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DEEP LEARNING ALGORITHMS FOR RICE LEAF DISEASE DETECTION

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Abstract. *Rice cultivation is integral to global agriculture, and the identification of diseases affecting rice plants is crucial for ensuring optimal crop yield and quality. This research presents a system that utilizes computer vision and techniques of deep learning to automatically detect diseases in rice plants. The study evaluates various machine learning and deep learning algorithms for their accuracy, recall, and precision in identifying common diseases of rice leaf such as "brown spot, leaf blast, bacterial leaf blight" and others and emphasizing the superior performance of deep learning models. The EfficientNetB0 model, fine-tuned with data augmentation, demonstrates remarkable accuracy at 98.2%, showcasing its potential for practical applications in precision agriculture. Future work involves expanding the dataset, exploring alternative model architectures, and implementing real-time disease detection in the field using edge computing or mobile applications. This research contributes to advancing agricultural technology and intelligent crop disease management, marking a significant step towards sustainable and efficient farming practices.*

Key Words: Rice plant, disease detection, EfficientNetB0, deep learning, precision agriculture, crop management, automated disease identification.

1. INTRODUCTION

This project focuses on using AI and deep learning for image classification to identify different types of plant diseases. Plants are vital to our ecosystem, and the threat of diseases that can harm crops and vegetation demands efficient detection methods. By leveraging a pre-trained neural network model, EfficientNetB0, as a starting point, we aim to build a systematic workflow that allows our AI system to accurately differentiate and classify images of leaves afflicted by various diseases. The project aims to achieve not only disease recognition but also the capacity to apply what it has learned to new, unobserved examples, making it a potential game-changer in plant disease identification.

Through data preprocessing, model customization, hyperparameter tuning, experimentation, and rigorous evaluation, this project seeks to gain invaluable insights into the world of image classification and the nuances of AI model development. The impact of this project extends beyond plant disease recognition, contributing to the broader field of AI research by shedding light on successful approaches in interpreting visual information. The anticipated outcomes include innovative strategies, enriching learning experiences, and transformative insights that can revolutionize AI applications across diverse domains.

This project focuses on image classification for identifying plant diseases, utilizing data preprocessing, model architecture customization, hyperparameter tuning, experimentation, and rigorous evaluation. Through this process, we aim to gain insights into AI model development and its practical implications. The project's impact extends beyond disease recognition, contributing valuable knowledge to AI research, shedding light on methodologies, challenges, and successful approaches for interpreting visual information. We anticipate unveiling groundbreaking strategies and gaining enriching learning experiences that can revolutionize AI applications across diverse domains.

Moreover, our project will involve collaborating with experts in plant pathology, agriculture, and environmental science. Their domain expertise will guide us in curating a diverse and representative dataset of plant images, ensuring the model's robustness in identifying various diseases across different plant species and environmental conditions.

In conclusion, the amalgamation of AI and domain expertise in image classification for plant disease identification holds great promise in making a meaningful impact on agricultural practices, global food security, and sustainable agriculture. By openly sharing our findings, collaborating with the wider AI community, and promoting responsible AI development, we can collectively unleash the full potential of AI to address complex challenges and create positive societal and environmental impacts.

2. Review of Literature:

(Rajpoot, 2023) Identification of plant leaf diseases early on is essential for sustainable agriculture. Using a random forest classifier and a Faster ‘R-CNN’ deep architecture with ‘VGG-16’ transfer learning, this research achieves a 97.3% accuracy in predicting three major rice diseases—bacteria-induced leaf destruction, brown spots, and leaf smuts—addressing the limitations of previous machine learning methods and ensuring effective disease detection in agriculture.

(Kumar, 2022) ‘Machine learning’ is being used in agricultural research to use pictures to identify plant illnesses, especially in rice crops. A prototype that uses “machine learning” and “image processing” techniques is able to recognize and classify illnesses including bacterial leaf blight, smut, and brown spot in rice plants with an accuracy of about 98.8%.

(Dogra, 2023) Rice is considered to be among the most essential crops in the world for agriculture because it feeds over fifty percent of humankind. Diseases that harm rice plants have the potential to affect the amount as well as the quality of the product, with crop losses potentially reaching 30 to 60%. This publication presents the “CNN-VGG19” model, which combines a transfer learning-based technique with a CNN (“Convolutional Neural Network”) and “Visual Geometry Group” (VGG) 19 to enable the precise diagnosis and categorization of rice leaf disorders.

(Kumar, 2023) In an effort to increase rice quality and decrease pesticide use, this study proposes a Multi-scale ‘YOLO v5’ detection network for the early detection and classification of illnesses affecting rice leaves. The model achieves high accuracy and recall rates by using

DenseNet-201 as the backbone network and “Bidirectional Feature Attention Pyramid Network” (Bi-FAPN) for disease detection. The RLD dataset is used to evaluate metrics such as ‘average precision’, ‘accuracy’, ‘recall’, ‘IoU’, ‘inference time’, and ‘F1 score’. (Sankareshwaran, 2023)Rice, a vital global cereal crop, serves as a staple for half of humanity, facing threats from various biotic and abiotic factors like viral infections and soil fertility. The major agricultural challenge is rice plant diseases, requiring time-consuming manual diagnosis by farmers. A breakthrough solution, the CAHA-AXRNet approach, achieves a remarkable 98.1% accuracy in detecting and categorizing rice plant diseases, surpassing existing methods and enhancing agricultural efficiency.

(Haruna, 2023) In the agricultural domain, a key challenge for researchers and developers is the lack of substantial, well-balanced datasets. This study demonstrates the effectiveness of synthetic data augmentation, specifically using StyleGAN2-ADA, in improving the detection of major rice diseases with “Faster-RCNN” and “SSD” models. With ‘Faster-RCNN’ and ‘SSD’, the suggested approach produced high mean average precisions (mAP) of 0.93 and 0.91 respectively, outperforming standard data augmentation with significant t-test p-values. Implementing this data augmentation pipeline is crucial for enhancing the speed and accuracy of detecting rice leaf illnesses in RCNN and SSD models, offering valuable insights for similar challenges in other fields.

(Ahad, 2023) Using a database of nine prevalent rice illnesses in Bangladesh, a comparison of six CNN-based ‘deep-learning’ architectures was carried out in this work to overcome the shortcomings in previous research on rice disease diagnosis. The greatest accuracy of 98% was attained by the ensemble framework, and accuracy was further increased by 17% by transfer learning, especially in the identification and localization of rice leaf disease. The study demonstrates how deep CNN models can be used in real-time agricultural systems to quickly and accurately identify rice infections, which is important for farmers to protect the quality and production of their crops. (Abasi, 2023) Precision in identifying illnesses affecting rice leaves is essential for contemporary farming and long-term food supply. In order to precisely classify grain leaf illnesses, this study presents a strong approach that uses a specific Convolutional Neural Network (CNN) model. With little overfitting and low loss, the CNN model achieves a competitive accuracy of 0.914. The suggested method showed better accuracy when compared to the “Transfer Learning Inception-v3” and “Transfer Learning EfficientNet-B2” models. In the rapidly changing field of precision agriculture, these models have the potential to significantly improve crop output and ecological sustainability through accurate sickness detection and management.

(Chaudhari, 2023)Agriculture is a vital income source in India, with rice being a staple crop. Diseases significantly impact rice crops, leading to economic losses and reduced product quality. In response, a hybrid CNN (Inception-ResNet)-SVM model that can distinguish and cure damaged rice leaves has been created. It outperforms earlier techniques in terms of accuracy (0.97) and precision (0.93). (Mavaddat, 2023)Artificial intelligence-based diagnostic software offers a cost-effective and efficient solution for farmers to identify pests in agriculture. In a study focusing on rice leaf diseases, two transfer learning techniques were explored, resulting in the development of four highly accurate CNN models, including VGG16, Inceptionv3, and Resnet152v2, with 100% accuracy and improved efficiency compared to similar studies. This advancement minimizes training time and memory usage, making it a promising tool for precision agriculture

(Simhadri, 2023) More than half of the world's population depends on rice as their main food and energy source, but both quantity and quality of the crop are threatened by a number of variables including climate, diseases, and insects. Infections with bacteria have a major negative influence on rice crops and cause large financial losses. Utilizing cutting-edge technology such as machine learning, a study that used transfer learning with pre-trained CNN models found that InceptionV3 was more accurate than AlexNet at 99.64% in autonomously diagnosing rice leaf diseases.

(Haridasan, 2023)Automated rice crop disease detection through a computer vision-based system, incorporating deep learning and image processing, proves vital for the farming industry. Targeting common Indian rice diseases, such as sheath rot and bacterial leaf blight, the method achieves a high validation accuracy of 0.9145, enabling proactive treatment recommendations post-diagnosis and empowering agriculture stakeholders to combat illnesses effectively.

(Shah, 2023)introduces an automated method for diagnosing rice blast disease, employing pre-trained models like Inception V3 and ResNet50, achieving an impressive accuracy of 99.75%. The connection-skipping ResNet50 outperforms other models, demonstrating improved disease prediction through the Gradio online application.

(Daniya, 2023) presents a hybrid optimization technique that combines deep fuzzy clustering with a neuro-fuzzy network trained using “Rider Henry Gas Solubility Optimization” to artificially identify and classify rice illnesses. Improved F1-scores and accuracy are obtained using the RHGSO-based ‘deep learning’ approach, which successfully classifies illnesses such as ‘Bacterial Leaf Blight’, ‘Blast’, and ‘Brown spot’. (Zhou, 2023) proposes a "residual-distilled transformer architecture" to enhance model interpretability and accuracy in identifying rice leaf diseases. With a 0.89 F1-score and 0.92 top-1 accuracy on a rice leaf disease dataset from paddy fields, the method beats state-of-the-art models. while preserving interpretability, thanks to distillation from pre-trained vision transformer models.

(Dubey, 2023) advocates for early plant disease identification, emphasizing the role of ‘machine learning’ algorithms to overcome challenges in workforce training and timely detection. The proposed method involves ‘image processing’, ‘feature extraction’, and ‘classification’ using an efficient artificial neural network and adaptive sunflowers optimization. Leveraging a level set segmentation technique, the approach achieves a maximum accuracy of 97.94% for predicting plant diseases, contributing to improved yield prediction and highlighting the significance of early leaf disease diagnosis.

(Zhang, 2023)Introducing ResViT-Rice, a hybrid architecture combining CNN and transformer elements, this study achieves highly accurate detection of rice diseases, including leaf explosion and brown spot. Through the incorporation of the convolutional block attention module, ResViT-Rice outperforms other deep-learning models with an accuracy of 0.9904, AUC of 0.9987, and precision, recall, and F1-score exceeding 0.96, highlighting its effectiveness in extracting features for reliable and precise classification of diverse rice illnesses.

(Sunil, 2023) highlights the crucial role that plant diseases play in reducing agricultural output and the necessity for automated, economical techniques because of the shortcomings of the existing expert-dependent systems. Reviewing 160 research papers, it provides a thorough summary of methods for plant disease detection and classification based on ‘deep learning’ and ‘machine learning’, including a variety of plants and datasets. The paper emphasizes unmet research needs and highlights the significance of hyperparameters in deep learning for advancing effective automated solutions in plant disease identification.

(Attaluri, 2023) highlights the global impact of plant diseases on agricultural productivity and emphasizes the importance of early detection to prevent financial losses. It explores various methods, including spectroscopy, enzyme-linked immunosorbent assays, and biosensors, for plant disease identification. The paper underscores the increasing role of artificial intelligence and neural networks in adaptive point-of-care systems for early pathogen detection, providing a concise overview of recent advancements in plant disease identification methods.

(Yang, 2023) Introducing DGLNet, a lightweight yet highly precise system for early identification of rice diseases, this study employs the “Global Attention Module” (GAM) and “Dynamic Representation Module” (DRM) to address challenges in noisy and dispersed symptoms. Using two real plant disease datasets, the recognition accuracy was 99.82% and 99.71% respectively, DGLNet outperforms existing approaches, showcasing its effectiveness in practical situations while maintaining computational efficiency. The research offers valuable technical support for disease detection, advocating precision farming and agricultural intelligence applications.

U M Gopal Krishna (2019) The study reveals that the investor's investment preferences vary across various investment vehicles. Investment objectives such as Risk, Return, Safety, and Liquidity will determine the investor's preference in Investment Avenue. The majority of investors enter the stock market for returns, while bond investors take on risk and receive periodic returns. Investors with a low tolerance for risk favour Mutual Fund Investment for Future Needs.

U M Gopal Krishna (2020) According to Operating Profit Margin and Price to Earnings ratio, the public sector banking industry is profitable. Net profit margin, return on capital employed, and earnings per share are profitable in private banking. Both public and private banks must introduce new instruments and innovations to survive. Banks must manage credit risk and diversify fee-based activities for long-term success in this competitive environment.

O Krishna, U. M. G., & Deepthi, S. (2024), Today's competitive business environment requires good decision-making. Financial Planning, Forecasting, Fund Management, and Internal Audit Management Systems affect decision-making quality and effectiveness. Academic researchers and business practitioners have recently focused on business intelligence (BI) because it improves Business Intelligence Systems, which are crucial to business success. Businesses perform better with business intelligence (BI). We hope this study will help us understand how BI systems improve decision-making. BI tool-Business Intelligence System relationships, Financial Forecasting, Fund Management System, Financial Planning, and Internal Audit Management System data were analyzed. To test the theoretical model, we surveyed 420 Indian IT professionals who use Financial Performance and Business Intelligence tools. The study found many valuable data assets in Indian IT companies. These assets facilitate fast, effective decision-making for Business Intelligence System implementation. Internal Audit Management System, Financial Planning, Fund Management, Forecasting. BI for quality decision-making is more important than Competitive advantage in Financial Forecasting, Fund

Management System, Financial Planning, and Internal Audit Management System.Business Intelligence System implementation can be improved by studying financial capabilities and performance measurement. How business intelligence tool statement quality boosts competitiveness. The study examined how Financial Capabilities affect BI implementation. It explains why companies should use and promote BI. It proves financial capabilities' importance in business intelligence tool implementation. The study found that business intelligence (BI) systems help Indian IT companies make better operational decisions, giving them an edge. To maximize business intelligence (BI) system ROI, the organization's long-term goals and BI strategy must align. Study: Financial capabilities aid business intelligence (BI) system implementation. According to relevant literature, financial capabilities improve operational performance, decision-making, and data availability. BI improves data-driven decisions, adding value.

U M Gopal Krishna (2024), This study measured the economic independence of Andhra Pradesh women entrepreneurs. Empowerment was measured at government, professional, and social levels. The scale measured measurement levels as high, medium, and low. Positive, moderate, and negative responses advanced to higher, medium, and lower levels, respectively. The empowerment analysis found that 67% of government employees, 45% of professional employees, and 69% of social employees felt empowered by entrepreneurship. The empowerment level analysis as a whole suggests that women business owners in Andhra Pradesh have a positive view of entrepreneurship and that it empowers women.

U M Gopal Krishna (2024),The researcher's empirical study shed light on the banking sector's green practices in India, a developing nation with growing environmental concerns. Through analysis, the study confirms the importance of "a) Commitment and Support from Management, and b) Pressure from competitors and customers," in Indian banks adopting green practices. The study also establishes the structural relationship between these factors and Indian banking sector environmental sustainability. This research also shows that top management and owners' active participation is most important. They should be convinced of green banking's benefits and enthusiastic about green program implementation.

Prathyusha, P., Madhavi, B., Velpula, T., Sujatha, M., & Krishna, U. M. G. (2024), suggests that SVR is a practical and adaptable strategy that may help the customer overcome distributional properties of key components, data geometry, and model overfitting in this rainfall estimation project. SVR display bit capacity must be chosen carefully. Clearly, SVR outperforms MLR as an expectation strategy. In datasets where MLR cannot detect nonlinearity, SVR is useful.

Sri Vardhan, Y. S. D. S., Krishna, U. M. G., Tejaswini, I., Samuel Johnson Israel, K., & Prathyusha, P. (2024), Overall, the study suggests that blockchain technology improves business processes and solves problems in the IT industry. Effective security reduces security risks in these industries. To achieve this, blockchain technology's benefits and drawbacks for IT businesses were briefly discussed. Secondary qualitative data was used to organize this article. Therefore, relevant research journals were examined and the necessary information extracted. Additionally, block chain systems' role in digital technology and food supply chain management systems has been thoroughly examined.

Sruthi, M., Sravanthi, T., Shaik, M. A., Padmaja, C., & Krishna, U. M. G. (2024), To protect private data, the research covered data security in depth. The study required secondary data collection and analysis to find flaws and improve data security. Past studies informed the study, and the researcher's opinion is included. The article suggests that integrating the right tools and technologies can reduce cyber security threats. Organizations can secure employee data with firewalls and antivirus software. This feature would help organizations comply with data security protocols.

According to the findings of their research, a large number of researchers have discovered that the concerns of customers motivated businesses to adopt green or environmental practises (Henriques and Sadorsky, 1996; Khanna and Anton, 2002). Henriques and Sadorsky (1996) came to the conclusion that "Customer Pressure" was the most influential factor and source that caused organisations to feel stress to implement an environmental policy. This was after they examined the effects of regulatory pressure.

3.Research Methodology

The code implements an image classification pipeline using the EfficientNetB0 architecture. There are three sets in the dataset: ‘test’, ‘validation’, and ‘training’. The training data is subjected to data augmentation. A custom dense head is added to the EfficientNetB0 base, and the model is compiled and trained with early stopping and learning rate reduction techniques. However, there are some issues and missing parts that need to be addressed, such as variable names and the definition of `validation_generator`. Once resolved, The `evaluate’ technique is used to assess the model's performance on the test set.

3.1 Model Architecture:

The model architecture utilizes EfficientNetB0 , a ‘deep convolutional neural network’ that has received instruction using the ImageNet dataset. In order to decrease spatial dimensions, a global ‘average pooling layer’ is implemented, two dense layers with ReLU activation came next. to capture higher-level features. The final output layer employs a softmax activation with 9 units, representing one unit for each class.

3.2 Model Compilation and Training:

For model compilation, the Adam optimizer with a specific learning rate is used, along with “categorical cross-entropy loss” and “Accuracy” as the evaluation metric. The early halting and learning rate reduction (ReduceLROnPlateau) callbacks are used to improve training “convergence” and prevent ‘overfitting’.

During training, Using training and validation data, the model is fitted using the `fit` method. Using a `ImageDataGenerator`, data augmentation techniques are applied to the training data.

3.3 Testing:

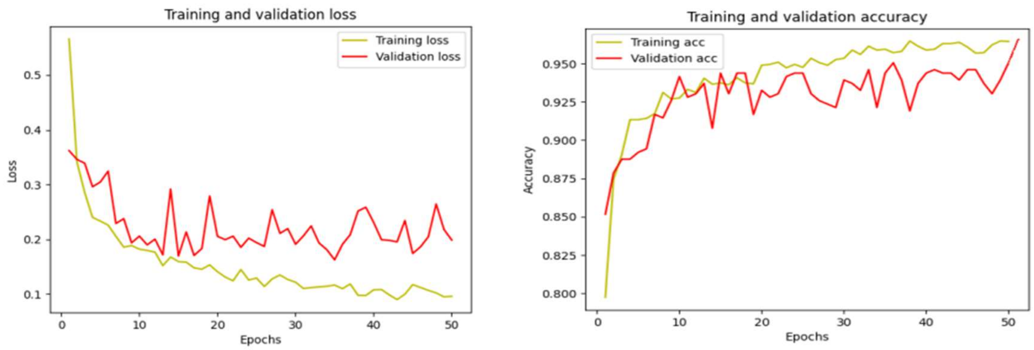
The `evaluate` technique is used to assess the model on the test set. The `ImageDataGenerator` is used to load the test data.

3.4 Issues and Corrections:

However, there are some issues in the code that need to be addressed. The variable names should be made consistent throughout the code. The repeated and redundant parts of the code should be removed or organized appropriately. The undefined variable `validation_generator` should be replaced with `validation_datagen`, which seems to be a missing part of the code.

To improve the code's clarity and functionality, the undefined parts should be completed or modified accordingly, and the variable names should be consistent. This will ensure a smooth and successful implementation of the image classification pipeline using the EfficientNetB0 architecture.

4. Analysis and interpretation:



4.1.1 Graph Overview:

The visualization illustrates training and validation losses at different epochs (0.5, 0.4, 0.3, 0.2, and 0.1) during model training. Training loss signifies the error on training data, while validation loss reflects error on validation data.

4.1.2 Initial Epoch:

Observation: Both training and validation losses are initially high. Interpretation indicates a substantial error in predictions on both training and validation sets initially.

4.1.3 Training Progress:

Observation: Both losses decreaseas training progresses. Comparison:Training loss decreases faster than validation loss. Implication Suggests potential overfitting, indicating the model is becoming overly specialized in learning training data.

4.1.4 Over fitting Explanation:

Definition: Over fitting occurs when a model excessively learns training data, leading to poor performance on unseen data. Identification Faster decline in training loss than validation loss signals overfitting.Performance Discrepancy Validation data lags behind training data improvement.

4.15 Additional Information (Graph Notation "N."):

Note: "N."suggests potential undisclosed data points or epochs.Consideration Incompletegraph visibility implies a concerning trend of overfitting.

4.1.6 Recommendations:

Mitigation Strategies: Implement regularization techniques (e.g., dropout, weight decay) to improve generalization. Early Stopping: Terminate training when validation loss stagnates or rises.

4.1.7 Conclusion:

The analysis highlights the challenge of overfitting. Strategies such as regularization and early stopping are crucial to prevent overfitting and enhance generalization.

The graph depicts training and validation accuracy over 50 epochs during model training. Training accuracy improves from approximately 99.75% to 98%, while validation accuracy starts at 99.5% and ends around 98%, consistently lagging behind training accuracy.

4.2.1 Key Findings:

Training Accuracy Improvement: Continuous enhancement in correctly classifying training data.
Validation Accuracy Trend: Mirrors training accuracy but consistently remains slightly lower.
Indication of Over fitting: Consistent gap implies potential over fitting.

4.2.2 Implications:

Over fitting Concern: Discrepancy between training and validation accuracy suggests a risk of over fitting.

4.2.3 Recommendations:

- Provide an intuitive mobile application that enables farmers to use their smartphones to take pictures of rice leaves.
- Implement regularization techniques (e.g., dropout, weight decay) to address over fitting.
- Apply image processing techniques to examine the photos that were taken. Train the system to detect diseases using machine learning techniques like convolutional neural networks (CNNs).
- Take into consideration cloud-based options for image processing, as they can offer effective and scalable computer power.
- To accommodate locations with spotty or nonexistent internet connectivity, make sure the mobile app includes an offline mode. Even while they are not online, farmers ought to be able to take pictures and get comments.
- Provide an extensive library of regionally specific rice leaf diseases. Certain diseases may be more common in some areas than others, therefore a tailored approach improves accuracy.
- Put in place an automatic notification system to notify farmers when crop illnesses are detected.
- Work together with agricultural extension agencies to give farmers more resources and support in light of the illnesses that have been detected.
- Permit farmers to comment on how accurately diseases are identified. The detection model's performance can be continuously enhanced by using this feedback loop.
- Hold training sessions for farmers to teach them how to use the equipment and stress the value of early disease identification.
- Ensure that the system adheres to data security and privacy standards. Farmers may have concerns about the safety of their data, so transparent and secure practices are essential

4.2.4 Conclusion:

The model shows positive learning on training data, but caution is required due to potential over fitting. Applying regularization techniques can enhance generalization and mitigate over fitting challenges.

In this project, we delve into the exciting realm of image classification to address the crucial issue of identifying various types of plant diseases using the power of deep learning. Our main approach involves utilizing the Efficient NetB0 pre-trained model, which has extensive knowledge from analyzing other images, and then customizing it with additional layers to enhance its ability to recognize specific plant diseases. To ensure better learning, we utilize methods such as "rotation, color variation, and flipping to the images" for data augmentation.

The training, validation, and testing sets of the dataset enable us to train the model, monitor its progress in learning, and analyze its performance on fresh, untested data. To determine the best settings for our model, we run a number of tests with regularization strategies, training lengths, and learning rates. Preventing over fitting and making sure the model comprehends the patterns instead of just learning them by heart are the objectives.

Throughout the project, we meticulously document our methodology and findings to share our insights with others and contribute to the development of more intelligent computer models in the area of image classification. By analyzing the model's accuracy and other performance measures, we aim to achieve a robust and accurate system for identifying plant diseases, thus making a valuable contribution to the broader field of AI research.

1. References

[1]Rajpoot, V., Tiwari, A., & Jalal, A. S. (2023). Automatic early detection of rice leaf diseases using hybrid deep learning and machine learning methods. *Multimedia Tools and Applications*, *82*(23), 36091–36117. https://doi.org/10.1007/s11042-023-14969-y

[2] Kumar K, K., & Kannan. (2022). Detection of rice plant disease using AdaBoostSVM classifier. *Agronomy Journal*, *114*(4), 2213–2229. https://doi.org/10.1002/agj2.21070

[3] Dogra, R., Rani, S., Singh, A., Albahar, M. A., Barrera, A. E., & Alkhayyat, A. (2023). Deep learning model for detection of brown spot rice leaf disease with smart agriculture. *Computers & Electrical Engineering: An International Journal*, *109*(108659), 108659. https://doi.org/10.1016/j.compeleceng.2023.108659

[4] Kumar, V. S., Jaganathan, M., Viswanathan, A., Umamaheswari, M., & Vignesh, J. (2023). Rice leaf disease detection based on bidirectional feature attention pyramid network with YOLO v5 model. *Environmental Research Communications*, *5*(6), 065014. https://doi.org/10.1088/2515-7620/acdece

[5] Sankareshwaran, S. P., Jayaraman, G., Muthukumar, P., & Krishnan, A. (2023). Optimizing rice plant disease detection with crossover boosted artificial hummingbird algorithm based AX-RetinaNet. *Environmental Monitoring and Assessment*, *195*(9). https://doi.org/10.1007/s10661-023-11612-z

[6] Haruna, Y., Qin, S., & Mbyamm Kiki, M. J. (2023). An improved approach to detection of rice leaf disease with GAN-based data augmentation pipeline. *Applied Sciences (Basel, Switzerland)*, *13*(3), 1346. https://doi.org/10.3390/app13031346

[7] Ahad, M. T., Li, Y., Song, B., & Bhuiyan, T. (2023). Comparison of CNN-based deep learning architectures for rice diseases classification. *Artificial Intelligence in Agriculture*, *9*, 22–35. https://doi.org/10.1016/j.aiia.2023.07.001

[8] Abasi, A. K., Makhadmeh, S. N., Alomari, O. A., Tubishat, M., & Mohammed, H. J. (2023). Enhancing rice leaf disease classification: A customized Convolutional Neural Network approach. *Sustainability*, *15*(20), 15039. https://doi.org/10.3390/su152015039

[9] Chaudhari, D. J., & Malathi, K. (2023). Detection and prediction of rice leaf disease using a hybrid CNN-SVM model. *Optical Memory and Neural Networks*, *32*(1), 39–57. https://doi.org/10.3103/s1060992x2301006x

[10] Mavaddat, M., Naderan, M., & Alavi, S. E. (2023). Classification of rice leaf diseases using CNN-based pre-trained models and transfer learning. *2023 6th International Conference on Pattern Recognition and Image Analysis (IPRIA)*.

[11] Simhadri, C. G., & Kondaveeti, H. K. (2023). Automatic recognition of rice leaf diseases using transfer learning. *Agronomy (Basel, Switzerland)*, *13*(4), 961. https://doi.org/10.3390/agronomy13040961

[12] Haridasan, A., Thomas, J., & Raj, E. D. (2023). Deep learning system for paddy plant disease detection and classification. *Environmental Monitoring and Assessment*, *195*(1). https://doi.org/10.1007/s10661-022-10656-x

[13] Shah, S. R., Qadri, S., Bibi, H., Shah, S. M. W., Sharif, M. I., & Marinello, F. (2023). Comparing Inception V3, VGG 16, VGG 19, CNN, and ResNet 50: A case study on early detection of a rice disease. *Agronomy (Basel, Switzerland)*, *13*(6), 1633. https://doi.org/10.3390/agronomy13061633

[14] Daniya, T., Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai 600119, Tamilnadu, India, Vigneshwari, S., Department of Information Technology, GMR Institute of Technology, Rajam 532127, Andhra Pradesh, India, & Department of Computer Science and Engineering, Sathyabama Institute of Science and Technology, Chennai 600119, Tamilnadu, India. (2023). Rice plant leaf disease detection and classification using optimization enabled deep learning. *Journal of Environmental Informatics*. https://doi.org/10.3808/jei.202300492

[15] Zhou, C., Zhong, Y., Zhou, S., Song, J., & Xiang, W. (2023). Rice leaf disease identification by residual-distilled transformer. *Engineering Applications of Artificial Intelligence*, *121*(106020), 106020. https://doi.org/10.1016/j.engappai.2023.106020

[16] Dubey, R. K., & Choubey, D. K. (2023). Reliable detection of blast disease in rice plant using optimized artificial neural network. *Agronomy Journal*. https://doi.org/10.1002/agj2.21449

[17] Zhang, Y., Zhong, L., Ding, Y., Yu, H., & Zhai, Z. (2023). ResViT-rice: A deep learning model combining residual module and transformer encoder for accurate detection of rice diseases. *Agriculture*, *13*(6), 1264. https://doi.org/10.3390/agriculture13061264

[18] Sunil, C. K., Jaidhar, C. D., & Patil, N. (2023). Systematic study on deep learning-based plant disease detection or classification. *Artificial Intelligence Review*, *56*(12), 14955–15052. https://doi.org/10.1007/s10462-023-10517-0

[19] Attaluri, S., & Dharavath, R. (2023). Novel plant disease detection techniques-a brief review. *Molecular Biology Reports*, *50*(11), 9677–9690. https://doi.org/10.1007/s11033-023-08838-y

[20] Yang, Y., Jiao, G., Liu, J., Zhao, W., & Zheng, J. (2023). A lightweight rice disease identification network based on attention mechanism and dynamic convolution. *Ecological Informatics*, *78*(102320), 102320. https://doi.org/10.1016/j.ecoinf.2023.102320

[21] Krishna, U. M. G., & Deepthi, S. (2024). Entrepreneurship empowers women. 7TH INTERNATIONAL CONFERENCE ON NANOSCIENCE AND NANOTECHNOLOGY.) https://doi.org/10.1063/5.0196176

[22 Madhavi, B., Prathyusha, P., Velpula, T., & Krishna, U. M. G. (2024). Importance of block chain in managing it business. 7TH INTERNATIONAL CONFERENCE ON NANOSCIENCE AND NANOTECHNOLOGY. https://doi.org/10.1063/5.0196134

[23] Mukella, G. K. U., Guddeti, K. K. R., & Kodamanchill, S. J. I. (2024). Applications of green banking practices. 7TH INTERNATIONAL CONFERENCE ON NANOSCIENCE AND NANOTECHNOLOGY. https://doi.org/10.1063/5.0196177

[24] Prathyusha, P., Madhavi, B., Velpula, T., Sujatha, M., & Krishna, U. M. G. (2024). Digital security for securing private information. 7TH INTERNATIONAL CONFERENCE ON NANOSCIENCE AND NANOTECHNOLOGY.) https://doi.org/10.1063/5.0196453

[25] Sri Vardhan, Y. S. D. S., Krishna, U. M. G., Tejaswini, I., Samuel Johnson Israel, K., & Prathyusha, P. (2024). Effects of business intelligence tools on financial performance of it industry. 7TH INTERNATIONAL CONFERENCE ON NANOSCIENCE AND NANOTECHNOLOGY. https://doi.org/10.1063/5.0196170

[26] Sruthi, M., Sravanthi, T., Shaik, M. A., Padmaja, C., & Krishna, U. M. G. (2024). Predicting natural increase of water level using machine learning. 7TH INTERNATIONAL CONFERENCE ON NANOSCIENCE AND NANOTECHNOLOGY.

https://doi.org/10.1063/5.0195782

[27] U M Gopal Krishna (2017). “Self-Help Groups for Women Empowerment in the Present Scenario – A Overview” *International Journal of Engineering Technology Science and Research (IJETSR),* Volume 4, Issue9, September 2017, pp 491 – 500, ISSN 2394-3386.

[28] U M Gopal Krishna (2017). “GST in India & Its Impact on Indian Economy*” International Journal of Research in Economics & Social Sciences (IJRESS)*, Volume 7, Issue 11, November 2017, pp 514 – 524, ISSN 2249-7382. Impact Factor: 6.939.

[29] U M Gopal Krishna (2019). “Investors Perception towards Investment Avenues”, *International Journal of Recent Technology and Engineering*, Volume-8 Issue-2, July 2019.

[30] U M Gopal Krishna, (2019), “Perception of Investors towards Risk in Investment Avenues”, *International Journal of Recent Technology and Engineering*, Volume-8 Issue-2, July 2019.

[31] U M Gopal Krishna, (2020), “Profitability Analysis of Public and Private Sector banks in India – A Fundamental Approach”, *Journal of Mechanics of Mechanics Continua and Mathematical Sciences,* Special Issue, No.-5, January (2020) pp 159-170. https://doi.org/10.26782/jmcms.spl.5/2020.01.00014,

[32] U M Gopal Krishna (2020). “Problem and Supporting System of Aged People in Sugali Tribes Chittor District, Andhrapradesh”, in *International Journal of Scientific & Technology Research (IJSTR),* Volume-09, Issue-2, pp 2277-8616, Impact Factor 7.466, February- 2020.

[33] U M Gopal Krishna (2022). “Employee Stress And Its Impact On Employee Performance Among Women Employees In Mysore District”, *Nat. Volatiles & Essent. Oils*,, Volume-8 Issue-4, January 2021.

[34] U M Gopal Krishna (2021). “An Analysis of the Lack of Large Scale Entrepreneurship in IT Industries of India”. *International Journal of Aquatic Science*, Volume-12, Issue-01, pp 14-27, July - 2021.

[35] U M Gopal Krishna (2022). “TRASE Model for Performance & Workload Management – Academic Scenario” *Turkish Journal of Physiotherapy and Rehabilitation*, Volume-32, Issue-03, ISSN 2651-4451 | e-ISSN 2651-446X, pp 39622 - 39631, January – 2022.