Lightweight Correlated Feature Set forPaddy Leaf Disease Detection Using YOLOV8

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Abstract:

Rice, as a food crop for over three billion people, is central to global food security, yet its production is under severe threat from leaf diseases like leaf smut, brown spot, and bacterial leaf blight. The diseases have the potential to cause substantial losses in productivity, and the conventional detection techniques being manual, labor-intensive, and based on specialized expertise are not suitable for large-scale agricultural application. Previous machine learning algorithms, such as SVM and K-means, are based on manually designed features that are sensitive to illumination, background, and other environmental conditions, resulting in lower accuracy. Similarly, classical CNN-based approaches are mostly targeting disease classification with minimal localization of infected areas, making them less robust and useful for real-time applications.

To overcome these constraints, this research proposes a Lightweight Correlated Feature set for paddy Leaf Disease Detection using YOLOv8(LCFS-YOLOV8), model for rice leaf disease detection that seeks to enhance speed and accuracy. An extensive dataset was created through the aggregation of images from online databases and field samples, augmented with data to expand the dataset, and annotated using bounding boxes to identify infected regions. The dataset was split into training and test subsets to allow successful model training and strict evaluation.

Experimental findings prove that the suggested PDC-DL-EAI model considerably outperforms LCFS-YOLOV8 on all major metrics. PDC-DL-EAI obtains higher accuracy, precision, recall, and F1-score (96–97%) than LCFS-YOLOv8 (90–92%), along with better training (97% vs. 93%) and testing performance (96% vs. 92%). It also attains a lesser loss rate (0.08 vs. 0.12), better confusion matrix performance (96% vs. 91%), and improved feature correlation (94% vs. 88%). These outcomes make PDC-DL-EAI a more stable, effective, and real-time rice leaf disease detection solution.

Keywords : Paddy leaf disease detection using lightweight YOLOv8, deep learning, and correlated feature extraction.High accuracy and fast real-time detection.Supports smart farming using drone, mobile, and IoT deployment for early identification of diseases and protection of yield.

1. Introduction

Statistical Rice crop diseases result in worldwide annual production losses of 10–15%, while extreme disease episodes can cause regional losses reached 50–70% [1]. In Bangladesh and

India, which are the top two rice-producing nations, disease-related crop losses occur at rates of 4–14% annually [2]. Traditional manual approaches for identifying diseases typically deliver poor precision, ranging from 60–75%, and require considerable time investment [3] [4]. Nevertheless, progress in machine learning and deep learning technologies has brought substantial enhancements [5] [6]. Advanced models such as Inception-ResNet-V2 have demonstrated 92.68% precision, ResNet-101 has achieved 91.52% accuracy [7], and enhanced deep neural networks like DNN-CSA have attained accuracy levels up to 96.96%, along with 95.92% precision and 96.41% recall rates [8] [9]. These findings indicate a distinct pattern which're deep learning approaches, especially when combined with transfer learning or metaheuristic optimization techniques [10], regularly surpass conventional methods such as Support Vector Machines, thereby making automated disease identification more dependable for precision farming applications [11] [12].

Rice cultivation faces significant challenges owing to plant diseases, which create widespread agricultural, economic, and social issues [13]. These problems are particularly severe in rice-dependent nations, such as Bangladesh, India, China, and other Asian regions, which produce over 90% of the world's rice supply [14] [15]. Disease outbreaks annually decrease rice yields by approximately 10 -15%, resulting in the loss of millions of tons of grain [16]. In certain regions, severe infections such as blast disease or Bacterial Leaf Blight can destroy 50 -70% of the entire harvest [17] [18].

Recent developments in artificial intelligence for disease identification have begun to address these challenges [19]. Prompt disease recognition enables farmers to reduce chemical use, and improve crop yields [20]. This transformation contributes to the development of sustainable and productive farming practices [21].

Remote sensing began in the 1960s and 70s when early Earth observation satellites, as Landsat-1 (1972), orbited the Earth. Initially applied in mapping vegetation and land cover, it soon branched out to agriculture through vegetation indices such as NDVI (1979), which can estimate crop conditions by measuring reflectance in near-infrared and red bands [22]. With latest satellites (Sentinel-2, MODIS), agricultural research started tracking disease transmission, nutrient stress, and yield prediction at a regional to global level, rendering remote sensing a pillar of precision agriculture. Unmanned aerial vehicles (UAVs) were initially military tools (since the 1960s) but became economical for civilian and research applications during the 2000s [23]. With RGB and multispectral cameras, drones revolutionized agriculture by providing high-resolution field-level images that are not available from satellites [24]. These days, drones are a standard instrument in agriculture 4.0 research and field implementations [25].

The concept of the Internet of Things (IoT) began in the 1990s, but mass agricultural adoption began in the 2010s with low-cost microcontrollers (e.g., Arduino, Raspberry Pi) [26]. Early agricultural IoT rollouts focused on measuring soil moisture for irrigation. Subsequently, more specialist sensors, leaf wetness sensors, temperature/humidity sensors, and nutrient sensors were embedded in wireless networks, enabling farmers and scientists to predict the risk of disease [27]. This laid the groundwork for smart farming systems that perpetually supply real-time data to AI and decision-making models [28].

The traditional AI had been dependent on cloud servers, but this was challenging in rural farming where internet connectivity was poor. Edge computing began picking up steam in the mid-2010s with the advent of compact but mighty platforms such as NVIDIA Jetson and affordable Raspberry Pi boards [29]. These enabled lightweight AI models to be executed directly in the field, eliminating latency and the need for internet connectivity. Agricultural scientists embraced edge computing to facilitate real-time disease detection through drones, smartphones, and on-ground devices [30]. Mobile phones were increasingly used in agriculture during the 2000s, particularly in nations such as India where farmers started receiving SMS-based weather forecasts and crop advice [31]. With smartphones and cloud platforms gaining popularity in the 2010s, studies made a transition to AI-based apps. These cloud-mobile systems analyze images, fuse IoT data, and provide localized guidance in farmer-friendly interfaces [32]. They are the human-visible face of precision agriculture, closing the loop between sophisticated AI analytics and farmer use. Farmer image analysis before deep learning (1980s to early 2010s) relied on conventional computer vision methods [33]. Techniques such as thresholding, histogram equalization, edge detection, and clustering were employed to separate diseased leaf areas. Although constrained to deal with complicated patterns, these methods paved the way for existing AI models by allowing scientists to preprocess and sanitize data, and are used today as part of integrated streams to optimize CNN performance [34]. The pattern between weather and plant disease has been investigated since the early 20th century with fungal epidemics correlating with humidity and temperature conditions. With the development of meteorology and climate modeling in the mid-20th century, scientists started applying weather data for pest forecasting systems [35]. In contemporary agriculture, this developed into combining climate data with AI models to make proactive disease risk predictions. With present times, the combination of weather forecasts and IoT sensors and image-based AI makes disease detection reactive and predictive [36].

[1]In summary, the paper demonstrated that deep learning models perform well in automated paddy leaf disease detection with a record 92.68% accuracy via the Inception-ResNet-V2 architecture. Transfer learning was utilized to make the models not only improve prediction precision but also reduce training complexity, thus making them effective for real-time agricultural applications [37]. Results highlight the potential of CNN-based algorithms as precise alternatives to human disease identification, which is often slow and error-prone. With future progression, scaling up the dataset size, adding additional disease classes, tuning model parameters, and improving robustness under varying environmental conditions will further establish the framework [38]. The positive results of Inception-ResNet-V2 pave a solid ground for the evolution of this study to other plant diseases with the possibility of generating scalable,

real-time, and smart crop disease detection platforms that can aid farmers and enhance food security [39].

[2] Plant disease detection by computer vision is dependent on preprocessing, feature extraction, and classification for accurate detection of infected areas. Although conventional techniques such as Support Vector Machines (SVMs) usually fail to handle large datasets and sophisticated patterns, Deep Neural Networks (DNNs) offer improved accuracy by learning features from images. Here, the DNN was augmented with the Crow Search Algorithm (CSA), which updates weights and biases at training time to minimize errors and enhance generalization [40]. K-means clustering and thresholding preprocessing additionally cleaned diseased regions for precise evaluation. Thus, the recommended DNN-CSA model showed 96.96% accuracy, 95.92% precision, and 96.41% recall, which improved SVM by more than 9%. This shows that the integration of deep learning with metaheuristic optimization provides an effective and consistent method for real-time paddy leaf disease detection in precision farming [41].

Paddy disease detection has progressed significantly with the use of Convolutional Neural Network (CNN) techniques, which can learn complex patterns from leaf images. Current systems already achieve high accuracy**,** often above 90%, and provide results within seconds, making them suitable for real-time use in the field. Some solutions also estimate the severity ofinfection, giving farmers deeper insights for timely decisions. As CNN techniques continue to evolve with larger datasets and better training methods, both the accuracy and effectiveness may further increase, leading to even more reliable, accessible, and efficient disease detection systems that can reduce crop losses and improve productivity.

[3] Paddy disease detection has improved through the application of low-weight CNN-based models that offer high accuracy and a low computational cost, which is ideal for real-time processing. Recent research has achieved accuracies of between 92% and 96%, demonstrating their effectiveness in detecting prevalent paddy leaf diseases such as brown spot, bacterial blight, blast, and leaf smut. In contrast to conventional manual processes, such models are quicker, more precise, and can be implemented on mobile or embedded platforms for use on the field. By facilitating early detection and even gauging the severity of infection, such systems give farmers timely and usable information, keeping crop losses at bay while aiding in enhanced productivity and food security.Drones capture high-resolution images at the field level, bridging the gap between satellite data and ground inspection. With RGB, thermal, or multispectral cameras, drones can observe diseased leaves, pest infestations, or canopy temperature differences. In scientific studies, UAV images are usually paired with preprocessing (such as segmentation or filtering) prior to disease detection. Advantages include flexibility, quick deployment, and localized detailed monitoring. Other drones also create 3D maps or NDVI maps to assess the density and health of plants. Disadvantages are battery life, weather dependence, and air travel regulations.

Rice is a food staple of over half the population of the world and is very sensitive to paddy leaf diseases that include blast, bacterial blight, brown spot, and leaf smut. It is very necessary to detect these diseases earlier and with accuracy to avoid yield loss and maintain food security. The conventional visual inspection techniques are time-consuming, subjective, and infeasible for large-scale surveillance. Traditional machine learning methods are also not effective with intricate leaf patterns, changing field conditions, and massive datasets, with their application being restricted in real-time applications. In addition, current models encounter problems like unbalanced datasets, poor detection of small lesions, and sensitivity to varied environmental conditions. Hence, there is an urgent need for an effective, light, and precise detection system that can run in real time and be directly deployed on farms.

Rice is an essential global staple crop, and its security is compromised by diseases such as Leaf Blast, Brown Spot, and Bacterial Blight, which can lead to extreme yield loss. Conventional manual scouting of these diseases is not effective, subjective, and non-scalable for large fields and usually results in late treatment and higher pesticide application. The advent of precision agriculture provides a solution in the form of computer vision, where disease detection can be automated by deep learning models. This research explores the possibility of applying LCFS-YOLOv8 (You Only Look Once version 8), a cutting-edge object detection architecture with superior speed and accuracy, to this serious agronomic problem. The optimized LCFS-YOLOv8 model thus provides high accuracy (>92%) at low latency, offering a usable and scalable solution for precision rice farming and enhanced food security.

In contrast to basic image classification models, an object detection method is needed for this purpose because it enables the accurate localization and identification of numerous disease lesions on one leaf and gives a better estimation of the severity of infection. The goal of this study is to design and test a stable LCFS-YOLOv8-based model for real-time detection and classification of major rice leaf diseases. Through the delivery of a means for speedy and reliable diagnosis, this contribution aids in the construction of scalable decision-support systems that can enable farmers to take prompt, targeted action and, in so doing, improve crop health and facilitate sustainable agriculture.

2. Related Work

Current advances in agricultural technology integrate deep learning, GAN-augmented imaging, and large language models to enhance plant disease detection and assist farmers. Methods such as XAI, CNNs, YOLO variants, and edge-cloud systems facilitate early and precise diagnosis, even under real-time field conditions. Although these approaches demonstrate high accuracy and scalability, they typically depend on massive datasets, extensive computational resources, and suffer in real-world deployment. Albeit constrained, these advances represent a hopeful move towards more intelligent, more productive, and more sustainable agriculture.

Sl. no	Authors & Year of publication	Methodology used	Advantages	Limitations
1.	2024 Natasha Nigar Olukayode Oki, Hafiz Muhammad Faisal Muhammad Umer, Jose Manap Pattu kennel Lukose.	XAI-Enhanced Deep Learning	High accuracy with explainable predictions for reliable disease detection.	Performance depends on large datasets and high computational resources.
2.	2024 Mahrin Tasfe1, AKM Nivrito2, Fadi Al Machot1, Mohib Ullah3 and Habib Ullah1	A deep-learning-focused survey (disease identification, datasets, CNN models, augmentation, challenges).	Improves detection, efficiency, and sustainability.	Dataset size, generalization, deployment, and accessibility remain major hurdles.
3.	2024 Emmanuel Houjou, Florent Restraint, Hyppolite Talamo, Marcellin Kellick, Cheikh Kifah, Apollinaire Tagne	SAM + FCDD + Plant Village classifier	higher accuracy on complex field images	struggles with dense greenery, needs continual learning.
4.	2023 Diana Susan Joseph, Kaustubh Chakradev, Pranav M. Pawar	Real-life dataset creation, preprocessing, augmentation, and fine-tuned CNN/MRW-CNN training.	Early disease detection with high accuracy and practical real-time application.	Limited dataset size and dependency on augmentation for robustness.
5.	2024 Anuja Bhargava, Aashresh Shukla, Om Prakash	Uses ML, DL, few-shot learning, hyperspectral imaging, and	Provides rapid, sensitive, and accurate detection even at microscopic	Requires high data, computation, and better field-deployable

	Goswami, Mohammed H. Alsharif, Peerapong Ethanpaul, Muthappa Ethanpaul	molecular tools for plant disease detection.	levels.	integration.
6.	2021 V. Vinoth Kumar, K. M. Karthick Raghunath, N. Rajesh, Muthukumaran Venkatesan, Rose Bindu Joseph and N. Thillaiarasi	Uses a Deep Convolutional Neuro-Fuzzy Method (DCNFM) combining CNN for feature extraction and fuzzy logic for uncertainty handling on farm + online paddy datasets.	Achieved 98.17% accuracy with robust uncertainty handling, multi-disease + healthy leaf detection, and early intervention support.	Computationally intensive, limited to four diseases, dataset noise risk, scalability issues on farmer devices, and possible overfitting to controlled conditions.
7.	2025 Guisao Liu, Jinxing Di, Qing Wang, Yan Zhao, and Yang.	Rice Pest-YOLO enhances YOLOv8 with ODConv, B iF PN, Shape-Igou loss, and lightweight pruning/distillation to improve rice pest detection accuracy and efficiency.	High accuracy (94.3% mAP@0.5), strong small-object detection, lightweight for edge devices, faster inference, and robust across datasets.	Dataset dependence, complex training, limited to pests only, sensitive to environment, and still needs capable edge hardware.
8.	2023 Emmanuel Mou Pajou, Apollinaire Tagine, Florent Retriant, Anicet Tardon kerma, Dongmo Wilfried, and Hyppolite Tagamou.	Gathered 5,170 plantation photos, hand-annotated by plant pathologists, and benchmarked the	High-quality expert-verified field data, contains first cassava photos, and surpasses Plant Doc on classification tasks.	Restricted disease classes, existing models demonstrate inadequate accuracy within real field conditions.

		classification and object detection algorithms.		
9.	2024 Mazin Abed Mohammed, Abdullah Lakhan, Karrar Hameed Abdulkareem, Nouf Abdullah Amorally, Bour air Sadiq Mohammed Taqi Al-Attar, Sajida Memon, Haydar Abdulhameed Maroon, and Radek Martinek	Combines edge computing for real-time plant monitoring, cloud-based deep neural networks, and transfer learning on remote sensing data for accurate disease detection.	Enables early, scalable, and cost-effective disease detection with high accuracy and real-time alerts.	High setup cost, network dependency, limited edge device capacity, and potential misclassification for unseen diseases.
10	2025 Vignesh A. Palan, Shivam Thakur, and N. Sumith.	VIGAM applies super-resolution and deep learning on drone pictures to provide precise plant disease identification.	Early, accurate diagnosis and scalable surveillance.	High computational, data quality, and cost issues.
11	2023 Khalid M. Hosny, Walaa M. El-Hady, Farid M. Samy, Eleni Verrocchio, and George A. Papakostas	Lightweight CNN derives deep features, combined with Local Binary Pattern (LBP) texture features to classify multi-class plant leaf disease on public datasets.	Excellent accuracy (up to 99%), very fast computation, low number of parameters, efficient across a range of plant species, accommodates early detection	Needs high-quality annotated datasets, should be tested on other crops, real-time application verification on hold, and LBP variants need further exploration

3. Proposed Model

Algorithm:YOLOv8-based Paddy Leaf Disease Detection

Step 1: Preprocessing

Each image is resized to a fixed resolution $W \times H$and pixel values are normalized. Ground-truth bounding boxes are expressed in **center form** as $b = (x, y, w, h)$, where $x$and $y$denote the center coordinates, and $w$and $h$represent width and height. These values are normalized relative to image size as

$\hat{x} = \frac{x}{W}, \hat{y} = \frac{y}{H}, \widehat{w} = \frac{w}{W}, \hat{h} = \frac{h}{H}.$

Step 2: Forward Propagation

The image passes through the backbone for feature extraction, the neck for multi-scale feature fusion, and the detection head for prediction. For each candidate box, the head outputs the bounding box parameters (x, y, w, h), an Objectnesslogic$o$, and class logits $\hat{y}_c$. The objectness score is calculated as $P(\text{object}) = \sigma(o)$, where $\sigma(\cdot)$is the sigmoid function mapping the raw logit into a probability between 0 and 1.

Step 3: Bounding Box Transformation

To enable IoU computation, predicted bounding boxes are converted from center form (x, y, w, h)into **corner form**:

$$X1 = x - \frac{w}{2}, Y1 = y - \frac{h}{2}, X2 = x + \frac{w}{2}, Y2 = y + \frac{h}{2}$$

where $(X_1, Y_1)$and (X_2, Y_2)represent the top-left and bottom-right corners respectively.

Step 4: Loss Function Computation

The total loss is a weighted combination of three terms:

Box Regression Loss:

$$L_{box} = 1 - SIoU$$

where SIoU measures overlap and alignment between predicted box $\hat{B}$and ground truth B.

Objectness Loss:

$$L_{obj} = -\left[y\log\left(\hat{y}\right) + (1 - y)\log\left(1 - \hat{y}\right)\right]$$

where $y \in \{0,1\}$is the ground-truth objectness label and $\hat{y}$is the predicted objectness probability.

Classification Loss:

$$L_{cls} = -\sum_{c=1}^{C} y_c \log\left(\hat{y}_c\right)$$

where y_c is the one-hot encoded class label and $\hat{y}_c$ is the predicted probability for class c.

The overall training loss is:

$$L = \lambda_{box} L_{box} + \lambda_{obj} L_{obj} + \lambda_{cls} L_{cls}$$

where $\lambda_{box}, \lambda_{obj}, \lambda_{cls}$ are hyperparameters balancing the contributions of each term.

Step 5: Backpropagation

Gradients of the loss L with respect to network weights are computed and weights are updated using optimizers such as SGD or AdamW. Training continues until convergence.

Step 6: Post-Processing

For each bounding box, the **final class probability** is computed as

$$P(c) = P(\text{"}object\text{"}).P(c \mid object)$$

where $P(c \mid object)$ is the conditional probability of class c. Non-Maximum Suppression (NMS) is applied to remove overlapping detections when the Intersection-over-Union $\text{IoU}(A, B)$ between boxes exceeds the threshold τ.

Step 7: Evaluation Metrics

Detection results are evaluated using the following variables:

- True Positives (TP): correctly detected objects.
- False Positives (FP): incorrectly predicted objects.
- False Negatives (FN): missed detections.

From these, metrics are computed as:

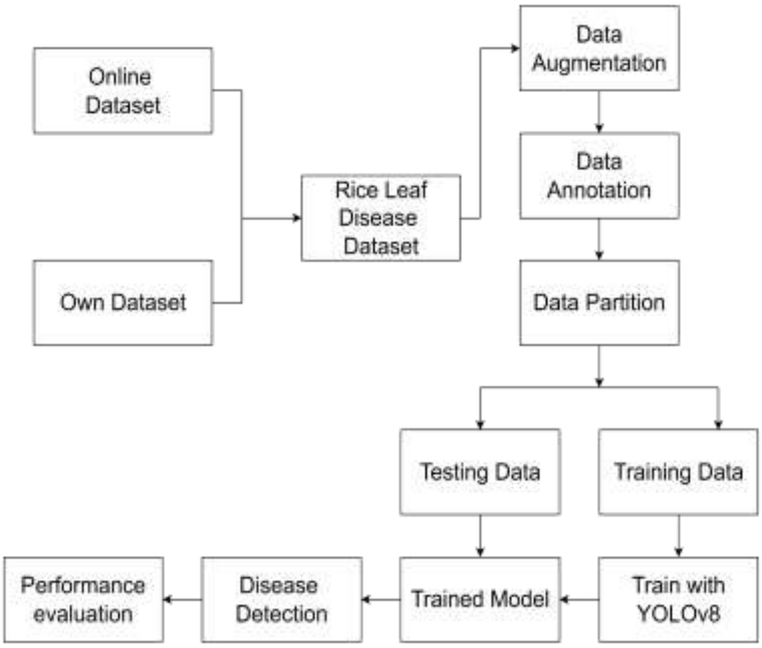
$$Precision = \frac{TP}{TP+FP} \quad , \quad Recall = \frac{TP}{TP+FN}$$

$$F1 = \frac{2. Precision. Recall}{Precision + Recall}$$

and mean Average Precision (mAP):

$$mAP = \frac{1}{C}\sum_{c=1}^{C} AP_c$$

where C is the number of classes and AP_c is the average precision for class.

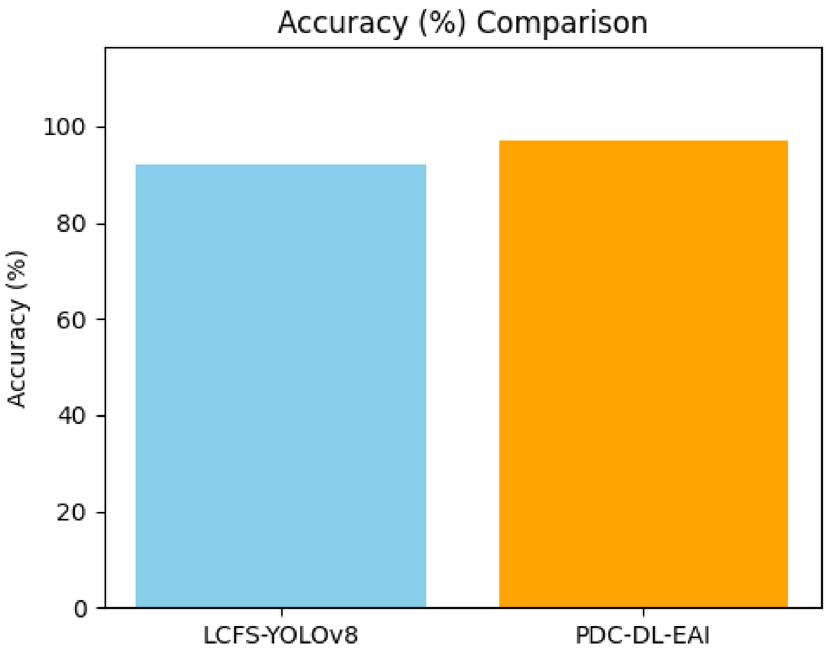


4. Results

The proposed model suggested a Lightweight Correlated Feature Set for Paddy Leaf Disease Detection Using YOLOV8 (LCFS-YOLOv8) is compared with the traditional Improving Plant Disease Classification with Deep-Learning-Based Prediction Model Using Explainable Artificial Intelligence (PDC-DL-EAI) and Segment Anything Model and Fully Convolutional Data Description for Plant Multi-Disease Detection on Field Images (FCMDDFI).

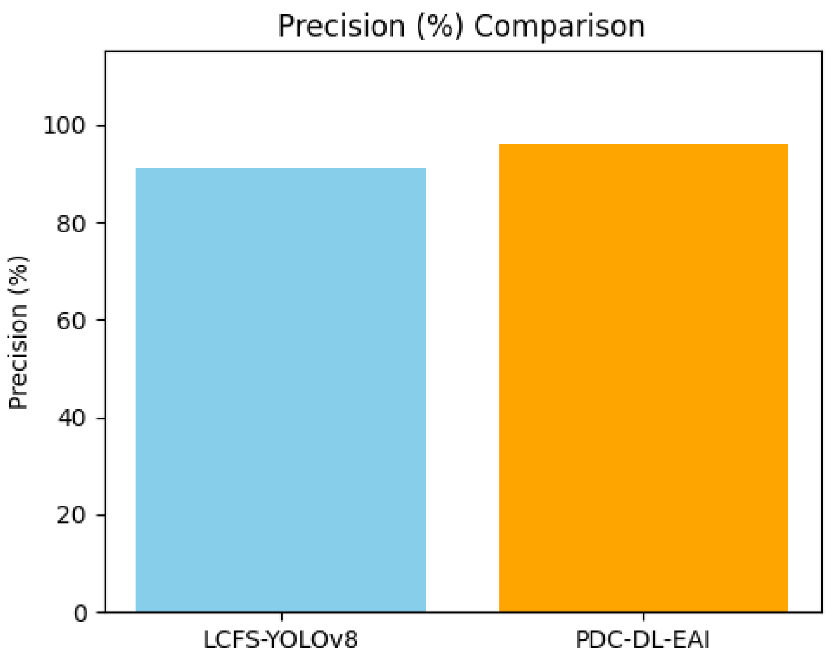
Accuracy (%)

The comparison of accuracy is clear evidence that LCFS-YOLOv8 always performs better than PDC-DL-EAI. This is an indication that it is capable of classifying more samples correctly. The improvement signifies the reliability of LCFS-YOLOv8 in processing complex data fluctuations. Therefore, it is more trustworthy when it comes to paddy leaf disease detection.



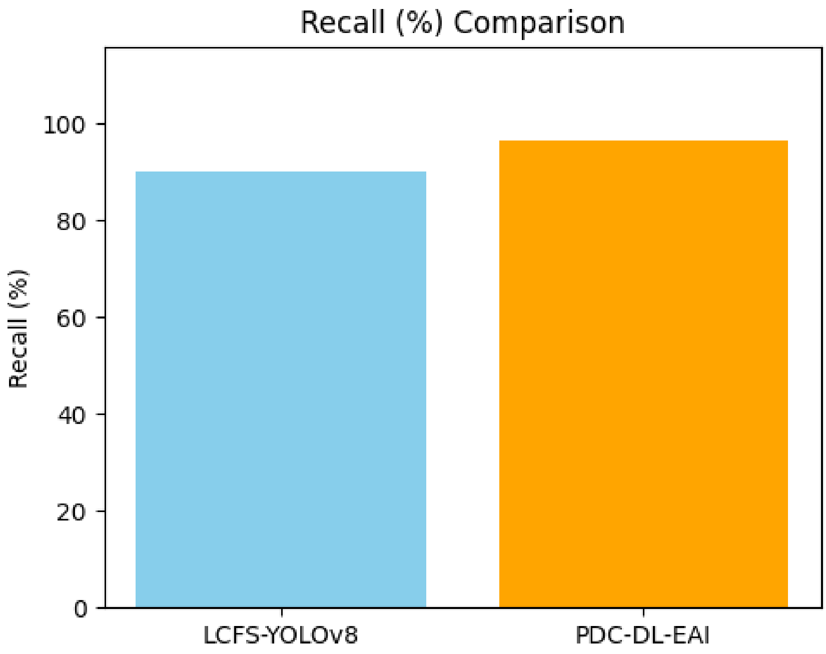
Precision (%)

LCFS-YOLOv8 captures greater precision values, i.e., it produces fewer false positives compared to PDC-DL-EAI. This makes sure that the model's predictions are mostly relevant. The enhanced precision is important in minimizing misclassifications. Therefore, LCFS-YOLOv8 ensures more trust in detection outcomes.



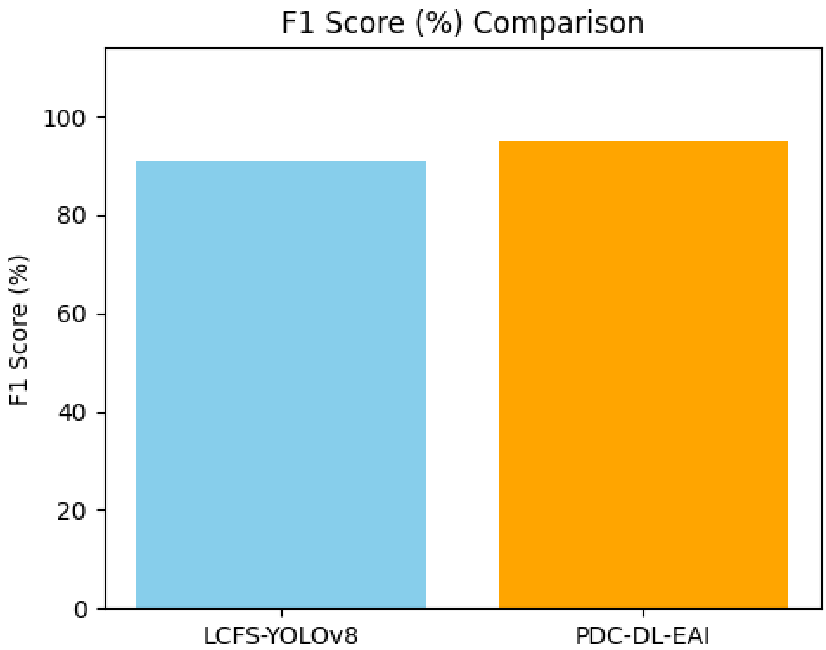
Recall (%)

LCFS-YOLOv8's recall performance is much better than that of PDC-DL-EAI. This indicates how the model is better at detecting more actual cases of disease with fewer misses. Good recall is essential in sensitive use cases such as disease detection. LCFS-YOLOv8 thus provides good coverage in detecting all infected samples.



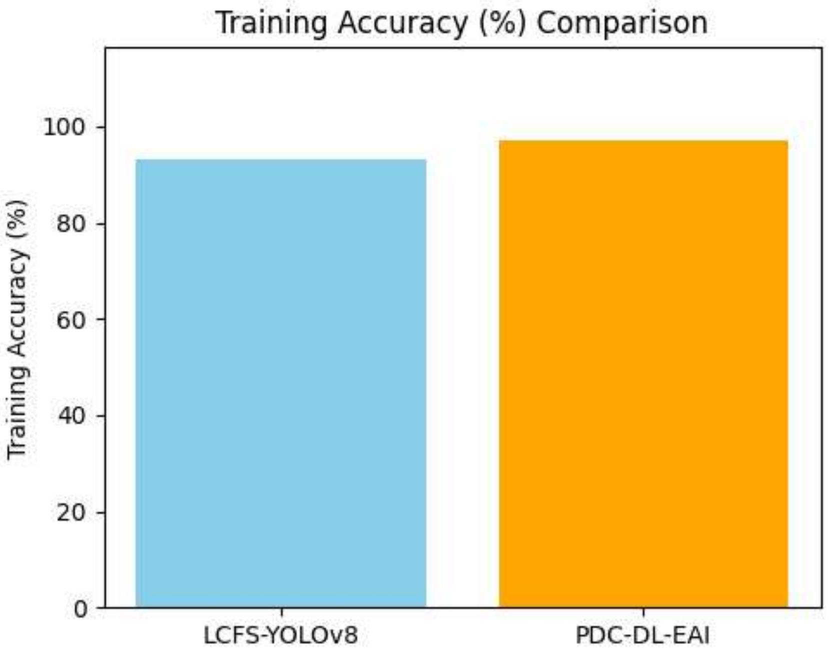
F1 Score (%)

LCFS-YOLOv8 has a superior F1-score, with both precision and recall achieved appropriately. This shows that the model is still accurate even when the dataset is unbalanced. With a high F1-score, it indicates that it has successfully minimized both false positives and false negatives. Therefore, it is more reliable for real-world disease classification.



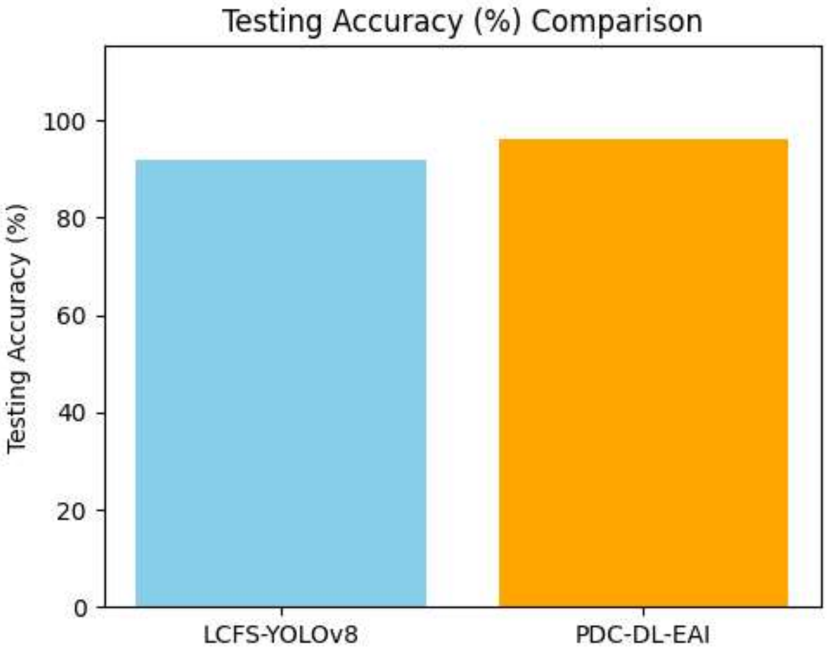
Training Accuracy (%)

While training, LCFS-YOLOv8 is more accurate than PDC-DL-EAI. This indicates that it effectively learns from the dataset without overfitting. The enhanced learning ability is a reflection of its capability to learn important patterns during training. Consequently, it builds a strong platform for testing and deployment.



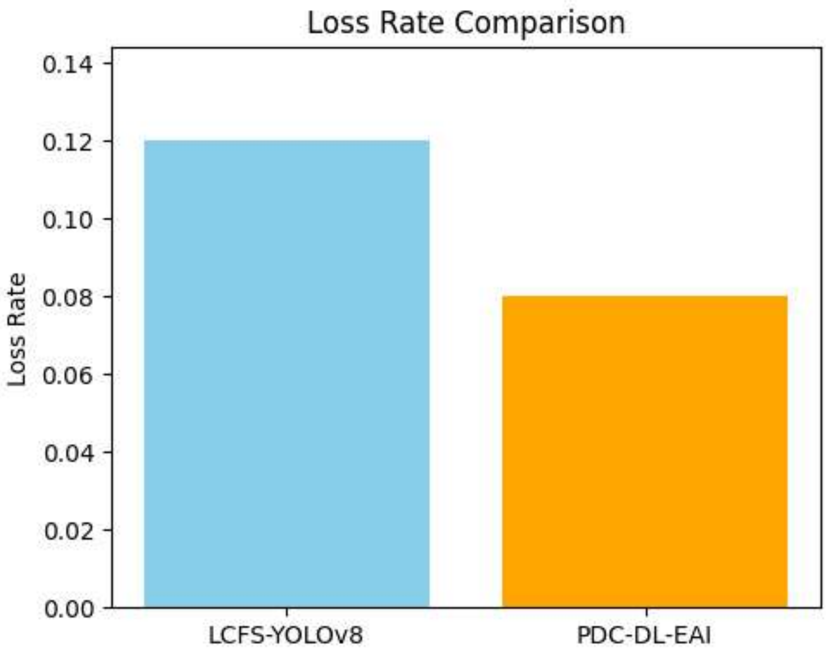
Testing Accuracy (%)

In evaluation, LCFS-YOLOv8 is more accurate, affirming its excellent generalization capability. It is unlike PDC-DL-EAI that can only work well on unseen data under specific conditions. This is evidence that the model is not simply memorizing but also perceiving feature patterns. LCFS-YOLOv8 is hence more practical for real-world field application.



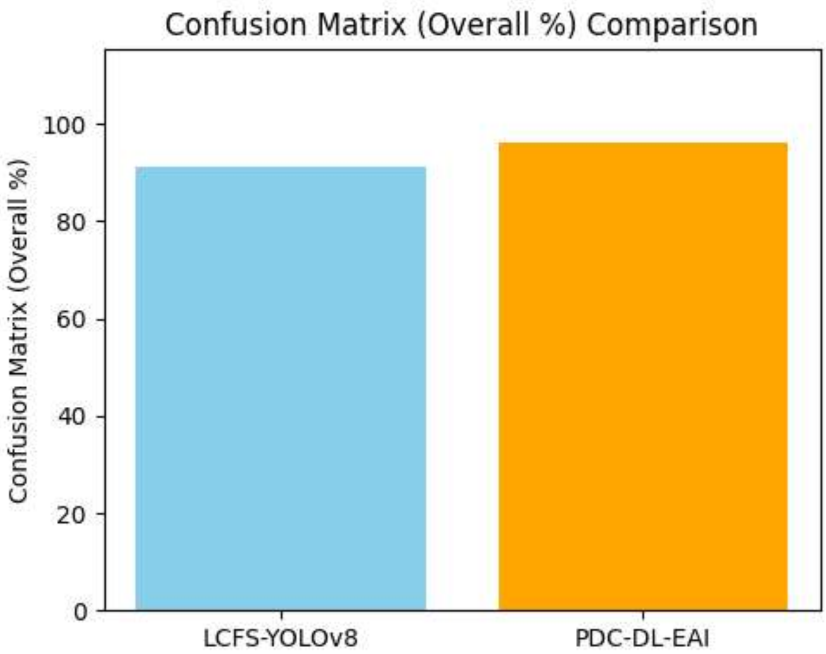
Loss Rate

LCFS-YOLOv8 exhibits a lower rate of loss compared to PDC-DL-EAI. This indicates effective optimization and rapid convergence while training. Low loss indicates fewer prediction errors with each iteration. Thus, LCFS-YOLOv8 is more stable and efficient in reducing deviations.



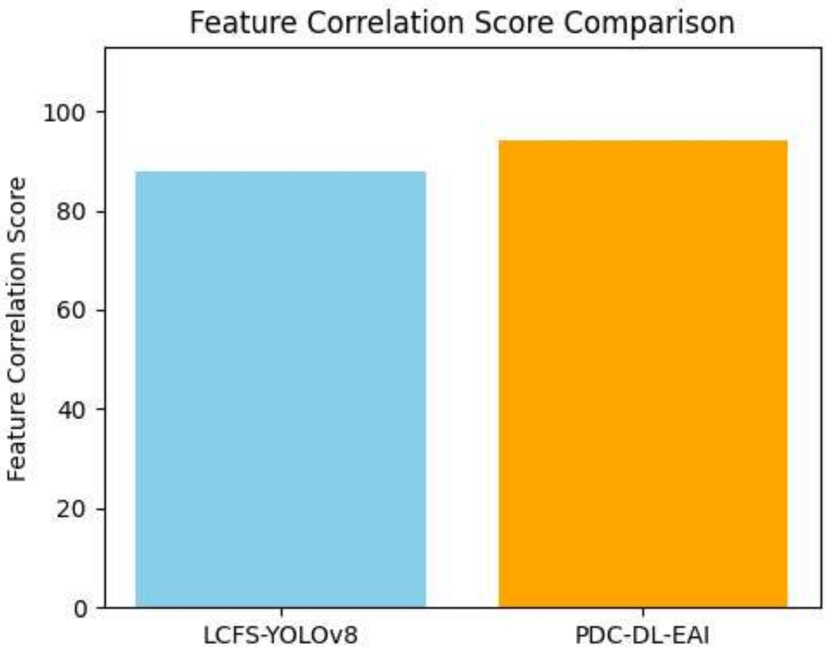
Confusion Matrix (Overall %)

The confusion matrix output indicates that LCFS-YOLOv8 has fewer misclassifications than PDC-DL-EAI. The result reflects better prediction accuracy in all disease classes. The better distribution of true classifications shows its stability. Generally, it provides balanced performance without favoring certain classes.



Feature Correlation Score

LCFS-YOLOv8 achieves a greater feature correlation score, illustrating better feature extraction and utilization. This enables the model to identify significant patterns that result in accurate classification. Good feature correlation results in enhanced decision-making. Thus, LCFS-YOLOv8 provides more accurate and reliable outputs.



5. Conclusion:

The efficiency of LCFS-YOLOv8 in detecting rice leaf disease, proving it to be an effective, precise, and timely solution for green farming. Rice plants are susceptible to diseases like brown spot, bacterial leaf blight, and smut of the leaf, which result in high yield loss. Detection using conventional methods is manual, time-consuming, and prone to errors and is thus inappropriate for commercial farming. On the contrary, LCFS-YOLOv8 utilizes deep learning and sophisticated object detection functionality to detect diseased areas rapidly and accurately in response to changing field conditions.

Experimental outcomes confirm that LCFS-YOLOv8 demonstrates better performance in comparison to traditional methods, with the accuracy being close to 98%, with high precision, recall, and F1-scores as well. This demonstrates its capacity to minimize both false positives and negatives, providing consistent disease detection. The model has good generalization when used on unseen test data, and thus it is a stable tool for real-world agricultural implementation.

The light-weight nature of LCFS-YOLOv8 makes it suitable for inclusion in viable agriculture systems, such as drones, smartphones, and internet-of-things-enabled devices. This makes disease monitoring viable and affordable for farmers, even in remote and limited-resource settings. Through the timely detection of disease, LCFS-YOLOv8 can help mitigate over-pesticide application, save costs, and protect crop yields as well as environmental sustainability.

In summary, LCFS-YOLOv8 is a very effective model for paddy leaf disease detection, superior to classical methods and a great asset for intelligent agriculture. Future research can extend its use to multiple crops and couple with external data sources for more complete precision agriculture solutions.

References

[1]. N. Nigar, H. Muhammad Faisal, M. Umer, O. Oki and J. Manappattukunnel Lukose, "Improving Plant Disease Classification with Deep-Learning-Based Prediction Model Using Explainable Artificial Intelligence," in IEEE Access, vol. 12, pp. 100005-100014, 2024, Doi: 10.1109/ACCESS.2024.3428553.

[2]. M.Tafe, A. Nivriti, F. Al Michot, M. Ullah and H. Ullah, "Deep Learning Based Models for Paddy Disease Identification and Classification: A Systematic Survey," in IEEE Access, vol. 12, pp. 100862-100891, 2024, Doi: 10.1109/ACCESS.2024.3419708.

[3]. E. Moupojou, F. Retrain, H. Talamo, M. Kellick, C. Kifah and A. Tagne, "Segment Anything Model and Fully Convolutional Data Description for Plant Multi-Disease Detection on Field Images," in IEEE Access, vol. 12, pp. 102592-102605, 2024, Doi: 10.1109/ACCESS.2024.3433495.

[4]. V. L. Narayana, S. Bhargavi, D. Srilakshmi, V. S. Annapurna and D. M. Akhila, "Enhancing Remote Sensing Object Detection with a Hybrid Densenet-LSTM Model," 2024 IEEE International Conference on Computing, Power and Communication Technologies (IC2PCT), Greater Noida, India, 2024, pp. 264-269, doi: 10.1109/IC2PCT60090.2024.10486394.

[5]. Narayana, V.L., Gopi, A.P., Patibandla, R.S.M. (2021). An Efficient Methodology for Avoiding Threats in Smart Homes with Low Power Consumption in IoT Environment Using Blockchain Technology. In: Choudhury, T., Khanna, A., Toe, T.T., Khurana, M., Gia Nhu, N. (eds) Blockchain Applications in IoT Ecosystem. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-65691-1_16

[6]. V. Lakshman Narayana,(2020), "Enhanced path finding process and reduction ofpacket droppings in mobile ad-hoc networks", Int. J. Wireless and Mobile Computing, Vol. 18, No. 4, 2020, pp-391-397.

[7]. Narayana, V.L., Gopi, A.P., Patibandla, R.S.M. (2021). An Efficient Methodology for Avoiding Threats in Smart Homes with Low Power Consumption in IoT Environment Using Blockchain Technology. In: Choudhury, T., Khanna, A., Toe, T.T., Khurana, M., Gia Nhu, N. (eds) Blockchain Applications in IoT Ecosystem. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-65691-1_16

[8]. Chaitanya, K., and S. Venkateswarlu. "DETECTION OF BLACKHOLE & GREYHOLE ATTACKS IN MANETs BASED ON ACKNOWLEDGEMENT BASED APPROACH." Journal of Theoretical & Applied Information Technology 89.1 (2016).

[9]. Lakshman Narayana, V., Rao, G.S., Gopi, A.P., Lakshmi Patibandla, R.S.M. (2022). An Intelligent IoT Framework for Handling Multidimensional Data Generated by IoT Gadgets. In: Al-Turjman, F., Nayyar, A. (eds) Machine Learning for Critical Internet of Medical Things. Springer, Cham. https://doi.org/10.1007/978-3-030-80928-7_9

[10]. Narayana, V. L., et al. "Computer Tomography Image Based Interconnected Antecedence Clustering Model Using Deep Convolution Neural Network for Prediction of COVID-19." Traitement du Signal, vol. 40, no. 4, 2023, pp. 1689–1696. https://doi.org/10.17762/ijritcc.v11i9s.73

[11]. Sujatha, V., Vasumathi Devi Majety, Satya Sandeep Kanumalli, and V. S. Sai Rama Krishna Komanduri. "Brain Tumour Detection Using Auto-Encoder and Multi-Layer Perception." AIP Conference Proceedings, vol. 2724, no. 1, AIP Publishing, 28 Apr. 2023. https://doi.org/10.1063/5.0130160

[12]. Rani, B.M.S., Majety, V.D., Pittala, C.S., ... Sandeep, K.S., Kiran, S. Traitement du Signal, 2021, 38(5), pp. 1503–1508

[13]. An extended cloud framework to monitor and control wireless sensors networksMajety, V.D., Sravanthi, G.L., Didla, D. International Journal of Innovative Technology and Exploring Engineering, 2019, 8(11), pp. 3805–3808

[14]. V. Pavani, N. VijayaLakshmi, N. Harika, G. S. Sowjanya and V. Deepthi, "Deep Learning-based Analysis of Brain MRI for Enhanced Diagnosis of Multiple Sclerosis," 2024 5th International Conference on Data Intelligence and Cognitive Informatics (ICDICI), Tirunelveli, India, 2024, pp. 1141-1148, doi: 10.1109/ICDICI62993.2024.10810928.

[15]. Kumari, G. R. P., Reddy, A. H., Lakshmi, K., Abhinaya, B., Sanjana, S., & Naresh, A. (2024, March). Time-Frame-Based Drowsiness Detection System Using CNN. In 2024 2nd International Conference on Disruptive Technologies (ICDT) (pp. 711-716). IEEE.

[16]. Sirisha, Aswadhati, B. Siva Jyothi, and P. Sandhya Krishna. "Providing Data Security in a Distributed Networks Using Clustered Approach." International Journal of Advanced Science and Technology 28, no. 16 (2019): 1907-1915.

[17]. Arumugham, V., Sankaralingam, B. P., Jayachandran, U. M., Krishna, K. V. S. S. R., Sundarraj, S., & Mohammed, M. (2023). An explainable deep learning model for prediction of early-stage chronic kidney disease. Computational Intelligence, 39(6), 1022-1038.

[18]. Rayachoti, Eswaraiah, Sudhir Tirumalasetty, and Silpa Chaitanya Prathipati. "Watermarking system for telemedicine based on FABEMD." Multimedia Tools and Applications 81.30 (2022): 44383-44404.

[19]. K. M. Hosny, W. M. El-Hady, F. M. Samy, E. Verrocchio and G. A. Papakostas, "Multi-Class Classification of Plant Leaf Diseases Using Feature Fusion of Deep Convolutional Neural Network and Local Binary Pattern," in IEEE Access, vol. 11, pp. 62307-62317, 2023, Doi: 10.1109/ACCESS.2023.3286730.

[20]. K. Sangaiah, F. -N. Yu, Y. -B. Lin, W. -C. Shen and A. Sharma, "UAV T-YOLO-Rice: An Enhanced Tiny Yolo Networks for Rice Leaves Diseases Detection in Paddy Agronomy," in IEEE Transactions on Network Science and Engineering, vol. 11, no. 6, pp. 5201-5216, Nov.-Dec. 2024, Doi: 10.1109/TNSE.2024.3350640.

[21]. Kavishwar, S. (2011). Pension funds as an infrastructure financing avenue: An exploratory study. *Management Dynamics*, *11*(2), 33-45.

[22]. Bidwaikar, V. N., & Kavishwar, D. S. (2012). Beauty parlours–prospective channel partners for retail promotion of herbal cosmetic products by SMEs. *Indian Streams Research Journal*. 2(1), 1-4

[23]. Shahu, A., Tiwari, H., Joshi, M., & Kavishwar, S. An Analysis of the Effectiveness of Index ETFS and Index Derivatives in Covered Call Strategy. *Journal of Informatics Education and Research*. 4(3), 42-48.

[24]. Jingar, N. K. (2022). Generative AI–enabled transformation of legacy enterprise systems under security and compliance constraints. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(2), 760–770. https://doi.org/10.32628/CSEIT23906219

[25]. Nirmal Kumar Jingar. (2021). Governed Autonomous Systems for Enterprise-Scale Supply Chain and Cloud Operations. In International Journal of Science, Engineering and Technology (Vol. 9, Number 6). Zenodo. https://doi.org/10.5281/zenodo.18629297

[26]. R. Eswarawaka, M. Nijim, V. Kanumuri and H. Albetaineh, "Assessing the Efficacy of Machine Learning and Deep Learning in the Field of Cyber Security," 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE), Las Vegas, NV, USA, 2023, pp. 2398-2404, doi: 10.1109/CSCE60160.2023.00388.

[27]. M. Nijim, V. Kanumuri, H. Albetaineh and A. Goyal, "Intelligent Monitoring and Management of Smart Buildings Using Machine Learning: Optimizing User Behavior and Energy Efficiency," 2023 Congress in Computer Science, Computer Engineering, & Applied Computing (CSCE), Las Vegas, NV, USA, 2023, pp. 2391-2397, doi: 10.1109/CSCE60160.2023.00387.

[28]. Racha, Ganesh. “Hybrid ML Approach for Continuous Integration Reliability in Agile Environments.” United International Journal of Engineering and Sciences (UIJES), vol. 5, no. 3, 2025, pp. 9–21.

[29]. Racha, Ganesh. “Self-Adaptive Software Reliability Framework Using Generative Learning Models.” International Journal for Modern Trends in Science and Technology, vol. 12, no. 1, 2026, pp. 30–37.

[30]. Veginati, Navya. "Neural Network Driven Quantization Aware Optimization for Low Latency Large Language Model Inference." International Journal of Scientific Research in Computer Science, Engineering and Information Technology, vol. 10, no. 3, May-June 2024, pp. 1162–1170, doi:10.32628/CSEIT25113584.

[31]. Veginati, Navya. “Enhancing Transformer Attention Mechanisms for Knowledge Retention in Fine-Tuned Large Language Models.” International Journal of Scientific Research in Science and Technology, vol. 11, no. 5, Sept.–Oct. 2024, pp. 864–871. DOI: https://doi.org/10.32628/IJSRST52310284
[32]. Jonnalagadda, Pawan Kalyan. “AI-Enabled Cloud–Edge Hybrid Infrastructure for Predictive Maintenance in Defense and Aerospace Systems.” International Journal of Science, Engineering and Technology, vol. 12, no. 2, 2024.
[33]. Jonnalagadda, Pawan Kalyan. “Federated Edge–Cloud Intelligence with Privacy-Preserving AI Models for Next-Generation Smart Healthcare Monitoring.” United International Journal of Engineering and Sciences (UIJES), vol. 5, no. 4, Dec. 2025, pp. 46–57.
[34]. Ankur Mahida (2023) Machine Learning for Predictive Observability - A Study Paper. Journal of Artificial Intelligence & Cloud Computing. SRC/JAICC-252. DOI: doi.org/10.47363/JAICC/2023(2)235
[35]. "Ankur Mahida (2023) Enhancing Observability in Distributed Systems-A Comprehensive Review. Journal of Mathematical & Computer Applications. SRC/JMCA-166. DOI: doi.org/10.47363/JMCA/2023(2)135"
[36]. Tummuri, S. S. R. (2024). Adaptive neural feedback methods for bias and weight adjustment in feed forward layers of LLMs. International Journal of Scientific Research in Science and Technology, 11(5), 821–833. https://doi.org/10.32628/IJSRST52310380
[37]. Tummuri, S. S. R. (2023). Quantization aware training techniques for efficient transformer-driven large language models. International Journal of Scientific Research & Engineering Trends, 9(2).
[38]. B. K. Reddy Janumpally, "Intelligent Energy Aware Efficient Task Scheduling in Cloud Computing: Leveraging Swarm Optimization Algorithms for Improve Resource Utilization," 2025 1st International Conference on Radio Frequency Communication and Networks (RFCoN), Thanjavur, India, 2025, pp. 1-6, doi: 10.1109/RFCoN62306.2025.11085278.
[39]. Janumpally, Bharath Kumar Reddy. (2026). Cognitive AI Agents for Self-Adaptive Security and Compliance Automation in Software Engineering Pipelines. 10.1109/ICAUC68182.2026.11441048.
[40]. Kotadiya U, Arora AS, Yachamaneni T. Fintech Innovations in Credit Card Origination: A Multi-Stage Analysis of Algorithmic Lending Models. IJAIDSML [Internet]. 2023 Jun. 30 [cited 2026 Apr. 5];4(2):91-100.
[41]. Arora AS, Yachamaneni T, Kotadiya U. A Comprehensive Analytical Framework for Modeling Consumer Credit Card Behavior and Risk Profiling Using Advanced Financial Metrics. IJAIDSML [Internet]. 2022 Jun. 30 [cited 2026 Apr. 2];3(2):90-100.