriented object detection in aerial images. IEEE Transactions on Geoscience and Remote Sensing, 59(5), pp.4370-4387.
[11]. Long, H., Chung, Y., Liu, Z. and Bu, S., (2019). Object detection in aerial images using feature fusion deep networks. IEEE Access, 7, pp.30980-30990.
[12]. Chalavadi, V., Jeripothula, P., Datla, R. and Ch, S.B., (2022). mSODANet: A network for multi-scale object detection in aerial images using hierarchical dilated convolutions. Pattern Recognition, 126, p.108548.

.