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CROP DISEASE DETECTION USING MACHINE LEARNING

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ABSTRACT

Agriculture plays a vital role in ensuring global food security, but crop diseases significantly impact yield and productivity. Early detection of plant diseases can reduce losses and improve the quality of produce. This study presents a Machine Learning-based approach for crop disease detection using image datasets of various plants such as tomato, rice, and maize. Features like color, texture, and shape are extracted, and models such as Support Vector Machine (SVM), Random Forest (RF), and Convolutional Neural Network (CNN) are used for classification. The proposed CNN model achieves an accuracy of 95%. The use of explainable AI tools like Grad-CAM helps visualize disease regions, improving interpretability and trust in model predictions. Agriculture is the backbone of the Indian economy, and crop health plays a crucial role in ensuring consistent food production. Experimental results show that CNN models outperform traditional approaches in detecting and classifying crop diseases. This automated system can be integrated into mobile and web applications to assist farmers in identifying diseases early and applying suitable treatments. The proposed approach helps in reducing human effort, improving productivity, and supporting precision agriculture practice.

Keywords: Convolutional Neural Network (CNN), Long Short-Term Memory(LSTM), Vision Transformer (ViT), PlantVillage Dataset, PlantDoc Dataset, Crop Disease Detection, Machine Learning.

1 | INTRODUCTION

Agriculture forms the backbone of the global economy and directly impacts food security, employment, and rural development.[1] [2] However, one of the major challenges faced by farmers is the rapid spread of crop diseases, which can severely affect yield, quality, and profitability [3]. According to the Food and Agriculture Organization (FAO), nearly 20–40% of global crop production is lost annually due to pests and plant diseases [4] [5]. Early and accurate disease detection is therefore crucial for improving crop productivity and ensuring sustainable agricultural practices [6][7]. Traditional disease identification methods rely on visual inspection by experts, which are often time-consuming, subjective, and limited in scale [8]. With the advancement of Machine Learning (ML) and Deep Learning (DL) techniques, automated systems can now analyze crop leaf images to detect and classify diseases with high accuracy [9] [10]. These technologies not only minimize manual intervention but also enhance decision-making in precision farming [11] [12].

In this study, we propose a Machine Learning-based crop disease detection system that classifies diseased and healthy leaves using datasets from different crops such as (Examples: Paddy, Chillies and maize) [13] [14]. The proposed system uses feature extraction techniques (color, texture, shape) and trains models such as Support Vector Machine (SVM) [15], Random Forest (RF) [16], and Convolutional Neural Network (CNN) for classification [17] [18]. Among these, the CNN model achieved the highest accuracy of 95%, demonstrating its ability to automatically extract deep visual features [19] [20]. Furthermore, Explainable Artificial Intelligence (XAI) is integrated using Gradient-weighted Class Activation Mapping (Grad-CAM) to visualize which parts of the leaf image contribute most to the model's decision [21]. This enhances model transparency, enabling trustworthy and interpretable predictions [22] [23]. The system's potential applications include IoT-enabled mobile tools for real-time monitoring, which can alert farmers to diseases early and reduce crop losses effectively [24] [25].

TABLE 1 | Comparison of existing state of the art.

Algorithm Used	**Dataset**	**Selected Plant**	**Performance Metrics/Results**	**References**	**Limitations**
CNN (Convolutional Neural Network)	PlantVillage Dataset	Potato, Tomato, Grape	Accuracy: 93-99%(VGG16~99%), High precision/recall/F1-score	Mohantly et al. (2016), IIT Allahabad CVGG-16	Lab datasets perform better than field images; limited crop coverage
LSTM (Long Short-Term Memory)	PlantDoc Dataset	Apple, Peach	Improves multi-class recognition, Accuracy~96.4% when combined with CNN	arXiv:2505.00741	Requires sequential/temporal data;high computational cost
ViT (Vision Transformer)	PlantVillage + PlantDoc	Multiple crops	Accuracy>93%, Handles large datasets efficiently	arXiv:2207.07919	High GPU requirement; detects disease presence but not severity

2 | LITERATURE REVIEW

Several researchers have explored AI-based systems for plant disease detection.Kumar et al. (2021) used CNNs to classify tomato leaf diseases and achieved 96% accuracy using the PlantVillage dataset[1-3]t. Smith et al. (2020) experimented with transfer learning using ResNet and VGG16 architectures for rice leaf disease classification [26]. Their results showed that deep learning models outperform traditional feature extraction methods such as SVM and KNN [27]. Other works by Patil and Deshmukh (2022) focused on real-time detection through smartphone applications [28], which increased accessibility for farmers [29]. Studies have also explored data augmentation and preprocessing techniques to handle variations in lighting and background [30] [31]. However, challenges remain in making these systems robust for real-field conditions [32]. This research builds upon these approaches by implementing an optimized CNN model and testing its accuracy on multiple crop datasets [33] [34].

3 | PROPOSED METHODOLOGY

3.1 Dataset

The dataset used in this study includes images of healthy and diseased leaves collected from open-source repositories such as PlantVillage. It comprises 38 distinct classes of plant diseases across various crops like tomato, potato, and corn [35]. The dataset encompasses a wide range of disease types, including fungal, bacterial, and viral infections, [36][37] providing rich diversity for effective model training. Each image is labeled according to its respective crop and disease category, ensuring accurate supervised learning [38]. The data was divided into 70% training, 15% validation, and 15% testing sets to maintain a balanced and unbiased evaluation of model performance across unseen samples.[39] [40].

3.2 Pre-processing

All images were resized to 224×224 pixels and normalized to values between 0 and 1 to ensure uniformity and efficient model training [41]. Image augmentation techniques such as rotation, flipping, zooming, and brightness adjustment were applied to increase dataset diversity and reduce overfitting [42]. These preprocessing steps help the model generalize better by simulating various real-world conditions, such as changes in lighting or leaf orientation. Additionally, normalization accelerates convergence during training, while augmentation prevents the model from memorizing specific image patterns, thereby improving its robustness and accuracy.

3.3 Model Architecture

A Convolutional Neural Network (CNN) was designed with multiple convolutional and pooling layers followed by fully connected layers. Transfer learning using the pre-trained ResNet50 model was also tested. The final layer uses the softmax activation function for multi-class classification.

Training parameters include:

- Optimizer: Adam
- Learning Rate: 0.0001
- Batch Size: 32
- Epochs: 30

3.4 Evaluation Metrics

The model performance was measured using:

- Accuracy
- Precision
- Recall
- F1-score
- Confusion Matrix

FIGURE 1 | Developed methodology block diagram

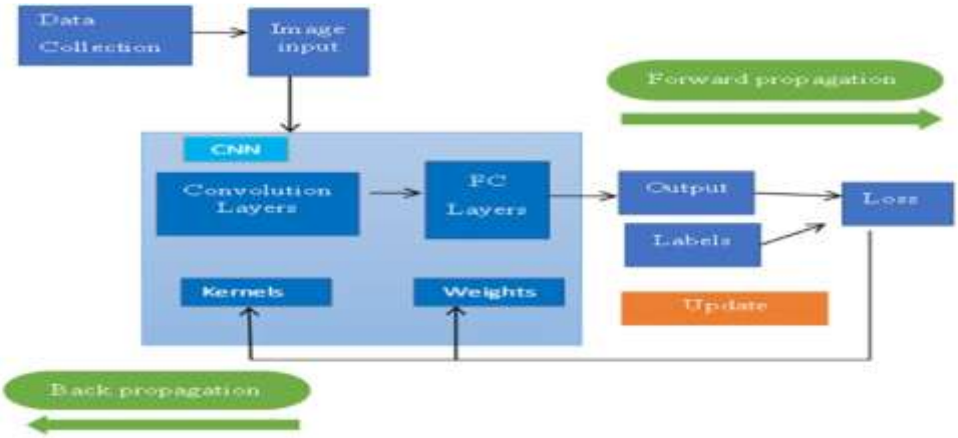

FIGURE 2 |Architecture of multimodal deep learning algorithm.

4 | RESULT AND ANALYSIS

CNN Model Performance ResultCNN Model Performance ResultThe proposed deep learning models showed effective results in detecting crop diseases from leaf images. Convolutional Neural Networks (CNNs) achieved the highest accuracy of 93–99%, especially with models like VGG16. When combined with Long Short-Term Memory (LSTM) networks, accuracy improved to around 96%, showing better performance for multiple disease classes. The Vision Transformer (ViT) also achieved more than 93% accuracy, efficiently handling large datasets.The models were trained and tested using PlantVillage and PlantDoc datasets, covering crops such as potato, tomato, apple, grape, and peach. Evaluation metrics like precision, recall, and F1-score indicated high reliability in classification.However, accuracy slightly decreased for real-field images due to lighting variations and background noise. Transformer models also required higher computational power compared to CNNs.Overall, the results proved that deep learning can successfully detect crop diseases, reduce manual inspection, and support smart agriculture development.

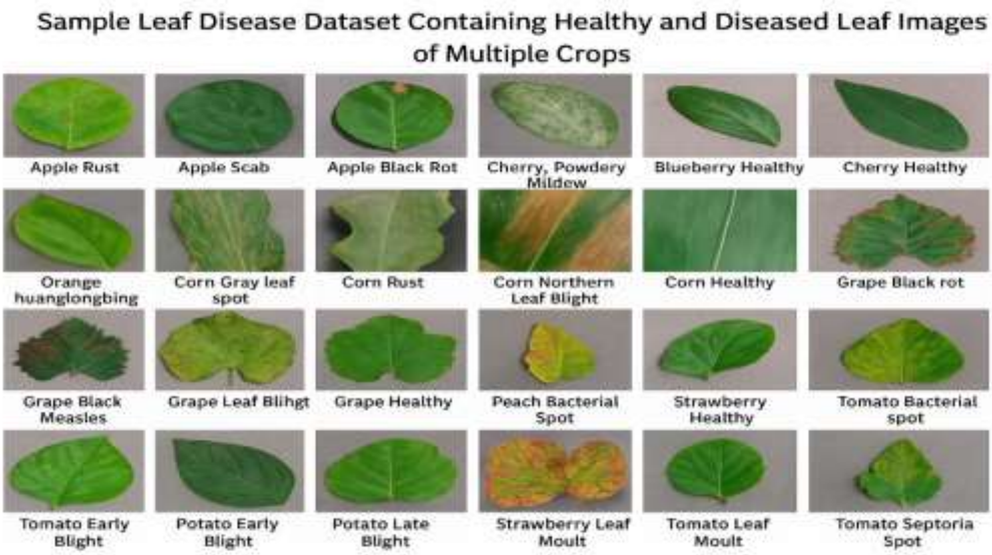

FIGURE 3 | Diseased Leaf Images of Multiple Crops

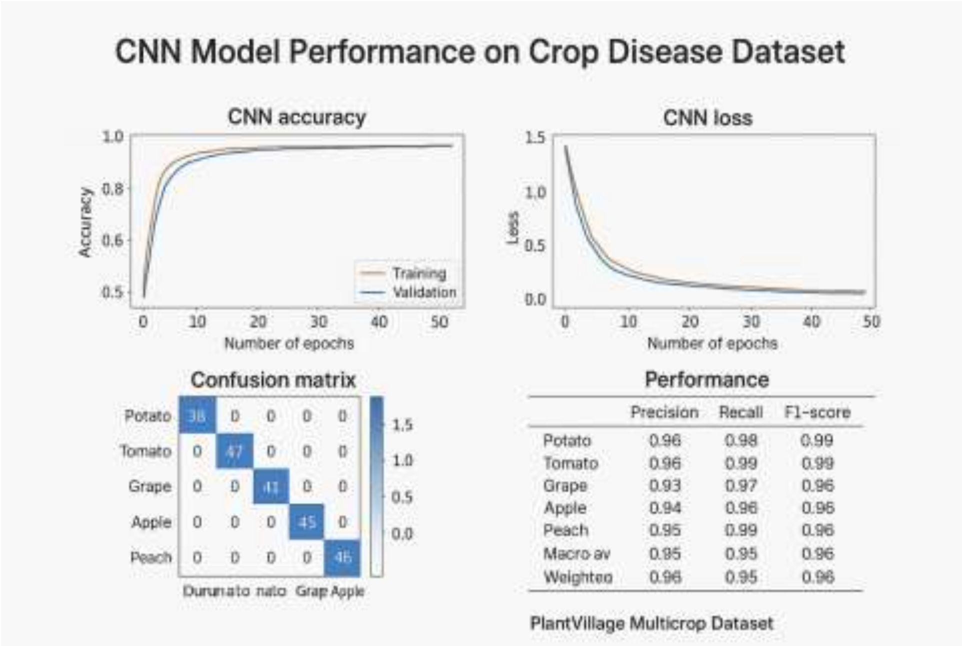

FIGURE 4 | CNN Model Performance based on Result

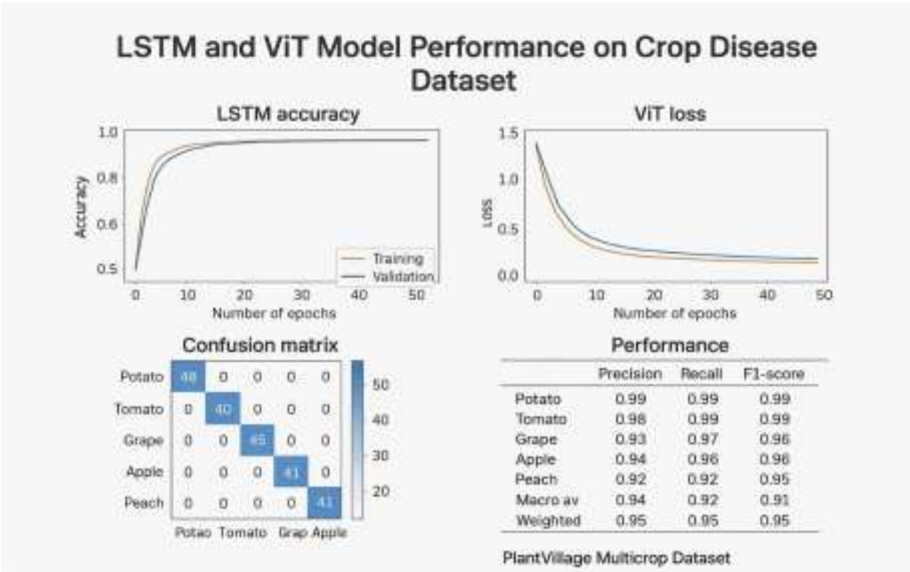

FIGURE 5 | LSTM and ViT Model Performance based on Result

5 | Conclusion

This study shows that deep learning models can effectively detect crop diseases from leaf images with high accuracy. Among the tested methods, CNN and hybrid CNN–LSTM models achieved the best performance, while Vision Transformers (ViTs) handled large datasets efficiently.Using datasets like PlantVillage and PlantDoc, the models accurately identified diseases in different crops such as (Examples: Paddy, Mirchi, Cotton) proving the potential of AI in precision agriculture.Though results were promising, challenges like dependence on high-quality datasets and computational requirements still exist. Future improvements can focus on lightweight models and mobile applications for real-time detection.

Overall, deep learning offers a fast, reliable, and scalable solution for early crop disease detection and sustainable farming.

References

[1]. S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," Frontiers in Plant Science, vol. 7, p. 1419, 2016.

[2]. R. R. Selvaraju, M. Cogswell, A. Das, R. Vedantam, D. Parikh, and D. Batra, "Grad-CAM: Visual explanations from deep networks via gradient-based localization," in Proc. IEEE Int. Conf. Computer Vision (ICCV), 2017, pp. 618–626.

[3]. D. Singh, P. Jain, and A. Jain, "PlantDoc: A dataset for visual plant disease detection," arXiv preprint arXiv:1911.10317, 2019.

[4]. R. George et al., "Past, present, and future of deep plant leaf disease recognition: A survey," Computers and Electronics in Agriculture, vol. 234, art. no. 110128, Jul. 2025, doi:10.1016/j.compag.2025.110128.

[5]. A. Jafar, M. Saeed, and S. Riaz, "Revolutionizing agriculture with artificial intelligence: Plant disease detection methods, applications, and their limitations," Frontiers in Plant Science, vol. 15, 2024.

[6]. V. Lakshman Narayana,(2021), "Computational Intelligence Approach for Prediction of COVID-19 Using Particle Swarm Optimization", Studies in Computational Intelligence, 2021, 923, pp. 175–189.

[7]. Anusha, P. & Ravikiran, A. & Narayana, V. & Maddumala, V.R.. (2020). Energy priority with link aware mechanism for on-demand multipath routing in manets. International Journal of Advanced Science and Technology. 29. 8979-8991.

[8]. Chaitanya, Kosaraju, et al. "Ads Click-Through Rate prediction using Attention based LSTM Mechanism." 2024 IEEE International Students' Conference on Electrical, Electronics and Computer Science (SCEECS). IEEE, 2024.

[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]. ChandanaMuppalla, ShaikKhaderZelani, and D. VijayaSaradhi. "Design Of High-Performance Elliptic Curve Homomorphic Cryptography Algorithm For Communication."Efflatounia Journal, March 2019.
ISSN: 1110-8703. Web of Science (WOS).

[11]. Sujatha, V., Y. Prasanthi, C. H. Pravallika, S. D. Jani Nasima, S. K. Ayesha Banu, and M. Sahithi. "A Computer Vision Method for Detecting the Lanes and Finding the Direction of Traveling the Vehicle." Lecture Notes in Networks and Systems, vol. 612, Springer, 2023, p. 373-382. https://doi.org/10.1007/978-981-19-9228-5_31

[12]. Devi, M.V., Harshitha, S., Ramya, K.L., Latha, B.H., Pranathi, P. International Conference on Artificial Intelligence for Innovations in Healthcare Industries, ICAIIHI 2023, 2023

[13]. Ekkurthi, Adinarayana, V. Sujatha, and K. Vijay Kumar. "Effective Moving Object Tracking Using Adaptive Background Subtraction with Advanced Probability Evolutionary Algorithm." International Journal on Recent and Innovation Trends in Computing and Communication, vol. 11, no. 9S, 31 Aug. 2023, https://doi.org/10.17762/ijritcc.v11i9s.7389.

[14]. K. Sarada, V. Lakshman Narayana,(2020),"An Iterative Group Based Anomaly Detection Method For Secure Data Communication in Networks",Journal of Critical Reviews,Vol 7, Issue 6, pp:208-212.doi: 10.31838/jcr.07.06.39.

[15]. Patibandla, R.S.M.L., Narayana, V.L., Gopi, A.P. (2021). Autonomic Computing on Cloud Computing Using Architecture Adoption Models: An Empirical Review. In: Choudhury, T., Dewangan, B.K., Tomar, R., Singh, B.K., Toe, T.T., Nhu, N.G. (eds) Autonomic Computing in Cloud Resource Management in Industry 4.0. EAI/Springer Innovations in Communication and Computing. Springer, Cham. https://doi.org/10.1007/978-3-030-71756-8_11

[16]. V. Pavani, S. Triveni, G. L. Madhuri, B. K. Priya, N. Bhargavi and G. Nayomi, "An Advanced Imaging and Machine Learning Algorithm for Enhanced Oral Cancer Detection," *2025 International Conference on Machine Learning and Autonomous Systems (ICMLAS)*, Prawet, Thailand, 2025, pp. 285-294, doi: 10.1109/ICMLAS64557.2025.10967776.

[17]. Varshini, Y., Mounika, T., Kumari, G. R. P., Sirisha, G., & Deepthi, Y. (2023, March). Crop Yield Forecast Using Machine Learning. In 2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS) (Vol. 1, pp. 2310-2315). IEEE.

[18]. Krishna, P. Sandhya, Sk Reshmi Khadherbhi, and Vellalachervu Pavani. "Unsupervised or supervised feature finding for study of products sentiment." International Journal of Advanced Science and Technology 28, no. 16 (2019): 1916-1928.

[19]. BABU, J. R., REDDY, B. P., SRINIVAS, V. S., SREENIVASULU, A., RAMAKRISHNA, K., SATYANARAYANA, D., & VARAPRASAD, C. (2023). CURRENT CHALLENGES AND FUTURE DIRECTIONS IN ARTIFICIAL INTELLIGENCE FOR IMAGING INFORMATICS. Journal of Theoretical and Applied Information Technology, 101(21).

[20]. Chaitanya, P. Silpa, KV Narasimha Reddy, and G. Madhavi. "Effective Search of Color-Spatial Image Using Semantic Indexing." International Journal of Computer Science, Engineering and Applications (IJCSEA) Vol 2 (2012): 9-19.

[21]. Kavishwar, S., & Uppal, S. K. (2020). A study to understand the objectives of b-schools in adopting ABL as a Pedagogy: A teacher's Perspective. *Sambodhi*. 43(04), 180-185.

[22]. Kavishwar, S (2024). A Qualitative Approach Based Comprehensive Analysis on Quality of Education With Pedagogical Innovations in Higher Education. *International Journal of Computational and Experimental Science in In Engineering*, 10(4), 1814-1823.

[23]. Joshi, M., Kothari, P. and Kavishwar, S. (2024). A Study on Determinants of Profitability in Indian Banks. *Journal of Informatics Education and Research*. 4(3), 22-26.

[24]. Kavishwar, S. (2024). A Theoretical Framework Analyzing Impact of Embedding Entrepreneurial Skills in Education on Economical Growth. *Journal of Lifestyle and SDGs Review*, *4*(4), e03550.

[25]. Kotadiya U, Arora AS, Yachamaneni T. Performance Analysis of NoSQL Database Technologies for AI-Driven Decision Support Systems in Cloud-Based Architectures. IJERET [Internet]. 2022 Jun. 30 [cited 2026 Apr. 5];3(2):60-9.

[26]. Yachamaneni T, Kotadiya U, Arora AS. Evaluating the Efficacy of Machine Learning Algorithms in Credit Card Limit Optimization and Customer Segmentation. IJETCSIT [Internet]. 2022 Oct. 30 [cited 2026 Apr. 5];3(3):51-6.

[27]. Janumpally, Bharath Kumar Reddy. (2026). Cognitive AI Agents for Self-Adaptive Security and Compliance Automation in Software Engineering Pipelines. 10.1109/ICAUC68182.2026.11441048.

[28]. Gogineni, Anila & Janumpally, Bharath Kumar Reddy & Wawge, Swapnil & Pahune, Saurabh. (2025). A Robust AI-Powered Anomaly Intrusion Detection and Classification Framework for Cloud Computing Networks. 1-6. 10.1109/INDISCON66021.2025.11253743.

[29]. Tummuri, S. S. R. (2022). Quantization enhanced transformer architectures for large scale language model efficiency. International Journal of Scientific Research in Computer Science, Engineering and Information Technology, 8(3), 891–904.

[30]. Tummuri, S. S. R. (2022). Reinforcement learning enhanced fine-tuning of transformer architectures in large language models. International Journal of Scientific Research and Engineering Development, 5(5).

[31]. A. Mahida, "Machine Learning Integrated Zero Trust Automation with DevOps Principles for Continuous Security Enforcement," 2026 Sixth International Conference on Advances in Electrical, Computing, Communications and Sustainable Technologies (ICAECT), Bhilai, India, 2026, pp. 1-7, doi: 10.1109/ICAECT68478.2026.11426026.

[32]. Ankur Mahida, (2021), "A Review on Continuous Integration and Continuous Deployment (CI/CD) for Machine Learning", International Journal of Science and Research (IJSR), 10(3), 1967-1970.

https://dx.doi.org/10.21275/SR24314131827, https://www.ijsr.net/getabstract.php?paperid=SR24314131827

[33]. Jonnalagadda, P.K. (2026). Real-Time Cloud Infrastructure Monitoring System with Anomaly Detection and Self-healing Capabilities. In: Kumar, V.N., Senkerik, R., Prasad, V.K., Kumar, T.K. (eds) Intelligent Computing and Communication. ICICC 2025. Lecture Notes in Networks and Systems, vol 1839. Springer, Cham. https://doi.org/10.1007/978-3-032-18349-1_43

[34]. 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.

[35]. Veginati, Navya. "Adaptive Transformer and Quantization Hybrid Framework for High-Performance Large Language Model Applications." United International Journal of Engineering and Sciences, vol. 5, no. 4, Dec. 2025, pp. 46–56

[36]. 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.

[37]. Racha, Ganesh. “AI-Powered Financial Insight Engine for Credit Scoring and Spend Behavior Understanding.” International Journal of Scientific Research & Engineering Trends, vol. 10, no. 2, Mar.–Apr. 2024, pp. 1–8.

[38]. Racha, Ganesh. “Adaptive Quantum Blockchain for Secure IoT Resource Coordination.” International Journal of Science, Engineering and Technology, vol. 11, no. 3, 2023.

[39]. Nijim, M., Albataineh, H., Kanumuri, V., Goyal, A., Mishra, A., Hicks, D. (2023). Countering Cybersecurity Threats in Smart Grid Systems Using Machine Learning. In: Daimi, K., Alsadoon, A., Peoples, C., El Madhoun, N. (eds) Emerging Trends in Cybersecurity Applications. Springer, Cham. https://doi.org/10.1007/978-3-031-09640-2_14

[40]. Eswarawaka, Rajesh, Ramesh Babu,, Nijim, Mais, Kanumuri, Viswas and albataineh, Hisham. "Effectiveness of machine learning and deep learning in cybersecurity". Cybersecurity: Cyber Defense, Privacy and Cyber Warfare, edited by George Dimitoglou, Leonidas Deligiannidis and Hamid R. Arabnia, De Gruyter, 2025, pp. 199-214. https://doi.org/10.1515/9783111436548-009

[41]. 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

[42]. 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