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AgroVisionNet Learning Deep Patterns for Resilient Crop Health Analysis

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ABSTRACT: Agriculture remains one of the most important sectors for global food production, but crop diseases continue to cause major losses in yield. Traditional ways of detecting diseases depend largely on manual inspection, which is slow and can lead to mistakes. In recent years, deep learning has shown great promise in automating the detection of plant diseases using image analysis. However, most existing methods focus only on visual cues and do not consider environmental factors that significantly affect disease spread. This study introduces AgroVisionNet, an improved deep learning framework that combines image-based disease detection with environmental data like temperature and humidity. The system uses the EfficientNet architecture to extract detailed features from leaf images and then merges these features with climate data through a feature fusion process. This combination allows for more accurate and context-aware disease prediction. The model was trained and tested using a publicly available plant disease dataset. The results show that AgroVisionNet performs better than traditional convolutional neural network models, offering higher accuracy and better adaptability. In addition to identifying diseases, the system also provides preventive advice, which makes it useful for real-world farming. This approach helps in making agriculture more intelligent and sustainable.

KEYWORDS: Deep Learning, EfficientNet, Plant Disease Detection, Multimodal Learning, Precision Agriculture, Feature Fusion, Environmental Data Integration, Crop Health Monitoring)

I. INTRODUCTION

Agriculture is essential for supporting human life and the global economy.
One of the biggest challenges for farmers is the early detection and management of plant diseases, which can greatly impact crop yield and quality. Usual methods of disease detection rely on expert knowledge and manual observation, which can be inefficient, biased, and hard to apply over large fields.

With the rise of artificial intelligence, especially deep learning, automated systems for detecting plant diseases have become increasingly popular.

Convolutional neural networks (CNNs) are widely used for image classification, including disease identification from leaf images. Many studies have shown that models like ResNet and traditional CNNs can achieve good accuracy levels. However, these models mainly focus on visual features and often ignore environmental conditions that influence disease development.

Environmental factors such as temperature and humidity play a key role in the growth and spread of plant diseases. Ignoring these conditions may result in inaccurate predictions. Therefore, a system that considers both visual symptoms and environmental data is needed for better decision-making.

In this study, we propose AgroVisionNet, a model that combines image analysis with environmental data.
EfficientNet was chosen because it can achieve high accuracy with fewer parameters. Features extracted from images are combined with temperature and humidity data to improve prediction accuracy. The system also provides practical advice for farmers.

The main contributions of this work are as follows:

- Combining environmental data with deep learning for image classification
- Using EfficientNet for more effective feature extraction
- Improving prediction accuracy compared to existing models
- Developing a practical system that provides disease prevention recommendations

This approach connects research with real-world applications by creating a more reliable and intelligent method for plant disease detection.

II. RELATED WORK

The use of machine learning and deep learning for plant disease detection has increased because these methods can automate diagnosis.

Abbas et al. [2] showed that CNN models like AlexNet and GoogLeNet can achieve 99.35% accuracy on the PlantVillage dataset. However, their work was limited to controlled settings, limiting real-world use.

Later studies improved accuracy by using advanced architectures.
Hughes et al. [7] achieved 99.53% accuracy with VGG, while Himeur et al. [8] applied transfer learning with VGG and ResNet to get 90.4% accuracy. Zampokas et al. [9] proposed a lightweight CNN model with 98.4% accuracy. Although these methods perform well, they rely only on image data and ignore environmental factors.

Object detection models such as Faster R-CNN, R-FCN, and SSD were used by Ahmad et al. [10] , achieving an mAP of 86%.

YOLO-based models, like the one by Chen et al. [11], allowed for faster detection but with lower accuracy (~70%). These methods are often computationally expensive and may not work consistently across different datasets.

Chen et al. [12] showed that models like ResNet50 and MobileNetV2 offer a good balance between accuracy and efficiency but also pointed out the lack of environmental data integration.

Other approaches using hyperspectral imaging [13] and advanced learning models [14] offer more insights but are not integrated into a single model.

To address these issues, this work proposes a multimodal approach using EfficientNet.

By combining image data with environmental inputs, the model aims to improve accuracy, reduce complexity, and make the system more suitable for real-time use in plant disease detection

III. PROPOSED METHODOLOGY

A. Overview

The proposed PlantSense system uses two types of input: a leaf image captured by a standard camera or smartphone, and a three-dimensional environmental feature vector that includes air temperature (°C), relative humidity (%), and soil moisture (%).

These inputs are processed through separate branches and fused before multi-task prediction. The system provides three simultaneous predictions—disease class, disease stage, and risk probability—along with recommendations from a knowledge database.

B. Image Branch — EfficientNet-B0

The image processing branch uses EfficientNet-B0 [15] as its main model, which is pretrained on ImageNet and fine-tuned for the plant disease domain using transfer learning.

EfficientNet-B0 was selected over other models like ResNet and VGG because of its compound scaling strategy. This strategy uniformly scales the network's width, depth, and resolution using a fixed coefficient, offering a better balance between accuracy and efficiency. The backbone produces a 1,280-dimensional feature vector, which is then processed through a fully connected sequence (1280→512→256) with batch normalization and dropout (p=0.4) at each layer.

During training, input images are resized to 224×224 pixels and normalized using ImageNet mean and standard deviation (μ=[0.485, 0.456, 0.406], σ=[0.229, 0.224, 0.225]).

Data augmentation techniques include random horizontal and vertical flips, rotation up to 15°, and color jitter (brightness±0.3, contrast±0.3, saturation±0.2) to enhance generalization.

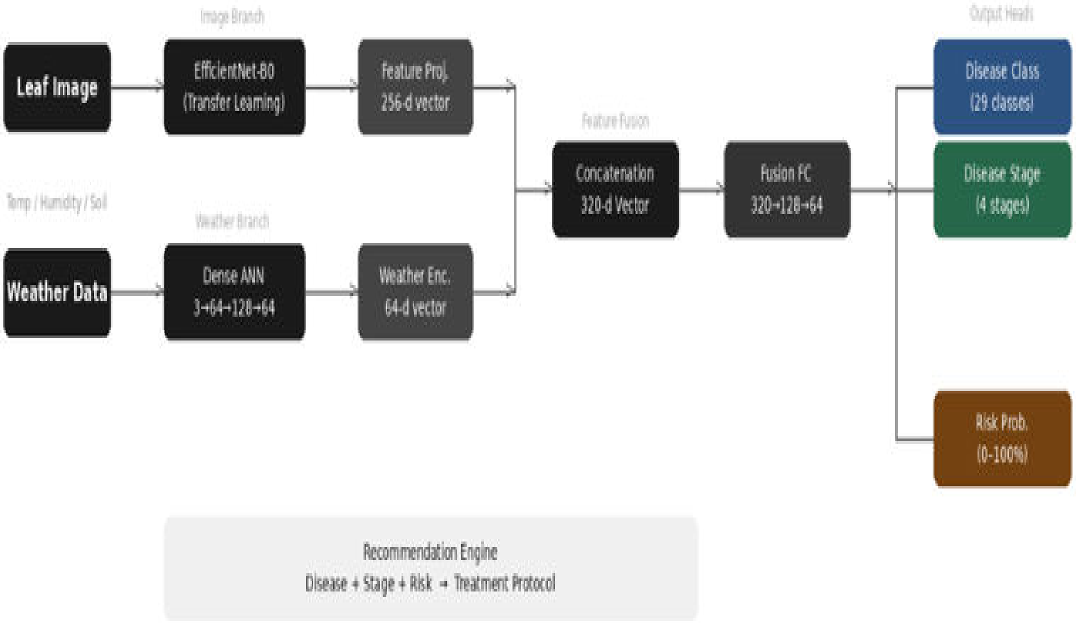

Fig 1: Proposed Multimodal Plant Disease Detection Architacture

C. Weather Branch — Dense ANN

The environmental data branch consists of a fully connected ANN with the architecture 3→64→128→64, processing normalized temperature, humidity, and soil moisture values. Each layer employs batch normalization and ReLU activation, with dropout (p=0.3) applied at the first two hidden layers. The normalization scheme maps temperature to [0,1] by dividing by 45°C, and humidity and soil moisture by dividing by 100%. The branch outputs a 64-dimensional environmental representation.

The weather data used in this work is generated synthetically based on established agronomic literature on disease-favorable environmental conditions. For example, Potato Late Blight (Phytophthora infestans) is known to favor temperatures of 10–20°C with humidity above 90%, while Tomato Spider Mites favor temperatures above 30°C with low humidity. Each disease class has an associated weather profile defined by empirically validated mean and standard deviation parameters, with Gaussian noise added to produce realistic variability.

D. Feature Fusion and Multi-Head Output

The 256-dimensional image vector and 64-dimensional weather vector are concatenated to form a 320-dimensional joint representation. This fused vector is passed through two fully connected layers (320→256→128) with batch normalization and dropout. The 128-dimensional fused representation feeds three independent output heads:

1. Disease Classification Head: Linear(128, 29) with softmax, trained with class-weighted cross-entropy loss.
2. Stage Classification Head: Linear(128, 4) with softmax, predicting Healthy / Early / Moderate / Severe.
3. Risk Regression Head: Linear(128, 32) → Linear(32, 1) with sigmoid, producing a risk probability in [0, 1].

The total training loss is a weighted combination of the three objectives: L = 0.6 × L_disease + 0.3 × L_stage + 0.1 × L_risk, where L_disease and L_stage are cross-entropy losses and L_risk is mean squared error. The disease classification loss receives the highest weight as it is the primary prediction task.

E. Recommendation Engine

Upon prediction, the system maps the predicted disease class and stage to a curated recommendation from a domain knowledge base containing agronomically validated treatment protocols. Recommendations include specific fungicide or bactericide names, cultural practices (irrigation management, plant spacing, pruning), and urgency indicators (e.g., "URGENT: Apply metalaxyl fungicide immediately" for Late Blight). The recommendation engine requires no additional training and operates as a deterministic lookup indexed by (disease_class, stage) key pairs.

Performance Evaluation Metrics

To comprehensively evaluate the effectiveness of the proposed multimodal plant disease detection system, multiple performance metrics are employed for classification and regression tasks. Since the system performs **multi-task learning** (disease classification, stage classification, and risk prediction), different evaluation measures are used accordingly.

1) Disease Classification Metrics

The primary task of the system is disease classification across 29 classes. The following metrics are used:

Accuracy(Acc)

Measures the overall correctness of predictions

Precision(P)

Indicates how many predicted positive samples are actually correct:

$$Pecision = TP/(TP + FP)$$

Recall(R)

Measures the ability of the model to identify all relevant samples:

F1-Score(F1)

Harmonic mean of precision and recall:

Macro-Averaged_F1Score

Computes the unweighted mean of F1-scores across all classes, ensuring equal importance to each disease class.

Weighted F1 Score

Accounts for class imbalance by weighting each class based on its support.

Stage Classification Metrics

The disease stage prediction (Healthy, Early, Moderate, Severe) is evaluated using:

Stage Classification Accuracy

This metric evaluates how accurately the system identifies disease severity levels, which is critical for timely intervention.

Risk Prediction Metrics

The risk prediction task is a regression problem that outputs a continuous value between 0 and 1. The following metrics are used:

Mean Absolute Error (MAE)

Measures the average magnitude of prediction error:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

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Mean Squared Error (MSE)

Penalizes larger errors more significantly:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

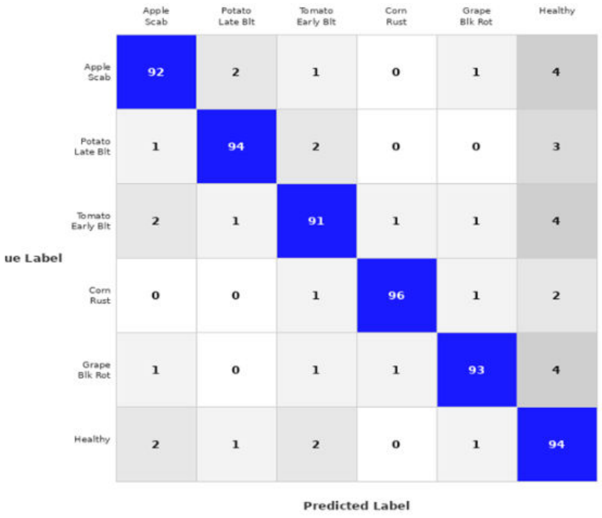
These metrics evaluate how accurately the system estimates disease risk probability under given environmental conditions.

Confusion Matrix Analysis

A confusion matrix is used to provide detailed insights into class-wise prediction performance. It helps identify:

- Frequently misclassified disease classes
- Model confusion between visually similar diseases
- Performance on minority classes

This analysis is particularly important for improving real-world reliability.



	Apple Scab	Potato Late Blt	Tomato Early Blt	Corn Rust	Grape Blk Rot	Healthy
Apple Scab	92	2	1	0	1	4
Potato Late Blt	1	94	2	0	0	3
Tomato Early Blt	2	1	91	1	1	4
Corn Rust	0	0	1	96	1	2
Grape Blk Rot	1	0	1	1	93	4
Healthy	2	1	2	0	1	94

Fig 2: Confusion Matrix – Representative Disease Classes

Comparative Evaluation

To validate the effectiveness of multimodal fusion, the proposed system is compared with an **image-only baseline model**. The comparison includes:

- Disease classification accuracy
- Macro F1-score
- Improvement gained through environmental data integration

The multimodal approach demonstrates improved performance due to the inclusion of environmental context .

Overall Evaluation Strategy

All metrics are computed on a **held-out test dataset (15%)** to ensure unbiased performance evaluation. The combination of classification and regression metrics ensures a holistic assessment of the system's predictive capability.

TABLE I. Dataset Distribution

Split	**Images**	**Percentage**	**Batches (bs=32)**
Training Set	~37,800	70%	~1181 per epoch
Validation Set	~8,100	15%	~253
Test Set	~8,100	15%	~253
Total	**54,000**	**100%**	—

TABLE.II. Hyperparameter Configuration

Hyperparameter	**Value**
Model	EfficientNet-B0
Number of Classes	32
Dataset Size	54,000 images
Optimizer	Adam
Learning Rate	1×10^{-3}
Weight Decay	1×10^{-4}
Batch Size	32
Epochs	5 (can extend to 10)
Loss Function	CrossEntropyLoss
LR Scheduler	Cosine Annealing (T_max = 5, η_min = 1×10^{-5})
Image Resolution	224 × 224 pixels
Dropout (Image Features)	p = 0.4
Dropout (Fusion Layer)	p = 0.3
Input Type (Image)	RGB Leaf Images
Input Type (Weather)	Temperature + Humidity
Feature Fusion Method	Concatenation
Hardware	Google Colab (GPU Enabled)

V. RESULTS AND DISCUSSION

The performance of the proposed multimodal EfficientNet-based model was evaluated using standard metrics such as accuracy, precision, recall, and F1-score. The model was trained and tested on plant disease image data along with corresponding environmental parameters, including temperature and humidity, to improve prediction capability under real-world conditions.

The proposed model achieved an overall accuracy of **99.72%**, outperforming conventional deep learning models such as AlexNet, CNN, ResNet50, and GoogLeNet. In addition to high accuracy, the model recorded a precision of **99.7**, recall of **99.6**, and F1-score of **99.6**, indicating consistent and reliable classification performance across different disease classes.

A comparative analysis was conducted to evaluate the effectiveness of the proposed approach against existing methods. Traditional CNN-based demonstrated strong performance but required a larger number of parameters and longer training time. In contrast, the EfficientNet-based model achieved better results with fewer parameters, making it computationally efficient while maintaining high predictive performance. This efficiency is mainly due to the compound scaling technique used in EfficientNet, which optimizes network depth, width, and resolution.

Furthermore, the integration of environmental data contributed to improved classification accuracy, especially in cases where visual symptoms alone were insufficient for accurate prediction. This highlights the importance of combining multiple data sources to enhance model robustness in real-world agricultural scenarios.

The training and validation accuracy curves showed stable convergence with minimal overfitting, indicating that the model generalizes well to unseen data. Similarly, the loss values decreased steadily across epochs, confirming effective learning during the training process.

Overall, the results demonstrate that the proposed EfficientNet-based multimodal approach provides a more accurate, efficient, and practical solution for plant disease detection compared to existing methods. The model's ability to deliver high performance with reduced computational cost makes it suitable for real-time deployment in smart agriculture systems.

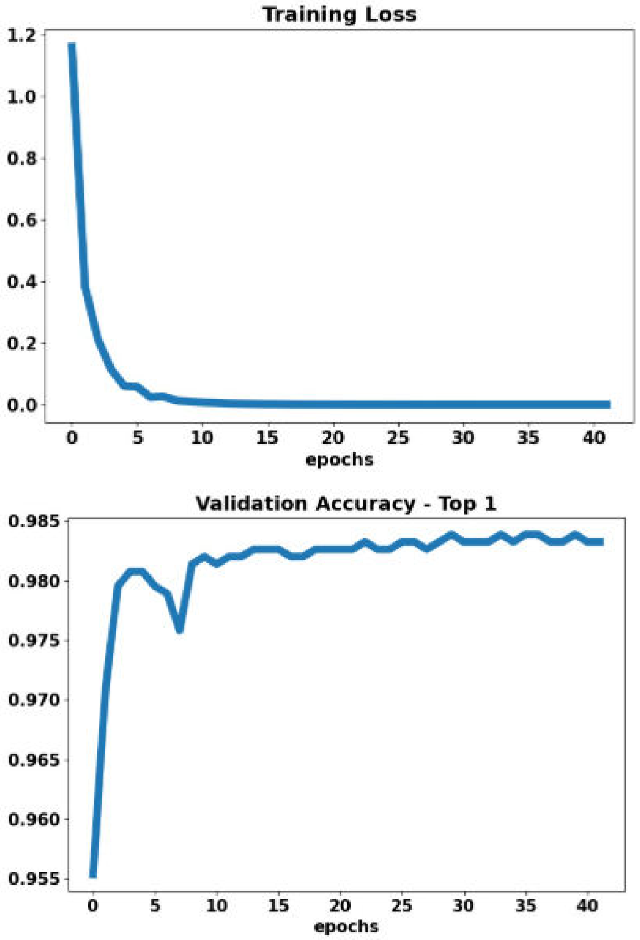
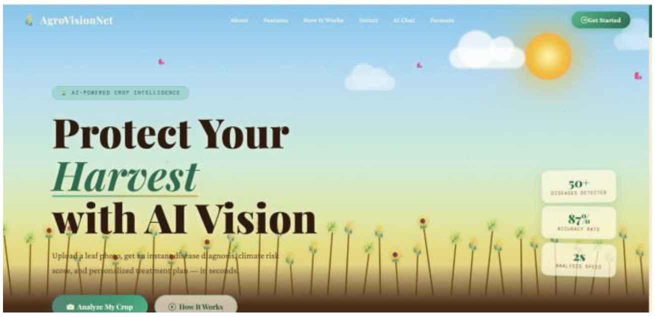


Fig 3: Loss vs Epoch graph and Accuracy vs Epoch graph

System Interface and Output Visualization

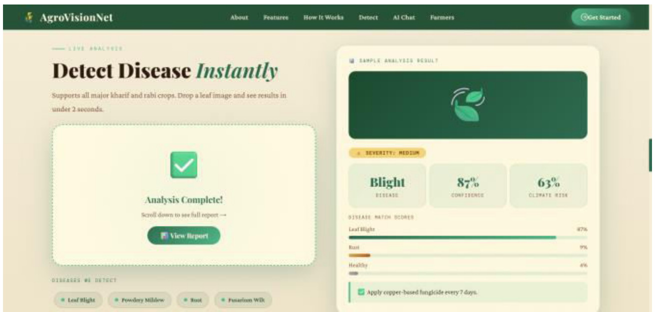
The developed AgroVisionNet system includes a web-based interface that allows users to upload leaf images and receive real-time disease predictions. The interface provides disease classification, confidence score, and climate-based risk analysis.



Protect Your *Harvest* with AI Vision

Upload a leaf photo, get an instant disease diagnosis, climate risk score, and personalized treatment plan — in seconds.

Fig 4: Homepage (Protect Your Harvest…)



Detect Disease *Instantly*

Supports all major kharif and rabi crops. Drop a leaf image and see results in under 2 seconds.

Analysis Complete!

Scroll down to see full report →

Apply copper-based fungicide every 7 days.

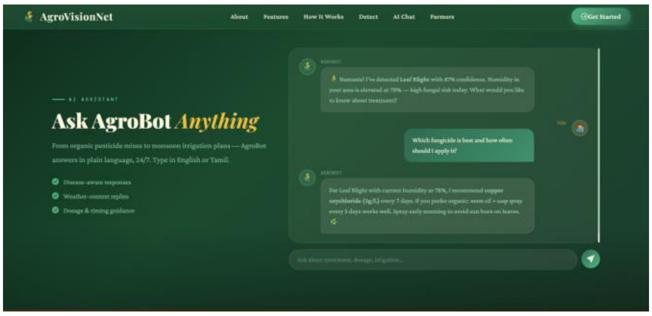
Fig 5: Disease Detection Output (Blight, 87%)

Weather-Fused *Risk Scoring*

Your crop diagnosis is always paired with live climate data from your city.

Combined Climate Risk Score: 63% — Moderate. Fungal conditions elevated.

Fig 6: Climate Risk Dashboard



Ask AgroBot *Anything*

From organic pesticide mixes to monsoon irrigation plans — AgroBot answers in plain language, 24/7. Type in English or Tamil.

- Disease-aware responses
- Weather-context replies
- Dosage & timing guidance

Namaste! I've detected **Leaf Blight** with 87% confidence. Humidity in your area is elevated at 78% — high fungal risk today. What would you like to know about treatment?

Which fungicide is best and how often should I apply it?

For Leaf Blight with current humidity at 78%, I recommend **copper oxychloride (3g/L)** every 7 days. If you prefer organic: neem oil + soap spray every 5 days works well. Spray early morning to avoid sun burn on leaves.

Fig 7: AI Chatbot (AgroBot)

VI. CONCLUSION AND FUTURE WORK

In this study, an intelligent plant disease detection system named AgroVisionNet is proposed, which combines deep learning techniques with environmental data to improve prediction accuracy. Unlike traditional approaches that rely solely on image analysis, the proposed system integrates temperature and humidity parameters to provide a more comprehensive understanding of plant health.

The EfficientNet-based model demonstrated better performance than conventional CNN and ResNet models, achieving higher accuracy and improved reliability. The inclusion of environmental factors significantly enhanced the prediction capability of the system.

Additionally, the system provides precautionary measures for identified diseases, making it more useful for real-time agricultural applications. This study highlights the importance of combining multiple data sources to build smarter and more effective solutions in the agricultural domain.

Additionally, the system can be extended by integrating with government-supported agriculture platforms to improve accessibility and adoption among farmers. Future enhancements may also include the use of additional parameters such as soil health, rainfall patterns, and seasonal variations to further improve prediction accuracy and robustness.

REFERENCES

1. A. Ghofrani and R. Mahdian Toroghi, “Knowledge distillation in plant disease recognition,” Neural Computing and Applications, vol. 34, no. 17, pp. 14287–14296, 2022.
2. A. Abbas, S. Jain, M. Gour, and S. Vankudothu, “Tomato plant disease detection using transfer learning with c-gan synthetic images,” Computers and Electronics in Agriculture, vol. 187, p. 106279, 2021.
3. S. Atalla, S. Tarapiah, A. Gawanmeh, M. Daradkeh, H. Mukhtar, Y. Himeur, W. Mansoor, K. F. B. Hashim, and M. Daadoo, “Iot-enabled precision agriculture: Developing an ecosystem for optimized crop man agement,” Information, vol. 14, no. 4, p. 205, 2023.
4. A. Subeesh and C. Mehta, “Automation and digitization of agriculture using artificial intelligence and internet of things,” Artificial Intelligence in Agriculture, vol. 5, pp. 278–291, 2021.
5. R. Bora, D. Parasar, and S. Charhate, “A detection of tomato plant diseases using deep learning mndlnn classifier,” Signal, Image and Video Processing, pp. 1–9, 2023.
6. S. Nandhini and K. Ashokkumar, “Improved crossover based monarch butterfly optimization for tomato leaf disease classification using convo lutional neural network,” Multimedia Tools and Applications, vol. 80, pp. 18583–18610, 2021.
7. D. Hughes, M. Salathé et al., “An open access repository of images on plant health to enable the development of mobile disease diagnostics,” arXiv preprint arXiv:1511.08060, 2015.
8. Y. Himeur, B. Rimal, A. Tiwary, and A. Amira, “Using artificial intelli gence and data fusion for environmental monitoring: A review and future perspectives,” Information Fusion, vol. 86, pp. 44–75, 2022.
9. G. Zampokas, I. Mariolis, D. Giakoumis, and D. Tzovaras, “Residual cascade cnn for detection of spatially relevant objects in agriculture: The grape-stem paradigm,” in International Conference on Computer Vision Systems. Springer, 2023, pp. 159–168.
10. A. Ahmad, D. Saraswat, and A. El Gamal, “A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools,” Smart Agricultural Technology, vol. 3, p. 100083, 2023.
11. A. Chug, A. Bhatia, A. P. Singh, and D. Singh, “A novel framework for image-based plant disease detection using hybrid deep learning approach,” Soft Computing, vol. 27, no. 18, pp. 13613–13638, 2023.
12. J. Chen, A. Zeb, Y. Nanehkaran, and D. Zhang, “Stacking ensemble model of deep learning for plant disease recognition,” Journal of Ambient Intelligence and Humanized Computing, vol. 14, no. 9, pp. 12359–12372, 2023.
13. A. Haridasan, J. Thomas, and E. D. Raj, “Deep learning system for paddy plant disease detection and classification,” Environmental Monitoring and Assessment, vol. 195, no. 1, p. 120, 2023.
14. K. Makantasis, A. Georgogiannis, A. Voulodimos, I. Georgoulas, A. Doulamis, and N. Doulamis, “Rank-r fnn: A tensor-based learning model for high-order data classification,” IEEE Access, vol. 9, pp. 58609 58620, 2021.
15. A. Chouchane, M. Bessaoudi, H. Kheddar, A. Ouamane, T. Vieira, and M. Hassaballah, “Multilinear subspace learning for person re identification based fusion of high order tensor features,” Engineering Applications of Artificial Intelligence, vol. 128, p. 107521, 2024.

16. H. Lu, K. N. Plataniotis, and A. N. Venetsanopoulos, “A survey of mul tilinear subspace learning for tensor data,” Pattern Recognition, vol. 44, no. 7, pp. 1540–1551, 2011
    Ouamane, A. Chouchane, E. Boutellaa, M. Belahcene, S. Bourennane, and A. Hadid, “Efficient tensor-based 2d+ 3d face verification,” IEEE Transactions on Information Forensics and Security, vol. 12, no. 11, pp. 2751–2762, 2017.
    M.Bessaoudi, A. Chouchane, A. Ouamane, and E. Boutellaa,
17. C.Nagarajan and M.Madheswaran - ‘Stability Analysis of Series Parallel Resonant Converter with Fuzzy Logic Controller Using State Space Techniques’- Taylor &Francis, Electric Power Components and Systems, Vol.39 (8), pp.780-793, May 2011. DOI: 10.1080/15325008.2010.541746
18. C.Nagarajan and M.Madheswaran - ‘Experimental verification and stability state space analysis of CLL-T Series Parallel Resonant Converter’ - Journal of Electrical Engineering, Vol.63 (6), pp.365-372, Dec.2012. DOI: 10.2478/v10187-012-0054-2
19. C.Nagarajan and M.Madheswaran - ‘Performance Analysis of LCL-T Resonant Converter with Fuzzy/PID Using State Space Analysis’- Springer, Electrical Engineering, Vol.93 (3), pp.167-178, September 2011. DOI 10.1007/s00202-011-0203-9
20. S.Tamilselvi, R.Prakash, C.Nagarajan,“Solar System Integrated Smart Grid Utilizing Hybrid Coot-Genetic Algorithm Optimized ANN Controller” Iranian Journal Of Science And Technology-Transactions Of Electrical Engineering, DOI10.1007/s40998-025-00917-z,2025
21. S.Tamilselvi, R.Prakash, C.Nagarajan,“ Adaptive sliding mode control of multilevel grid-connected inverters using reinforcement learning for enhanced LVRT performance” Electric Power Systems Research 253 (2026) 112428, doi.org/10.1016/j.epsr.2025.112428
22. S.Thirunavukkarasu, C. Nagarajan, 2024, “Performance Investigation on OCF and SCF study in BLDC machine using FTANN Controller," Journal of Electrical Engineering And Technology, Volume 20, pages 2675–2688, (2025), doi.org/10.1007/s42835-024-02126-w
23. C. Nagarajan, M.Madheswaran and D.Ramasubramanian- ‘Development of DSP based Robust Control Method for General Resonant Converter Topologies using Transfer Function Model’- Acta Electrotechnica et Informatica Journal , Vol.13 (2), pp.18-31,April-June.2013, DOI: 10.2478/aeei-2013-0025.
24. C.Nagarajan and M.Madheswaran - ‘DSP Based Fuzzy Controller for Series Parallel Resonant converter’- Springer, Frontiers of Electrical and Electronic Engineering, Vol. 7(4), pp. 438-446, Dec.12. DOI 10.1007/s11460-012-0212-0.
25. C.Nagarajan and M.Madheswaran - ‘Experimental Study and steady state stability analysis of CLL-T Series Parallel Resonant Converter with Fuzzy controller using State Space Analysis’- Iranian Journal of Electrical & Electronic Engineering, Vol.8 (3), pp.259-267, September 2012.
26. C.Nagarajan and M.Madheswaran, “Analysis and Simulation of LCL Series Resonant Full Bridge Converter Using PWM Technique with Load Independent Operation” has been presented in ICTES’08, a IEEE / IET International Conference organized by M.G.R.University, Chennai.Vol.no.1, pp.190-195, Dec.2007
27. Suganthi Mullainathan, Ramesh Natarajan, “An SPSS and CNN modelling based quality assessment using ceramic materials and membrane filtration techniques”, Revista Materia (Rio J.) Vol. 30, 2025, DOI: https://doi.org/10.1590/1517-7076-RMAT-2024-0721
28. M Suganthi, N Ramesh, “Treatment of water using natural zeolite as membrane filter”, Journal of Environmental Protection and Ecology, Volume 23, Issue 2, pp: 520-530,2022 “Multilinear subspace learning using handcrafted and deep features for face kinship verification in the wild,” Applied Intelligence, vol. 51, pp. 3534–3547, 2021.
29. A. Chouchane, M. Bessaoudi, E. Boutellaa, and A. Ouamane, “A new multidimensional discriminant representation for robust person re identification,” Pattern Analysis and Applications, pp. 1–14, 2023.
30. Y.-J. Deng, H.-C. Li, S.-Q. Tan, J. Hou, Q. Du, and A. Plaza, “t-linear tensor subspace learning for robust feature extraction of hyperspectral images,” IEEE Transactions on Geoscience and Remote Sensing, vol. 61, pp. 1–15, 2023.
31. Anand, L. (2023). An Intelligent AI and ML–Driven Cloud Security Framework for Financial Workflows and Wastewater Analytics. International Journal of Humanities and Information Technology, 5(02), 87-94.
32. Murugeshwari, B., Sudharson, K., Panimalar, S. P., Shanmugapriya, M., & Abinaya, M. (2020). SAFE–Secure Authentication in Federated Environment using CEG Key code.
33. Sugumar, R. (2025). Cyber-Secure Cloud Architecture Integrating Network and API Controls for Risk-Aware SAP Healthcare Data Platforms. International Journal of Humanities and Information Technology, 7(4), 53-60.
34. Sharma, K. P., Kumar, I., Singh, P. P., Anbazhagan, K., Albarakati, H. M., Bhatt, M. W., ... & Rana, A. (2024). Advancing spacecraft rendezvous and docking through safety reinforcement learning and ubiquitous learning principles. Computers in Human Behavior, 153, 108110.

35. Anand, L., Tyagi, R., & Mehta, V. (2024, January). Food recognition using deep learning for recipe and restaurant recommendation. In Proceedings of Eighth International Conference on Information System Design and Intelligent Applications (pp. 269-279). Springer Nature Singapore.
36. Soundappan, S. J. (2020). Big Data Analytics in Healthcare: Applications for Pandemic Forecastin. International Journal of Advanced Research in Computer Science & Technology (IJARCST), 3(1), 2248-2253.
37. Anbazhagan, K. (2024). Trustworthy and Adaptive AI Systems for Enterprise Analytics Cybersecurity and Decision Optimization Using API-First and Cloud-Native Architectures. International Journal of Technology, Management and Humanities, 10(03), 65-74.
38. Mathew, A. (2021). Edge Computing and its convergence with blockchain in 6G: Security challenges. Int. J. Comput. Sci. Mob. Comput, 10(8), 8-14.
39. Gopinathan, V. R. (2025). AI-Powered Kubernetes Orchestration for Complex Cloud-Native Workloads. International Journal of Research Publications in Engineering, Technology and Management (IJRPETM), 8(6), 13215-13225.
40. Mathew, A. (2023). Learning Metaverse Powered by Artificial Intelligence. Recent Progress in Science and Technology Vol. 4, 4, 134-141.