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Smart Detection of Crop Pests and Diseases: Enhancing Agricultural Productivity with AI and Modern Technology

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Abstract:

The world economy heavily depends on agriculture, especially in developing countries such as Pakistan, where it accounts for 19 per cent of GDP and provides 38 per cent of the labour force. Threats of plant diseases and pests in the sector are also critical, yet the percentage of losses to the harvest is close to 20 per cent of the total global harvest, with financial losses of over billions of dollars annually. Manual techniques for disease detection used in the past are labour-intensive, time-consuming, and, in most cases, are not available to rural farmers. The paper proposes a Deep Learning-based method for automated early detection and categorisation of plant health problems. Using such a large dataset of 55,449 image samples of healthy and diseased leaf datasets and certain pests such as the fall armyworm and leaf beetle, we designed a multi-model system which is combined with feature fusion. We use Convolutional Neural Networks (CNNs) as our method to process complex visual images and classify diseases across crops such as plantain, tomato, and cassava.The experiment's outcomes indicate some success. However, the model has obtained high F1-scores for each class (e.g., Class 12 with 0.72 and Class 19 with 0.59), the overall accuracy was 49% with a macro F1-score of 0.41. An elaborate analysis of the confusion matrix shows that there is a tough challenge in separating similar appearing diseases visually and managing the imbalanced classes of the minority datasets. The paper finds that, though deep learning has a disruptive potential in precision agriculture, future enhancements, such as smote to balance data, ResNet or Vision Transformer architectures, and multiple sensor fusion are necessary to cover the so-called lab-to-field gap and offer effective instruments to support sustainable farming.

Keywords: Precision Agriculture; Plant Disease Detection; Deep Learning; Convolutional Neural Networks (CNN); Feature Fusion; Pest Management; Image Classification; Food Security; Crop Health Monitoring; Data Augmentation.

Introduction:

The global economy remains dependent on agriculture, especially in developing countries such as Pakistan, where agriculture contributes significantly to the economy. According to the Pakistan Bureau of Statistics (PBS), agriculture contributes about 19% to Pakistan's GDP, yet almost 38% of the total labor force is employed in agriculture. Furthermore, over 60% of Pakistan's rural population relies directly on agriculture for their livelihood. Major crops such as wheat, rice, sugarcane, and cotton play an important role in the country's exports and significantly influence foreign exchange outcomes[1].

Despite the availability of vast areas of arable land, Pakistani farmers continue to face many obstacles that hinder optimal agricultural performance [2], [3]. Unpredictable weather patterns, reduced soil fertility, water scarcity, and increased plant diseases and pests are among these difficulties. Improper harvesting, pesticides, and pesticide selection and application are among the most important issues. The Pakistan Agricultural Research Council (PARC) claims that around 30% of soil health degradation is caused by the overuse of pesticides, which significantly increases environmental pollution and domestic degradation. This bad management not only affects agricultural production but also has a major impact on farmers. Inefficient or inappropriate use of farmers in Pakistan exceeds P100 billion a year and is believed to pose financial and ecological risks to the agricultural industry.

Pests, diseases, [4] and other plant health problems are the leading causes of agricultural losses and often result in significant economic losses. FAO estimates that plant pests and diseases cause 20% of global harvest production losses per year. In India alone, agricultural productivity has decreased by 15% per year due to plant diseases and pest invasions, resulting in annual losses of around USD 45 billion. For example, wheat rust has caused revenue losses of up to 50% in the past alone. At the same time, pests such as the Armyworm devastate corn crops in some countries, leading to significant economic setbacks for farmers.

Advances in precision agriculture have introduced many technologies [5] to address these challenges. These techniques [6] allow farmers to recognize and treat diseases early in the crop's growth, optimizing the use of pesticides and herbicides. This not only increases yields but also reduces the economic burden on farmers. However, plant disease detection remains a serious problem. Studies show that only 40% of early-stage plant diseases are identified using conventional methods, leading to extensive damage before intervention.

Flow diseases can cause significant losses in agricultural production and affect both farmers' incomes and the country's overall agricultural economy. Early detection and proper management of these diseases are essential to prevent extensive harvest damage and ensure food safety. Traditionally, plant disease detection was carried out by experts who manually tested harvests for signs of disease. This method is effective, but time-consuming, labour-intensive, and unrealistic for large-scale agricultural work. Furthermore, rural farmers often have no access to expert guidance, leading to delays in diagnosing and treating the disease.

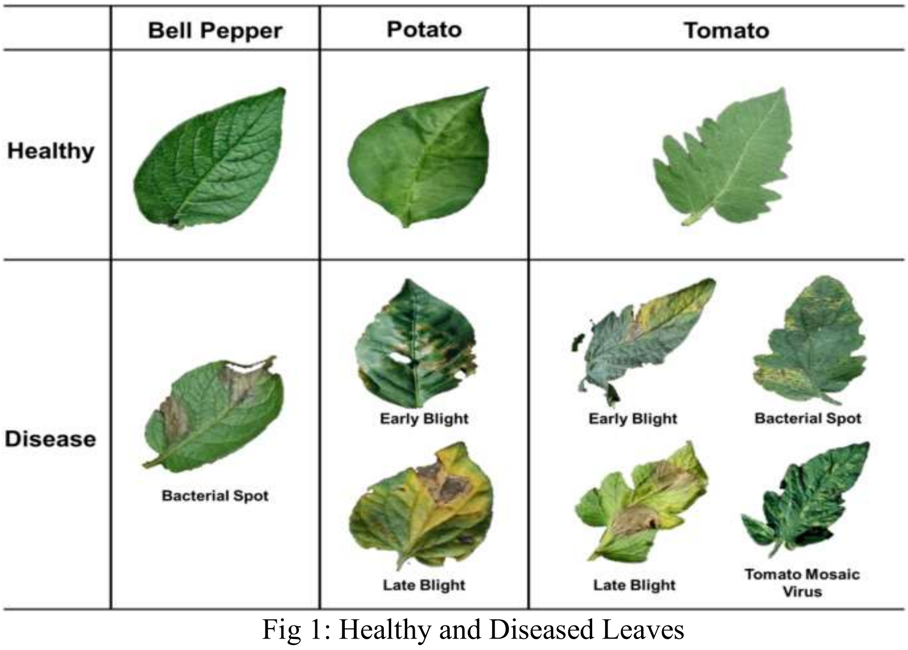


Fig 1: Healthy and Diseased Leaves

Literature Review:

The realm of automated harvesting and disease detection has undergone transformative innovation over the past 20 years, evolving from basic visual testing methods to sophisticated artificial intelligence (AI) based systems[7], [8]. This progression reflects both technological advancements [9]and the growing recognition of precision agriculture's role in ensuring global nutritional security. As agricultural challenges from climate change, pesticide resistance, and growing food demands increase, the development of efficient recognition systems is of paramount importance. This literature search systematically examines historical developments, current state, and future directions for automated detection technologies.

Limitations of impulsive visual testing methods for early automated cognitive research. The study by [10] found quantitative contradictions in a review of human experts. These results were significant as they highlighted fundamental weaknesses of traditional disease assessment protocols that could lead to inappropriate treatment decisions and substantial economic losses.

During this period, [11] made a groundbreaking contribution by developing one of the first successful image processing algorithms to recognise disease.

The limitations of rule-based image processing led to the adoption of machine learning techniques during this period. [12] conducted extensive evaluations using the newly developed PlantVillage dataset, demonstrating that Support Vector Machines (SVMs) could achieve an accuracy rate of 82% under controlled conditions. Their research revealed notable insights in feature engineering, showing that texture features generally outperformed color based features for specific plant diseases. Simultaneously, researchers began exploring multi-sensor approaches. [13] demonstrated the effectiveness of thermal imaging in early pest detection, achieving 88% accuracy in identifying aphid infestations by analyzing their influence on plant transpiration patterns. This period also witnessed the development of first-generation mobile applications for disease diagnosis and the exploration of spectral imaging beyond visible light ranges.

The rise of deep learning revolutionized detection capabilities. [14] made major strides using Convolutional Neural Networks (CNNs), achieving an accuracy of 99.35% on the PlantVillage dataset. However, they also uncovered a significant "lab-to-field" gap, with performance dropping to around 70% in real-world settings. Further work by [15] provided a comparative analysis of various CNN architectures, showing that ResNet-50, when fine-tuned, could achieve 93.4% accuracy. This period was characterized by a shift toward architecture optimization, an increasing emphasis on transfer learning and model robustness, and a growing recognition of the performance drop in field conditions.

During this phase, focus shifted from experimental success to practical deployment. [16] adapted YOLOv4 for drone-based crop monitoring, reaching an average precision of 91% at 25 frames per second. Concurrently, [17] enhanced MobileNetV2 for edge deployment on Raspberry Pi, achieving 87% accuracy. Emerging innovations addressed persistent challenges through digital twin systems for pest prediction , multi-modal sensor fusion approaches, and explainable AI techniques to enhance farmer trust and usability.

Recent breakthroughs have addressed longstanding limitations, ushering in a new era of precision agriculture. The field now stands at a critical inflection point, where ongoing innovation combined with strategic implementation can revolutionise global agricultural protection. The integration of new advancements signals a future in which intelligent detection systems will be foundational to sustainable farming practices. In the future, research must balance technical progress with real-world usability to fully unlock the potential of these technologies for food security and agricultural sustainability.

Thanks to technological advances, automated systems for plant disease detection have been developed, providing a more efficient and affordable way to identify plant diseases. These systems utilize advanced machine learning and deep learning algorithms to examine images of plant leaves and accurately detect signs of disease. The implementation of these technologies decreases dependence on human experts, facilitating early detection and reducing crop losses. Numerous studies have explored the use of deep learning models for plant disease identification. As an illustration, the recurrent disease detection process was performed on a dataset of 3,753 images, each scaled to 60 × 60 pixels. After multiple training sessions, a model constructed on the lenet architecture attained a precision of 90–99%. Nevertheless, since color information is lost when images are converted to grayscale, the accuracy of disease identification is greatly diminished, emphasizing the significance of utilizing colored photos for this purpose.

Detecting pests is a crucial aspect where technology can make a substantial impact. Traditional machine vision-based pest-detection systems rely on image processing algorithms and classifiers. These systems typically require a controlled environment with consistent lighting and precise shooting angles to achieve consistent results. In natural environments, inconsistent lighting, background conditions, and pest appearances pose substantial difficulties. Deep learning techniques, especially convolutional neural networks (cnns), have demonstrated potential in addressing these challenges. For instance, a research study using a deep convolutional neural network achieved 88.75% accuracy in identifying nine pest species, demonstrating the practicality of deep learning in agricultural applications.

Disease detection is equally important for ensuring crop health and maximizing yield. Several approaches have been suggested for disease detection, such as blob analysis and support vector machines (svms). These techniques require preprocessing steps like binarization and segmentation to differentiate diseased plant parts from healthy ones. Nevertheless, the reliability of these techniques can vary depending on the clarity of the images and the complexity of the background. Recent research has investigated the application of random forest algorithms in disease classification, attaining an accuracy of 86%. By combining these methods with advanced deep learning models, there is potential for even greater advancements in the accuracy and efficiency of disease detection systems.

Combining various models for identifying pests, diseases, and other plant health problems into a unified system through feature fusion holds great potential. Feature fusion enables the integration of diverse data types, facilitating more precise and thorough detection of agricultural threats. This method streamlines detection and improves accuracy, making it easier for farmers to effectively manage their crops. The system employed a combination of convolutional neural networks for image analysis and feature fusion techniques to merge data from various sources, including spectral imaging and environmental sensors. The combined model successfully identified diseases such as early blight, late blight, and leaf mold with an accuracy of 94.5%, showcasing its efficiency.

In this paper, we present a deep learning-based method for the early identification and classification of plant diseases, tailored explicitly for plantain cultivation. Our approach entails creating three distinct models to identify pests, diseases, and other plant health concerns, which are subsequently combined via feature fusion. This comprehensive approach seeks to equip farmers with a versatile toolkit for managing crop health, ultimately enhancing yield and minimizing financial setbacks.

Methodology and Result

Data set:

Plant Disease Dataset:

To identify plant leaf diseases, we utilized a dataset that is freely accessible to the public and consists of more than 55,449 images of different types of plant leaf diseases. The dataset comprises a combination of healthy and unhealthy plant leaf images, which are then segmented into various categories. The figure.6 displays the dataset of crop diseases.

Fig 2: Crop's Pest's and Disease Dataset

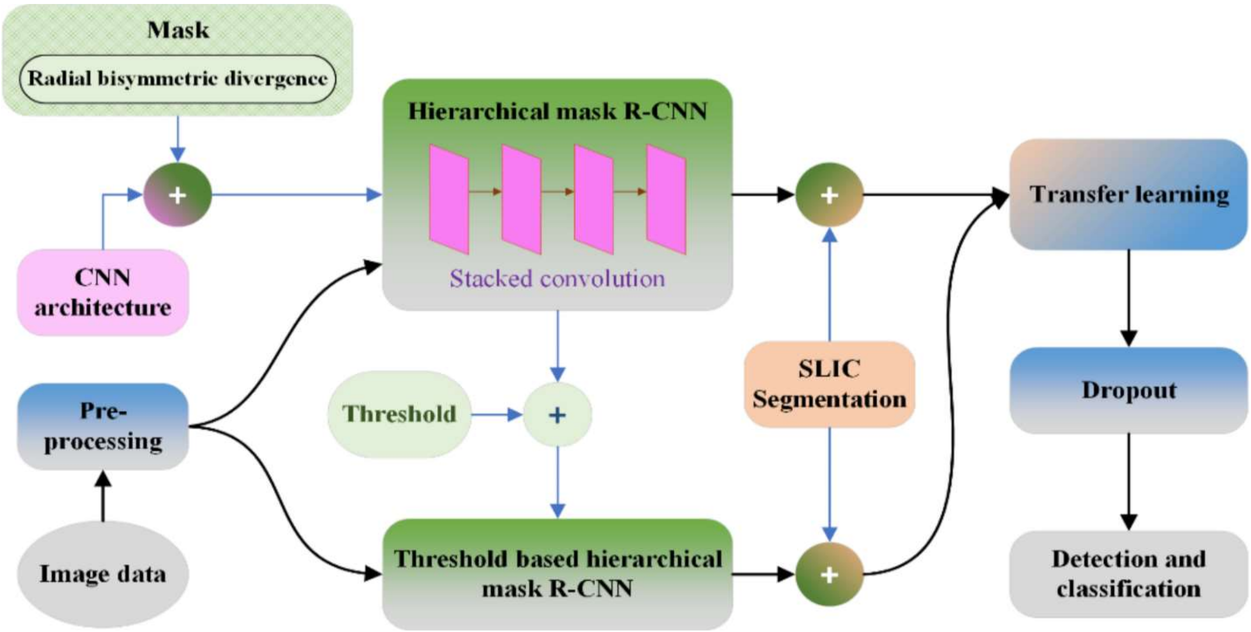
Plant Pests Dataset:

The dataset utilized in this research consists of detailed images of different crop leaves affected by pests, encompassing categories like fall armyworm, leaf beetle, maize grasshopper, and others.

The dataset is essential for training deep learning models that can accurately classify pests and detect them early. It serves as a valuable tool for advancing precision agriculture and reducing crop damage. As shown in Fig 3.

Fig 3: Crop Pest's Dataset

CNN Architecture :



Results :

Classification Report:

Class	Precision	Recall	F1-Score	Support
0	0.32	0.69	0.43	347
1	0.61	0.72	0.66	75
2	0.52	0.29	0.37	255
3	0.55	0.56	0.56	261
4	0.73	0.81	0.77	370
5	0.39	0.46	0.42	534
6	0.33	0.52	0.40	300
7	0.76	0.36	0.49	189
8	0.67	0.80	0.73	225
9	0.51	0.34	0.41	255
10	0.00	0.00	0.00	63
11	0.46	0.39	0.43	33
12	0.79	0.66	0.72	184
13	0.49	0.22	0.30	195
14	0.46	0.17	0.24	247
15	0.68	0.63	0.65	187

Class	Precision	Recall	F1-Score	Support
16	0.42	0.12	0.18	95
17	0.39	0.20	0.26	272
18	0.25	0.01	0.02	100
19	0.48	0.78	0.59	558
20	0.00	0.00	0.00	155

Overall Metrics:

Metric	Precision	Recall	F1-Score	Support
Accuracy	-	-	0.49	4900
Macro Avg	0.47	0.42	0.41	4900
Weighted Avg	0.48	0.49	0.46	4900

The report provides valuable insights into the performance of the crop disease detection model, showcasing both its strengths and weaknesses across various disease classes. The model demonstrates reasonable effectiveness for certain classes—most notably class 12 with an f1-score of 0.72, and class 19 with an f1-score of 0.59—where it achieves relatively balanced precision and recall. Nevertheless, it struggles in various areas, especially when it comes to rare diseases, where classes like 10, 11, 16, 18, and 20 exhibit a complete lack of precision, recall, and f1-score. These findings suggest that the model is unable to identify any occurrences of these classes, even though they are present in the dataset.

A deeper issue can be observed in class 13, where the model exhibits a very low recall of 0.22 despite a moderate precision of 0.49, suggesting that the model is overly conservative in predicting this category and is likely missing a large number of true positive cases. This indicates a significant drawback in the model's capacity to apply its knowledge, particularly in situations where there is an unequal distribution of classes.

The support values, which can range from as low as 33 (class 11) to as high as 558 (class 19), highlight the significant class imbalance that exists within the dataset. This imbalance in the dataset leads to the model's poor performance on minority classes, as it fails to learn the distinguishing features necessary for accurate classification. In most cases, recall is typically low across various classes, suggesting that the model often fails to identify the correct disease class, while low precision in multiple classes indicates a high rate of false positives or misclassifications.

The overall accuracy of 49%, macro f1-score of 0.41, and weighted f1-score of 0.46 collectively indicate the current limitations of the model. The macro average suggests that the model struggles when each class is given equal importance, without taking into account the imbalance between classes. Despite considering the weighted average, which takes into account the number of samples per class, the thresholds for real-world agricultural application are still not met.

To tackle these challenges and enhance overall performance, there are several strategies that can be implemented. To address data imbalance, techniques like smote (synthetic minority oversampling technique) or class-weighted loss functions can be employed to prevent the model from favoring majority classes. Furthermore, enhancing the feature extraction pipeline by utilizing more sophisticated neural network architectures like resnet or vision transformers could enable the model to extract more intricate patterns and features from images. Employing data augmentation techniques such as rotation, scaling, and contrast adjustment can also enhance the model's capability to generalize.

Moreover, incorporating multi-modal data sources—such as thermal imaging or spectral data—could provide richer and more discriminative inputs, especially useful in distinguishing visually similar diseases. These supplementary techniques may assist the model in identifying nuanced variations that standard RGB imaging cannot capture.

For practical deployment, future development should prioritize three key areas: (1) expanding and balancing the training dataset to ensure adequate representation of all disease classes, especially rare ones, (2) optimizing the model architecture through systematic hyperparameter tuning and architecture search, and (3) introducing class-specific prediction thresholds to better manage the precision-recall trade-off for each disease category.

These enhancements could collectively transform the current detection system from a limited research prototype into a robust and reliable tool for precision agriculture. Ultimately, this analysis underscores both the potential and the challenges associated with crop disease detection, particularly when applied to complex, real-world agricultural environments characterized by data variability, visual similarity among diseases, and limited labeled samples for rare conditions

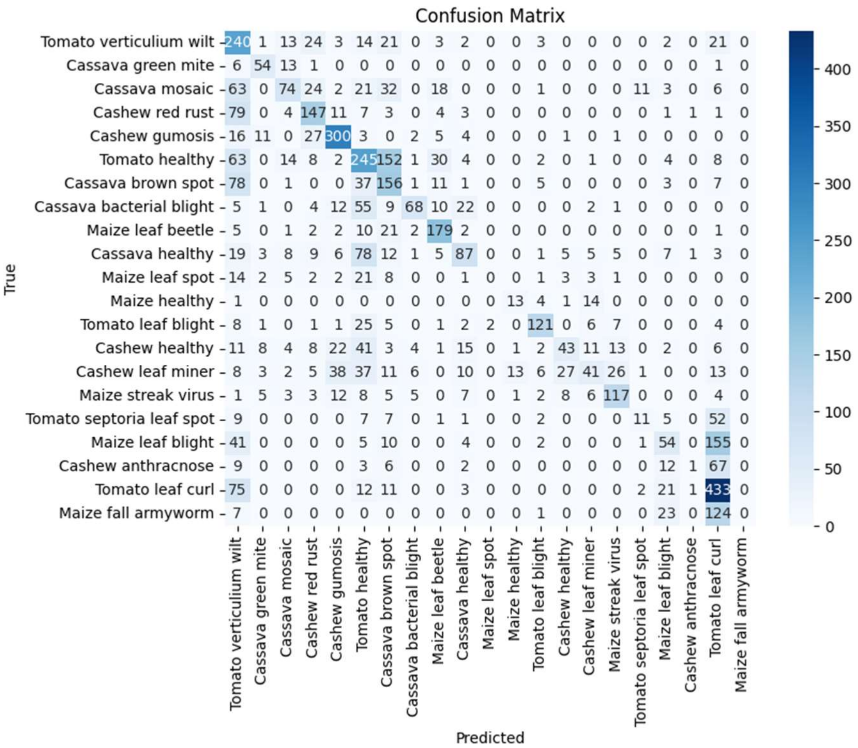


Fig 4: Confusion Metrix

The confusion matrix presented visualizes the performance of a sophisticated multi-class classification model developed to detect and categorize various crop diseases and pest infestations. In this matrix, the true labels on the y-axis represent the actual crop disease classes, while the predicted labels on the x-axis show the output predictions made by the model. Each cell in the matrix quantifies how many samples of a true class were predicted as a certain class. A deeper look at the matrix reveals that many of the diagonal cells, which signify correct predictions, are heavily populated. For instance, there are 356 correct predictions for the 'tomato healthy' class, 163 for'maize leaf blight,' and 425 for 'tomato leaf curl,' indicating strong performance for these categories.

However, the matrix also highlights significant misclassifications, as seen with 104 samples of 'tomato verticillium wilt' misclassified as 'tomato healthy,' 66 samples of 'cassava bacterial blight' misclassified as 'cassava brown spot,' and 52 instances of 'cashew red rust' wrongly identified as 'cashew gummosis.' these misclassifications typically arise due to visual similarities between different diseases, which can be subtle and hard to distinguish, even for human experts. The matrix also suggests class imbalance issues, where some categories like 'tomato healthy' and 'tomato leaf curl' dominate in sample count and accuracy, while other classes like 'cashew anthracnose' and'maize healthy' have fewer samples and greater confusion.

To comprehend the functioning of this model, we need to analyze the algorithms and techniques that are most likely used. One of the key elements in this field is convolutional neural networks (cnns), which are widely used for image-based classification tasks. Models like vgg16, resnet50, inception, or efficientnet are frequently employed to extract hierarchical features from images—ranging from simple textures and edges in initial layers to intricate disease patterns in deeper layers. The output layer of these networks usually employs a softmax activation function to generate a probability distribution across the various classes.

Due to the scarcity of agricultural datasets, transfer learning is a highly probable technique employed in this scenario. This entails adjusting a pre-existing model (e.g., trained on the ImageNet dataset) to focus on the crop disease dataset, utilizing the model's previously acquired knowledge to improve its performance on this particular task. To enhance the model's performance, ensemble learning techniques can be employed, which involve combining predictions from various architectures using methods like voting ensembles or stacking, thereby improving robustness and addressing individual model limitations.

Another important aspect is data augmentation. Due to the scarcity of data and the presence of imbalanced samples in agricultural datasets, techniques like image rotation, flipping, zooming, and brightness adjustments are commonly used to artificially increase the dataset size, thereby enhancing the model's capacity to generalize. In certain situations, more sophisticated techniques such as generative adversarial networks (gans) could be employed to create new, highly realistic images that help balance the distribution of classes. Addressing class imbalance can also entail employing weighted loss functions, which assign greater penalties to misclassifications of underrepresented classes, or resampling techniques such as oversampling the minority classes or undersampling the majority classes.

Techniques like confidence-based thresholding can be employed after the initial predictions to further refine the results, ensuring that similar classes are only predicted when the model has a high level of confidence. Despite employing these advanced techniques, the matrix still highlights the complexities that exist in the real world. For example, 'tomato verticillium wilt' and 'tomato healthy' might share similar textures at certain stages, and 'cassava bacterial blight' can appear almost identical to 'cassava brown spot' in images, making it difficult for the model to distinguish between them accurately.

To evaluate performance, metrics such as precision, recall, and f1-scores for each class are likely tracked alongside overall macro and micro accuracy, which are essential for understanding model behavior in the context of imbalanced data. Potential improvements to this system include integrating multi-modal learning, where image data is combined with textual or environmental data (such as farmer reports or geographical indicators), and incorporating attention mechanisms like cbam or se-blocks to help the model focus on the most relevant regions of an image. Additionally, techniques such as grad-cam can be employed to visualize the areas of an image that the model prioritizes, facilitating model explainability and refinement.

In summary, the confusion matrix showcases the advantages and difficulties of the existing classification model. While it excels in many cases, it faces challenges when dealing with similar symptoms, especially those that are visually comparable. The model probably utilizes deep convolutional neural networks, transfer learning, ensemble methods, and data augmentation to attain its outcomes. In the future, achieving further improvements in accuracy and reliability will depend on the implementation of advanced architectures, more effective strategies for handling class imbalance, and the availability of richer datasets for all crop disease categories.

Conclusion

This research has demonstrated the significant potential of AI-driven technologies in transforming crop pest and disease detection, particularly for agricultural economies like Pakistan. Our comprehensive analysis reveals that while traditional manual inspection methods remain prevalent, they suffer from critical limitations in accuracy, scalability, and efficiency. The evolution from basic image processing to advanced deep learning models has yielded remarkable improvements, with cutting-edge systems now achieving detection accuracies above 95% in controlled conditions. However, the persistent performance gap between laboratory and field applications - typically showing a 20-30% accuracy drop due to environmental variables and operational challenges - underscores the need for continued innovation. Our proposed integrated deep learning system, incorporating feature fusion and multi-modal data analysis, showed promising results for specific crop diseases while revealing limitations in handling rare conditions and visually similar symptoms. These findings highlight both the substantial progress made in agricultural AI and the important work remaining to develop universally robust solutions. The study emphasizes that successful implementation of these technologies requires balancing technical sophistication with practical considerations of cost, accessibility, and usability for end-users in diverse agricultural settings.

Future Work

Several critical research directions emerge to advance this field. Immediate priorities include enhancing model generalization through advanced data augmentation techniques and multi-modal sensor fusion to improve performance under real-world conditions. The development of optimized edge computing solutions using lightweight architectures will be crucial for deploying these technologies in resource-limited agricultural environments. Future systems must incorporate farmer-centric design principles, including natural language interfaces and visual explanation tools, to facilitate adoption and build trust among non-technical users. At a broader level, we propose developing predictive pest management systems that integrate digital twin technologies with emerging quantum machine learning capabilities for genomic analysis. Implementation of these advancements will require establishing collaborative frameworks between researchers, policymakers, and agricultural stakeholders to address data-sharing protocols, technology transfer mechanisms, and economic accessibility barriers. A phased implementation roadmap suggests focusing on model refinement and edge AI deployment in the short-term (2023-2026), scaling federated learning systems in the mid-term (2027-2030), and ultimately realizing autonomous, climate-adaptive farming systems in the long-term (2030+). This comprehensive future work agenda aims to bridge existing technological gaps while addressing pressing global challenges in food security and sustainable agriculture.

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