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A Comprehensive Study on Machine Learning and Deep Learning Models for paddy diseases and weeds detection

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Abstract

Agriculture plays a crucial role in economic development by providing food, raw materials, and employment. With the global population increasing and limited agriculture land, enhancing food production is essential. Precision farming, which utilizes advanced technologies like sensors, GPS, and automated systems, aims to improve crop productivity and reduce resource usage. This research focuses on paddy (Oryza sativa), a staple food for many Asian countries, examining its structure, prevalent diseases, and common weeds. Key diseases such as Tungro and Bacterial Leaf Blight, and weeds like Barnyardgrass and Purple Nutsedge, significantly impact yields. Traditional manual inspection methods for disease and weed detection are labor-intensive and error-prone. Implementing advanced monitoring and early detection strategies is vital for effective crop management. By integrating real-time data and precision farming techniques, farmers can optimize their operations, reduce costs, and ensure sustainable agricultural practices, ultimately contributing to global food security. In this paper, various related works on paddy disease detection and weed detection in paddy field is studied.

Deep Learning (DL), Machine Learning (ML), and Image Processing (IP) are revolutionizing agricultural practices, especially in paddy disease and weed detection. IP has long utilized remote sensing to capture and analyze high-resolution crop images. Traditional ML methods, like k-Nearest Neighbors (k-NN) and Support Vector Machines (SVM), rely on manually engineered features for classification but can struggle with large datasets. DL, particularly Convolutional Neural Networks (CNNs), offers automated feature learning and end-to-end processing, enhancing accuracy and scalability in image analysis. The integration of these technologies improves disease and weed management in paddy cultivation.

Keywords: Agriculture, paddy, diseases, weeds, detection, precision farming, IP, ML, DL, Early

1. INTRODUCTION

Agriculture plays a crucial role in economic development by consistently providing food resources, harvesting industrial raw materials, and creating job opportunities for many people [1]. It emphasizes the production of safe, high-quality food products with reliable yields. With the population rapidly growing, it is essential to significantly boost food production in the coming years despite having limited agricultural land [2]. Effective food production requires careful management of tasks such as harvesting, planting, cultivation, controlling plant diseases, and managing weeds.

Several significant factors contribute to the reduction in food production worldwide, as weeds, climatic changes, and plant diseases playing pivotal roles. In many developing countries like India, small-scale farmers are the backbone of agricultural output, contributing approximately 80% of the global food supply [3]. 50% of crop yield reductions can be attributed to the severity of pests, weeds, and diseases [4].

To address these challenges, a multitude of strategies have been developed to minimize yield losses caused by diseases and weeds. While preventive measures during the seedling stage are crucial, they are often insufficient. Therefore, rigorous monitoring and early detection of diseases and weeds are essential practices in crop management.

In traditional farming practices, the primary method of disease and weed detection involves manual inspection by skilled agricultural personnel. This approach, conducted row by row, is time-consuming, labor intensive, and susceptible to human error's. Moreover, access to expert phytopathologists is limited, especially in economically disadvantaged and isolated regions [5]. Despite these challenges, accurately identifying plant diseases and weeds remains the critical initial step towards implementing effective disease and weed management strategies.

1.1 Precision Farming

Precision farming represents a significant evolution in agriculture practices. By leveraging advanced science and technology, it aims to enhance crop productivity while minimizing, usage of fertilizers and pesticides, thereby reducing overall farm expenses. The components and benefits of precision farming are below:

1.1.1 Key Technologies in Precision Farming

- Sensors and Remote Sensing: Used to collect data in real time about crop health, weather and soil conditions. Helps in monitoring moisture levels, nutrient content, and identifying disease or pest infections early.
- Mapping and Surveying: Provides detailed maps of fields, identifying variations in soil types and conditions. Assists in planning efficient planting patterns and irrigation systems.
- High Precision Positioning Systems (HPPS): Utilizes technologies like GPS (Global Positioning System) for accurate positioning. Ensures precise use of inputs such as pesticides, fertilizers, and seeds.
- Variable Rate Technology (VRT): Allows, variable usage of inputs based on field requirements. Ensures that crops receive the right amount of nutrients and treatments.
- Global Navigation Satellite System (GNSS): Provide's accurate location data to guide machinery and optimize field operations.
- Automated Steering Systems: Enhances the efficiency and accuracy of field operations by automating machinery guidance. Reduces overlaps and gaps in planting and treatment applications.
- Computer-Based Applications: Software tools for data analysis, farm management, and decision support. Helps farmers make informed decisions based on data trends and predictions.

1.1.2 Benefits of Precision Farming

- Increased Crop Productivity: By providing crops with accurate amount of inputs within the right time, precision farming enhances yields.
- Cost Reduction: Minimizing the use of fertilizers and pesticides reduces overall farm expenses.
- Environmental Sustainability: Targeted application of inputs reduces chemical runoff and environmental pollution.

- Better Resource Management: Efficient use of water, nutrients, and land resources through data-driven decisions.

Precision farming integrates various technologies to create more effective, productive, and sustainable agriculture system. By using real-time data and advanced tools, which help farmers optimize their operation's and achieve better outcomes [6] [46][47].

India's agricultural landscape is characterized by a diverse array of major crops grown across different regions. Rice, wheat, and maize are staples widely cultivated, with rice production concentrated in states such as Uttar Pradesh and West Bengal. Wheat dominates in Punjab, Haryana, and Uttar Pradesh. Millets such as jowar, bajra, and ragi are crucial in drier regions like Maharashtra and Karnataka. Pulses such as chickpea, pigeon pea, and lentils are grown extensively in states like Madhya Pradesh and Maharashtra. Cash crops like cotton thrive in Gujarat and Maharashtra, while sugarcane is a key crop in Uttar Pradesh and Maharashtra. Tea is predominantly grown in Assam and West Bengal, while coffee is produced in Karnataka and Kerala. Oilseeds like groundnut and mustard are significant in states like Gujarat and Madhya Pradesh. This agricultural diversity underscores India's status as a major global producer across a wide range of crops, shaped by varied climatic conditions and local agricultural practices. This research work concentrates on paddy [48][49][50].

1.2 Paddy

Paddy (Oryza sativa) is the raw form of rice, consisting of the grain enclosed in a husk. It's harvested from flooded fields, undergoes drying and threshing to remove the husk, and then milling to produce edible rice. Paddy is the staple food to many countries, particularly in Asia, and is vital for global food security and economies. Paddy plant structure is shown in figure [1].

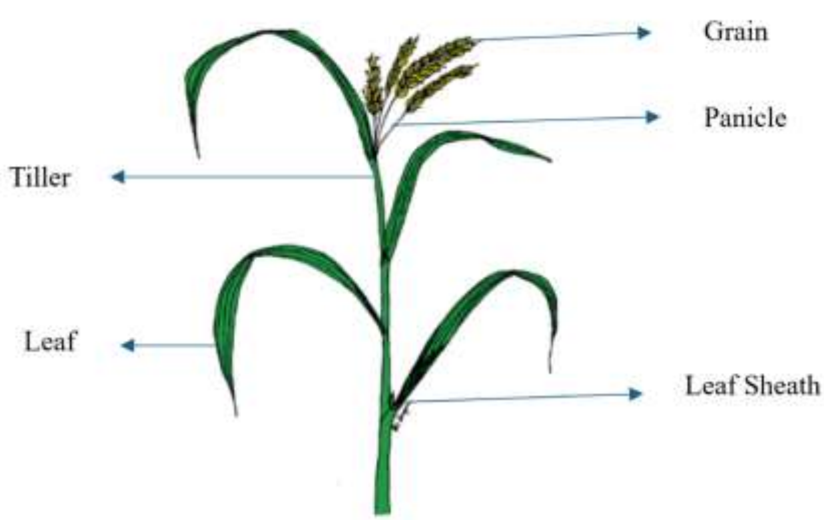

Figure 1. Structure of paddy Plant

Paddy plant structure consists of several key parts:

1. Leaf: The green, flat part of the plant responsible for photosynthesis and growth.

2. Leaf sheath: The protective covering of the leaf base, which surrounds and supports the stem.

3. Tiller: A secondary shoot that grows from the base of the main stem, contributing to the overall structure and productivity of the plant.

4. Panicle: The reproductive structure of the paddy plant, where flowers develop and grains form after pollination.

5. Grain: The edible seed of the paddy plant, produced within the panicle, which is harvested for consumption as rice [7][51][52].

1.3 Diseases Occur in Paddy Crop

The table 1 summarizes the diseases in paddy, detailing their season, Infection factors, Infection stage, symptoms, Diseases they occur in. Each disease presents specific challenges and requires tailored management strategies to minimize crop losses [8][53].

Table 1. Paddy diseases with symptoms, infection stage, factors and season

Diseases	Symptoms	Infection stage	Infection Factors	Season
Tungro	Yellow and stunting of plants, lowered tillering	Early to late growth stage	Viruliferous insects transmitting virus	Wet season
Stemborer	Entry holes in stems, frass (excreta) in tunnels	Larval stage inside stems	Moth oviposition on rice plants, presence of eggs/larvae	Early wet season
Sheath Blight	Lesions on leaf sheaths, elongated lesions on leaves	Mid to late growth stages	High humidity, prolonged leaf wetness	Warm, humid weather
Neck Blast	Neck rot, dark brown lesions on neck and panicles	Booting to flowering stages	High humidity, warm temperatures	Wet season
False Smut	Formation of green to yellow spore balls on spikelets	Flowering and grain filling stages	High humidity, nitrogen application	Warm, humid weather
Brown Spot	Tiny, dark brown dots on leaves with golden haloes	Early to mid growth stages	High humidity, prolonged leaf wetness	Warm, humid weather
Bacterial Leaf Blight	Water-soaked leaf lesions, leaf tips may die	Early to mid growth stages	Rain or irrigation, wounds on leaves	Warm, humid weather
Bacterial Blight	Yellow-haloed lesions soaked in water on leaves	Early to mid growth stages	Rain or irrigation, wounds on leaves	Warm, humid weather

1.3 Weeds

Table 2, provides the scientific name, common name, and preferred land type (where the weed commonly grows) for various types of paddy weeds, which are categorized into broadleaf weeds, sedges, and grassy weeds [9]:

Table 2. Common weeds in paddy fields

Category	Scientific Name	Common Name	Preferred Land Type
Broadleaf Weeds	Eclipta prostrata	False Daisy	Wetlands, damp areas
	Caesulia axillaris	Climbing Aster	Moist areas, open fields
	Ludwigia octovalvis	Mexican Primrose-willow	Wetlands, rice paddies
	Monochoria vaginalis	Heartleaf False Pickerelweed	Aquatic, wetlands
	Ludwigia adscendens	Creeping Primrose-willow	Wetlands, rice paddies
	Sphenoclea zeylanica	Sri Lanka Mudplantain	Marshes, flooded fields
	Commelina benghalensis	Benghal Dayflower	Moist areas, open fields
	Ipomoea aquatica	Water Spinach	Aquatic, marshy areas
Sedges	Cyperus rotundus	Purple Nutsedge	Wetlands, rice paddies
	Cyperus difformis	Smallflower Umbrella Sedge	Moist areas, flooded fields
	Cyperus iria	Rice Sedge	Paddy fields, wetlands
	Fimbristylis miliacea	Fimbristylis Sedge	Wetlands, shallow water
	Fimbristylis littoralis	Spike Sedge	Wetlands, riverbanks
Grassy Weeds	Digitaria sanguinalis	Large Crabgrass	Paddy fields, disturbed soils
	Echinochloa crus-galli	Barnyardgrass	Paddy fields, wetlands
	Echinochloa colona	Jungle Rice	Paddy fields, wetlands
	Eleusine indica	Goosegrass	Paddy fields, disturbed soils
	Paspalum species	Paspalum	Wetlands, disturbed soils
	Ischaemum rugosum	Wrinkle Grass	Paddy fields, open areas
	Leptochloa chinensis	Chinese Sprangletop	Paddy fields, disturbed soils

2. DEEP LEARNING (DL), MACHINE LEARNING (ML), IMAGE PROCESSING (IP) IN PADDY

IP, ML, DL are transforming agricultural practices, especially in detecting and classifying of Paddy disease's and weeds.

2.1. IP in Paddy

IP methods has been employed in Paddy for over two decades, primarily through remote sensing technologies. These technologies capture high-resolution images of crops, which are then processed to extract meaningful information. IP tasks typically include:

- Preprocessing: Adjusting image quality, removing noise, and enhancing contrast to improve subsequent analysis.
- Segmentation: Identifying and delineating regions of interest within the image, such as plant leaves, fruits, or stems.
- Feature Extraction: ML methods depend on manually created features extracted from segmented images. These features capture characteristics like texture, color, and shape, which are crucial for disease and weed classification.

2.2. ML Approaches

Traditional ML methods have been extensively used in paddy image analysis. Key steps in this approach include:

- Feature Engineering: Experts manually design features based on domain knowledge and extract them from segmented images. These features serve as inputs to ML classifiers.

- k-Nearest Neighbors (k-NN): A straightforward yet efficient technique that groups samples according to the dominant class among the neighbors.
- Support Vector Machines (SVM): builds high-dimensional hyperplanes to divide classes according to features that are extracted.
- Fully Connected Neural Networks: Also known as multilayer perceptrons, these models learn complex relationships between features and classes through multiple layers of interconnected neurons.

Traditional ML approaches are advantageous when interpretability of features is crucial or when datasets are limited in size. However, their performance heavily relies on the quality of manually engineered features and may struggle with large and diverse datasets.

2.3. DL Revolution

The use of DL, in particular “Convolutional Neural Networks (CNNs)”, has increased recently for revolutionized image analysis tasks in paddy:

- Feature Learning: Hierarchical data representations are automatically learned by CNNs, directly from raw images. They can capture intricate patterns and features that are difficult to extract manually, such as spatial relationships between pixels and textures.
- End-to-End Learning: Unlike traditional ML pipelines that separate feature extraction and classification, CNNs perform end-to-end learning. This means they can learn to classify images directly from pixels, eliminating the need for explicit feature engineering.
- Scalability: Deep learning models thrive on large-scale datasets, which are increasingly available in paddy due to advancements in data collection through drones, satellites, and IoT devices. This scalability enables CNNs to generalize well across diverse conditions and crop types.

3. RELATED WORK FOR PADDY DISEASE DETECTION

One of the primary methods used by ML algorithms to classify images according to similarities is image processing. Pre-processing, feature extraction, and classification are the three stages that ML algorithms typically include. We can determine if the classifier is unsupervised or supervised based on its mathematical structure. Deep learning methods have been widely used by researchers recently. Deep learning techniques are used to identify the suggested images by classifying them according to their features. Both ML and DL tools, may utilize to expand their study in a variety of fields by scientists. It is used in every prior industry that has an impact on humans, including education [10], healthcare [11,12], smart cities [13], and others. The aim is to automate tasks that are typically performed by individuals. People will benefit greatly from this since machines will be able to perform tasks that people previously handled.

Hybrid approaches involve integrating various models of various types, like DL and ML, to tackle complex problems beyond the capabilities of single models.

[14] uses novel hybrid Dense-Net approach integrated with an enhanced U-Net architecture, is used to automate the identification process, addressing issues of inefficiency and inconsistency in manual identification methods. Improved U-Net is utilized for precise “Region of Interest (ROI)” extraction, while Dense-Net handles image classification tasks. The study evaluates several familier Neural Network(NN) models like DenseNet, AlexNet, VGG16, GoogleNet, ResNet50, SVM, and CNN, under both standard image classification and hybrid ROI extraction scenarios. In experiments without ROI extraction, accuracy varies among models: SVM 82%, CNN 81%, ResNet50 59%, GoogleNet 86%, VGG16 78%, AlexNet 78%, and DenseNet excels with 86%. With ROI extraction, accuracy improves significantly: Simple CNN reaches 88%, SVM 92%, ResNet50 77%, GoogleNet matches at 86%, VGG16 86%, AlexNet 85%, and

DenseNet achieves the highest at 96%. Overall, ROI extraction based on U-Net, classification results across all tested models, with DenseNet demonstrating the best overall performance.

A hybrid CNN (Inception-ResNet)-SVM model has been developed to address the challenge of accurately detecting and treating diseased rice leaves. The model uses images captured in agricultural fields, which are refined and enhanced for clarity. Through a process that includes the Grab-Cut algorithm for image segmentation, the model extracts features and classifies them using the hybrid CNN-SVM approach. Results show the model achieves high accuracy (0.97) and precision (0.93), outperforming previous methods, making it a promising tool for aiding farmers in pesticide selection based on the specific characteristics of diseased rice leaves [15].

[16] The study introduces ResViT-Rice, a hybrid architecture combining transformer components and CNN for precise detection of brown spot and leaf blast diseases in rice plants. It integrates ResNet as the backbone and incorporates transformer encoder and "convolutional block attention module" to improve feature extraction. Highest accuracy 99.04% is attained by the model with AUC 0.9987, F1-score, recall and precision exceeding 0.96. ResViT-Rice proves effective in extracting disease features, leads to accurate, robust classification of rice diseases.

[17] This study investigates 3 kinds of rice diseases: Leaf Smut, Brown spot, Bacterial leaf spot, Bacterial Leaf blight Bacteria. To extract features, it uses "Faster R-CNN deep architecture in conjunction with VGG-16 transfer learning". Following transfer learning, extracted features are classified by Random Forest (RF). RF classifier partitions rice field into 3 unique regions based on these features. Images of rice leaves were taken from the UCI Machine Learning Repository and used in this investigation. Method achieves 97.3% accuracy for classifying rice disease images. Experimental results validate effectiveness of the proposed technique in accurately detecting rice diseases.

Table 3. Summary of related work in paddy disease detection

Study	Dataset	Category	Key Models/Methods	Results
[14]	Kaggle	Hybrid	DenseNet, AlexNet, VGG16, GoogleNet, ResNet50, SVM, Simple CNN	Without ROI extraction: DenseNet 86%, AlexNet 78%, VGG16 78%, GoogleNet 86%, Resnet50 59%, SVM 82%, SVM 82%, Simple CNN 81% With ROI Extraction : DenseNet 96%, AlexNet 85%, VGG16 86%, GoogleNet 86%, ResNet50 77%, SVm 92%, simple CNN 88%
[15]	Private	Hybrid	CNN (Inception-ResNet), SVM, Grab-Cut algorithm	Accuracy: 97%, Precision: 93%
[16]	Private	Hybrid	ResNet, transformer encoder, convolutional block attention module	Accuracy: up to 99.04%, AUC: 0.9987, Precision, Recall, F1-score > 0.96
[17]	Private	Hybrid	VGG-16, Faster R-CNN, random forest classifier	Average accuracy: 97.3%
[18]	Public	Ensemble	Ensemble Model, ResNet-50, SE-ResNet-50, DenseNet-121	91% accuracy

[19]	Public(UCI[22]) Private	Ensemble	Ensemble Model (DEX), Seresnext101, Resnet152v, resNet101, MobileNetv2, Inceptionv3, DenseNet121	Highest accuracy: 98%
[20]	Public[21], Private	Ensemble	Enhanced AlexNet, SVM, MobileNetV3, ResNet50, GoogleNet	99.69% accuracy
[23]	Kaggle[32]	Transfer Learning	ResNet34	98.54
[24]	Public [32]	Transfer Learning	VGG	97.10
[25]	Public(Kaggle [33], Mendeley [34])	Transfer Learning	XceptionNet	94.33
[26]	Public(GitHub [35])	Transfer Learning	EfficientNetV2B3	94
[27]	Private	Transfer Learning	EfficientNetB3	99
[28]	Public & Private	Custom CNN	Deep learning model optimization	98.64
[29]	Public (Kaggle [36])	Custom CNN	IoT-based framework using ML/DL techniques	90.98
[30]	Public(IDADP [37])	Custom CNN	DHLC-DETR (DHLC-FPN integrated with DETR)	97.44
[31]	Private	Custom CNN	ADAM, SGDM	Achieves maximum accuracies of 99.83% with Adam and 99.66% with SGDM by the 7th epoch

[18] A smartphone app was used in the development and implementation of an automated diagnostic approach. Utilizing DL on dataset of 33,026 images encompassing 6 kinds of rice diseases, including brown spot, bacterial stripe, sheath blight, neck blast, false smut, leaf blast, employed an Ensemble Model integrating top-performing submodels: ResNeSt-50, SE-ResNet-50, DenseNet-121. The Ensemble Model achieved 91% accuracy, effectively reducing misdiagnosis and improving disease recognition. Accessible via a web server, the smartphone app provided efficient field diagnosis for rice diseases, offering convenience to users.

[19] This study compares 6 CNN architectures (Seresnext101, ResNet152V, ResNet101, MobileNetV2, InceptionV3, DenseNet121) for classifying nine prevalent rice diseases in Bangladesh. It also explores transfer learning with Seresnext101, ResNet152V, MobileNetV2, DenseNet121, and an ensemble model named DEX "Densenet121, EfficientNetB7, Xception". Ensemble approach achieves the highest accuracy of 98%, demonstrating a 17% improvement over Seresnext101 in disease detection and localization. This study underscores potential of CNN models in real-time agricultural disease detection, crucial for timely interventions to safeguard rice yields and quality in farming communities.

[20] Introduces the "stacking-based integrated learning" approach aimed at enhancing the efficiency and precision of rice leaf disease detection. The model incorporates 4 CNN's (MobileNetV3, ResNet50, Improved GoogleNet, Enhanced AlexNet) as base learner's, supplemented by SVM as the sublearner.

Achieved detection rate of 99.69% on a rice dataset, this approach explores how various enhancement techniques impact learning and training across various classification tasks. Comparative experiments include evaluations of individual models versus different combinations of stacking-based ensemble models, as well as comparisons across diverse datasets.

[23] This paper examines four CNN architectures for identification and classification of diseased and healthy leaves, including Leaf Blast, Hispa, Brown spot. Initially, ResNet34 and ResNet50 are employed to mitigate vanishing gradient issues that can degrade network performance. While traditional CNN models handle feature extraction, the incorporation of self-attention with ResNet34 and ResNet18 architectures enhances the feature selection process. This improved feature extraction significantly enhances accuracy of rice leaf disease identification and classification. Ultimately, proposed ResNet34 with self-attention architecture achieves a high accuracy of 98.54%, surpassing other CNN models evaluated in the study. This approach shows better performance than state-of-the-art methods in multiclass classification problems.

[24] This paper addresses the issue of the large parameter size in CNN models by proposing the recognition model which integrates multi scale convolution module with NN architecture based on the VGG. Model performance is evaluated based on loss metrics and accuracy for both test and train sets. Test accuracy of proposed model reaches 97.1%, marking a significant 5.87% improvement over VGG. Additionally, model demonstrates reduced memory requirements, totaling 26.1M, which is only 1.6% of the memory used by VGG. Experimental results indicate superior performance in terms of memory efficiency, recognition speed, accuracy.

[25] Introduces “Dynamic Mode Decomposition (DMD)” approach with Attention-driven preprocessing for identifying rice leaf diseases. It evaluates ten CNN models using transfer learning, highlighting DenseNet121 with 93.87% accuracy. ML models constructed using deep features from the last layers of DCNNs, especially DenseNet121 with a Random Forest classifier, show superior performance. The study explores DMD-based preprocessing to localize infected regions using hard attention maps, enhancing segmentation. Evaluations on both original and DMD-preprocessed images show XceptionNet with SVM achieving 100% test accuracy. Field tests confirm XceptionNet's superior performance with 94.33% classification accuracy compared to other models, demonstrating enhanced metrics like F1-score, Recall, Precision, Accuracy with DMD-preprocessed images.

[26] This research uses a variety of deep learning approaches to propose a robust system for predicting diseases in rice leaves. Images of diseases affecting rice leaves were gathered and prepared in accordance with algorithm specifications. Prior to classifying diseases including brown spot, blast, bacterial blight using several ensemble and machine learning classifiers, features were first retrieved using 32 pre-trained models. Results were compared, demonstrating that proposed approach outperforms current methods, achieving 90–91% identification accuracy along with metrics like Kappa statistics, Matthews coefficient, F1-score, recall rate, precision on a standard dataset. Post-segmentation, the accuracy further improves to 93–94% with the EfficientNetV2B3 model using HGB and ET classifiers. Proposed approach effectively identifies rice leaf diseases with 94% accuracy, supported by experimental results validating its validity and effectiveness in disease identification.

[27] For the purpose of identifying rice leaf diseases while maintaining data privacy, this study suggests a lightweight federated deep learning architecture. It employs client-server architecture to ensure privacy across distributed clients with both non-IID and IID data. Experimental validation included traditional learning and federated learning approaches, with EfficientNetB3 achieving a baseline accuracy of 99%. Federated learning on IID data achieved 99% train and evaluation accuracies with minimal loss, while non-IID data maintained strong performance with 99% training accuracy and 95% evaluation accuracy. This

highlights the framework's effectiveness in comparison to conventional models, making it suitable for early disease classification in resource-constrained environments.

[28] Focuses on improving the identification of rice diseases, specifically bacterial leaf blight, rice false smut, rice blast. Initial challenges include variations in image specifications due to distance, lighting, size, and angle differences. The study expands and standardizes the dataset through resizing, rotation, and mirroring. A new deep learning model is developed with optimized parameter initialization. Experimentation refines the model using key parameters such as optimization algorithms, learning rate, batch size, iteration time. Evaluation using the confusion matrix compares the model against ResNet and VGG, achieving an accuracy of 98.64%, effectively meeting the goal of precise disease identification.

[29] This paper proposes the IoT-based framework for detecting, forecasting rice diseases using ML and DL, aiming to enhance decision making in smart farming systems. The framework focuses on detecting pest infection in rice cultivation. Results indicate that, framework achieves accurate classification and efficient prediction of rice disease types. It demonstrates professional-grade disease prediction with results reaching up to 87.97 - 97.27% accuracy using ML and DL models, respectively. Moreover, framework outperforms current benchmark algorithm’s in terms of F1-Score, Recall, Precision, Accuracy, ensuring effective rice diseases detection.

[30] Introduces “Dense Higher-Level Composition Feature Pyramid Network (DHLC-FPN) integrated into the Detection Transformer (DETR)” algorithm, forming “Dense Higher-Level Composition Detection Transformer (DHLC-DETR)”. This approach effectively detects 3 diseases: flax spot, rice blast, sheath blight. DHLC-FPN replaces DETR's backbone network by merging with Res2Net to create the feature extraction network. Res2Net extract 5 scales of features, integrated via ‘high-density rank hybrid sampling’ from DHLC-FPN. These features, along with location encoding, feed into the transformer for class and box predictions. Predictions are refined via binary matching using Hungarian algorithm. On IDADP datasets, DHLC-DETR, enhanced by data augmentation, achieved the 17.3% increase in mAP compared to DETR. Specifically, mAP to the smaller target detection improved by 9.5%, and hyperparameter size reduced by 324.9 M. Results underscore, optimizing feature extraction significantly enhances detection accuracy, achieved 97.44% accuracy on IDADP rice diseases dataset.

[31] CNN is trained on the dataset comprising 1400 healthy and 4 common rice disease images for comparison. Using ‘Stochastic Gradient Descent with Momentum (SGDM) and Adaptive Moment Estimation (Adam)’ optimization techniques, the model achieves maximum accuracies of 99.66% and 99.83% on testing set on 7th epoch. When including healthy leaf dataset, the Adam-optimized model performs better, reaching accuracies of 99.66% and 97.61% compared to SGDM by the same epoch. Table 3. Summarizes the related work in paddy disease detection.

4. RELATED WORK FOR WEED DETECTION IN PADDY FIELD

[42] UAV images is obtained from the rice field in South China for weed distribution mapping using a semantic labeling approach. Adapted the pre-trained CNN (residual framework into a fully convolutional form) and fine-tuned it on the dataset. Atrous convolution expanded the convolutional filter's field of view, and evaluated multi-scale processing performance. Following CNN processing, ‘fully connected conditional random field (CRF)’ refined spatial details. The method was benchmarked against ‘pixel-based SVM and classical FCN-8s’, demonstrating superior accuracy. Particularly in detecting small weed patches, Approach performed noticeably better than previous approaches. Achieved 0.7751 accuracy, 0.9128 kappa coefficients, 0.7751 mean IU. These results underscore the approach's potential for precise weed mapping in UAV imagery.

[43] Effective SSWM is essential for maximizing crop yields. In large-scale SSWM, remote sensing plays a pivotal role by providing precise information on weed distribution. Unlike satellite and piloted aircraft remote sensing, UAV captures higher resolution images, offering detailed data for weed mapping. This study aims to create accurate weed cover map with UAV imagery. RGB imagery is acquired in October 2017 in the rice field in South China. Employed FCN for weed mapping, leveraging transfer learning to enhance generalization and integrating skip architecture for improved prediction accuracy. FCN approach was benchmarked against the 'Patch_based CNN and Pixel_based CNN' methods. Results demonstrated superior performance of the FCN method, achieved 0.935 accuracy and the weed recognition accuracy of 0.883. These findings highlight the capability of the algorithm to generate precise weed cover maps from UAV imagery.

[50] A semi-automatic procedure utilizing an unsupervised clustering algorithm was developed and applied to a multi-spectral ortho-mosaic derived from UAV Sequoia images captured over a rice field. The objective was to identify weeds during early stage of growing season. Among the various input feature sets evaluated, spectral information exhibited superior accuracy compared to textural features. Spectral indices, particularly SAVI and GSAVI, yielded the most promising results, achieving an overall accuracy greater than 94%. The output weed map generated by the semi-automatic procedure was utilized in conjunction with additional data derived from the same Sequoia dataset. This integration facilitated the creation of geospatial gridded layers that encompassed information on weed distribution and the fractional cover of rice germination. Such detailed spatial information is invaluable for enhancing precision agronomic practices in rice field management.

[77] Chemical control is crucial for managing weeds and ensuring rice yield, but excessive herbicide use poses environmental and agronomic risks. 'Site-specific weed management (SSWM)' optimizes herbicide application based on weed coverage to reduce usage while improving effectiveness. High-resolution UAV imagery and FCN-based pixel classification were used to generate precise weed cover maps. Experimental results showed FCN-4s achieved 0.9196 overall accuracy and 0.8473 mean IU for weed mapping, with mapping completed in under 30 minutes for a 50 × 60 m field. Threshold-based prescription maps resulted in herbicide savings of 58.3% to 70.8%. This method promises accurate SSWM applications.

[94] 'DL and Object-based image analysis (OBIA)' are employed to map weeds using UAV imagery. In OBIA, the imagery was segmented into objects using multi-resolution segmentation and the enhanced k-means method. Color, texture features are extracted and combined as feature vector. Classification utilized RF, SVM, NN, Back Propagation (BP) after rigorous hyperparameter tuning and model selection. OBIA achieved 66.6% MIU accuracy on test set, with 2343.5 ms per image as interface speed. For DL, 'fully convolutional network (FCN)' is adopted for pixel-wise classification. Transfer learning involved fine-tuning 4 pretrained models (ResNet, GoogleNet, VGGNet, AlexNet). Spatial detail enhancement employed conventional architecture and 'fully connected conditional random fields (CRF)', followed by a partially connected-CRF as post processing to expedite inference. Hybrid methods combining 'conventional architecture and partially connected CRF' were also tested. Results demonstrated that VGGNet-based FCN has higher accuracy. Hybrid approach achieved MIU 80.2% on test set, with an inference speed of 326.8 ms per image sample. This study illustrates the efficacy of UAV remote-sensing and deep learning for supporting site-specific weed management (SSWM) in rice fields.

[96] This study introduces an innovative approach integrating vision and tactile data to accurately assess weed density. Initially, tactile information containing weed density details was acquired using a custom tactile sensor, alongside simultaneous capture of corresponding visual images. Subsequently, improved the correlation between differentiating characteristics taken from the tactile and visual datasets using "kernel canonical correlation analysis (KCCA)" technique. Fusion eigenvectors, which accurately represent weed density, were produced by this approach. These eigenvectors are inputed into 'broad learning system (BLS)',

where a cascade feature node replaced random feature mapping, resulting in 'KCCA-based cascade feature broad learning system (KCCA-CFBLS)'. Method demonstrated precise evaluation of weed density across high, medium and low weed conditions with a new dataset from the specialized paddy field setting. Performance analysis, including accuracy and processing time, revealed that KCCA-CFBLS surpassed YOLOv5-Lite & SVM methods by 7.56% and 11.56% higher accuracy, with reduced time consumption. Outcomes highlighted substantial benefits of the approach in terms of real-time capability and accuracy over purely visual methods, offering the foundation for intelligent decision-making in implementing mechanical and chemical weeding in specialized paddy environment's.

[97] Introduces an weeding robot designed specifically for paddy field, utilizing an enhanced version of YOLOv5 for adaptive weeding operations. Initially, real time method for recognizing rice seedlings is proposed using MW-YOLOv5s, leveraging a dataset covering various growth stage, environments of paddy. The model replaces GIoU_loss with WIoU_loss and combines MobileViTv3 with Backbone network structure. This leads to significant gains in rice seedling detection speed and accuracy. Then, MW-YOLOv5s is incorporated into a paddy weeding device, utilizing the least squares approach to extract seedling navigation lines. Lastly, a control system uses feedback control gleaned from the navigation path to autonomously steer the weeding machine in real time. Test outcomes demonstrate robust performance of MW-YOLOv5s in recognizing rice seedling across diverse paddy field conditions, achieving mAP 92.32% and 90.05% precision. Real-time processing capabilities reach 19.51 FPS, meeting operational requirements for paddy fields weeding machines. Agronomic criteria for mechanical weed management in rice fields are satisfied by the experimental findings, which show an 82.4% weed control rate and a 2.8% seedling damage rate.

Based on provided excerpts from different studies related to weed mapping using UAV imagery in rice fields, here's a summarized table 4 that highlights key methods and performance metrics from each study:

Table 4. Summary of related work in paddy weed detection

Paper	Key Techniques	Performance Metrics	Dataset/Imagery Details	Advantages	Limitations
[38]	CNN, FCN, CRF	Mean IU: 0.7751, Overall Accuracy: 0.9445, Kappa Coefficient: 0.9128	UAV imagery, Rice field in South China	Superior accuracy in detecting small weed patches	Computationally intensive, requires fine-tuning
[39]	FCN, Transfer Learning	Overall Accuracy: 0.935, Weed Recognition Accuracy: 0.883	RGB imagery, October 2017, Rice field in South China	High accuracy, detailed weed cover mapping	Dependence on quality of training data
[40]	Clustering, Spectral Indices	Overall Accuracy > 94%	UAV Sequoia images, Rice field	High accuracy with spectral information	Limited to specific spectral bands
[41]	FCN, Pixel Classification	Overall Accuracy: 0.9196, Mean IU: 0.8473	High-resolution UAV imagery, 50 × 60 m field	Significant herbicide savings, fast processing	Sensitivity to image quality and lighting conditions
[42]	OBIA, FCN, VGGNet	MIU: 80.2%, Inference Speed:	UAV imagery, Deep learning models	High accuracy with hybrid	Complexity in parameter tuning

		326.8 ms per sample		approach	
[43]	KCCA, BLS	Higher accuracy than SVM and YOLOv5-Lite	Specialized paddy field setting	Precision in weed density evaluation	Requires additional sensor integration
[44]	YOLOv5s, MW-YOLOv5s	Precision: 90.05%, mAP: 92.32%, FPS: 19.51	Diverse paddy field environments	Real-time processing capabilities	Limited to specific types of weeds

This table 4 provides a comparative view of the different methodologies used across studies, along with their respective performance metrics such as "mean intersection over union" and accuracy, and other relevant outcomes like herbicide savings where applicable. Each study employs variations in deep learning models, image processing techniques, and evaluation metrics to address the challenges of weed mapping using UAV imagery in rice fields.

5. COMPARATIVE ADVANTAGE, CURRENT RESEARCH AND FUTURE DIRECTIONS

Comparative Advantages

Both traditional ML and deep learning approaches have distinct advantages

- Traditional ML: Offers interpretability through manually engineered features and can perform well with smaller datasets. It's useful when understanding the reasons behind predictions is crucial (e.g., for regulatory purposes).
- Deep Learning: Excels in tasks requiring complex pattern recognition and benefits from large datasets. It's particularly effective for tasks like image classification, where accuracy is paramount and when data is abundant.

Researchers continue to explore hybrid approaches that combine the strengths of traditional ML and deep learning. For instance, integrating CNNs with traditional ML classifiers for improved interpretability or using transfer learning techniques to adapt pretrained deep learning models to specific agricultural domains.

Future research directions include

1. Improving Robustness: Addressing challenges such as variability in lighting conditions, occlusions, and image quality inherent in field conditions.
2. Real-time Applications: Developing algorithms capable of real-time and early disease and weed detection and decision-making to enhance paddy crop management practices.
3. Data Fusion: Integrating data from multiple sources (e.g., images, weather data, soil conditions) to provide comprehensive insights into crop health and optimize agricultural operations.

Image processing, machine learning, and deep learning techniques are pivotal in advancing precision agriculture. Their integration enables more efficient paddy disease detection, weed management, and overall crop monitoring, contributing to sustainable and productive agricultural practices.

6. RESEARCH OBJECTIVES

Overall aim of this research is to design, develop, and analyze algorithms for automated detection of diseases and weed in paddy fields. The following are the objectives of the research;

- Exposure weeds in paddy fields using multispectral satellite images and estimate the weed density within the sub-fields.
- Accomplish early detection of commonly occurring disease in paddy fields using Machine Learning algorithms.
- Recognize the cause of the disease using different vegetation indices derived from the multi-spectral satellite images.

7. CONCLUSION

Agriculture is important for economic growth, food security, and jobs, especially in developing areas. With the world's population growing and less land available for farming, increasing agricultural productivity is essential. Precision farming uses advanced technologies like sensors, GPS, and automated systems to improve efficiency and save resources. This study focuses on the challenges in growing paddy (Oryza sativa), such as diseases like Tungro, Bacterial Leaf Blight and so on and weeds like Barnyardgrass, Purple Nutsedge and so on. Traditional methods of detecting these issues are time-consuming and can be inaccurate.

Precision farming helps by providing real-time monitoring and early detection, allowing for timely solutions and better crop management. Furthermore, using precision farming techniques promotes environmental sustainability by reducing the excessive use of fertilizers and pesticides. This helps prevent chemical runoff and soil degradation, ensuring that farming practices are productive and eco-friendly. By adopting precision farming, farmers can achieve higher yields, lower costs, and reduce their environmental impact. This approach is vital for meeting future food needs, ensuring sustainable agriculture, and supporting global food security. Embracing these advanced technologies helps build a strong and productive agricultural system to support the growing global population.

The integration of Deep Learning (DL), Machine Learning (ML), and Image Processing (IP) significantly enhances the detection and classification of diseases and weeds in paddy cultivation. While traditional IP and ML methods have provided valuable insights through manual feature extraction and classification techniques, the advent of DL, particularly Convolutional Neural Networks (CNNs), has revolutionized the field by automating feature learning and enabling end-to-end image analysis. DL's ability to process large datasets and capture complex patterns directly from raw images offers improved accuracy and scalability, addressing the limitations of earlier methods. Overall, these advanced technologies are crucial for advancing paddy management practices, ensuring better crop health and yield.

Traditional ML offers interpretability and performs well with smaller datasets, making it ideal for scenarios where understanding predictions is crucial. In contrast, deep learning excels in complex pattern recognition and requires large datasets, making it particularly effective for tasks such as image classification. Current research is focused on integrating these approaches, such as combining convolutional neural networks (CNNs) with traditional ML classifiers or using transfer learning for specific agricultural applications. Future research aims to enhance robustness against field variability, develop real-time detection algorithms, and integrate diverse data sources to optimize crop management. The integration of image processing, ML, and deep learning is essential for advancing precision agriculture, improving paddy disease detection, weed management, and overall crop monitoring for sustainable agricultural practices.

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