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# SURVEY ON DISEASE DETECTION IN PADDY AND WHEAT CROP

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**Abstract -** Worldwide security of food hinges on two essential staple crops paddy and wheat. However, their yield is sometimes threatened by a number of diseases, such as Russet leaves, Explosion and bacterial blight, which can cause significant production losses. The goal of this project is to develop a precise and effective technique for identifying agricultural diseases in wheat and paddy using state-of-the-art image processing and machine learning approaches. The technique analyzes high-resolution images of crop leaves and applies deep learning models to precisely identify and classify disease symptoms. The proposed approach offers a rapid, scalable, and cost-effective early disease detection option, enabling farmers to conduct targeted and timely corrective action. This project's goals are to boost Production from farming and minimize monetary losses, and promote sustainable farming techniques.

**Keywords**: Crop disease detection, rust on leaves, microbial blight, blast disease, precision farming, plant health monitoring, artificial intelligence in agriculture, and plagues of wheat and rice, deep learning, machine learning, image detection and prompt identification of infection.

## I. OVERVIEW

Both of them most vital essential crops, rice and wheat, provide food for billions of individuals worldwide. Their productivity is, however, increasingly at risk from a number of diseases, such as rust on leaves, blast, and microbial blight. Particularly in regions where agriculture is a significant industry, these diseases may cause significant crop losses, which may affect food security and economic stability. Rapid and realistic detection of crop diseases is vital to reducing these impacts and ensuring sustainable farming practices. Traditional disease detection methods usually rely on skilled audits via together, which may involve time-consuming, labor-intensive, and prone to mistakes. With the advent of advanced technologies like computer vision, machine learning, and remote sensing, automated sickness detection systems are becoming a reality. These technologies offer a rapid, accurate, and cost-effective way to acknowledge and classify plant diseases, enabling timely interventions. The intent of this project aims to develop a trustworthy framework for diagnosing diseases in wheat and paddy crops by using frameworks for neural networks and excellent quality images. By enabling farmers with relevant information, the proposed strategy seeks to boost agricultural productivity, reduced monetary losses, and promote Crop management deemed sustainable practices.

### 1.1 Approaches

The process of diagnosing illnesses that affect wheat and paddy involves several key steps:

1. Insight Collection

Image Acquisition: High-resolution images of paddy and wheat plant are taken using cameras, drones, and cellphones. These images depict disease symptoms like spots, lesions, and yellowing of the leaves. Getting the dataset ready: Expert annotations are employed to determine the collected photographs in the interest of differentiate between wholesome and sick crops, encompassing specific Particular kinds of ailments such as rust on leaves, blast, and microbial blight.

2. Visual Data Refinement:

Techniques including Image Rescaling, Artifact Removal, and Contrast Optimization are applied to enhance the quality of the images and standardize inputs. Segmentation: Picture segmentation methods are employed to remove background elements so that the focus is on the relevant leaf or plant portions.

3. Feature Identification:

Visual components: Crucial components including Coloration, textural elements, and morphological traits are identified. to highlight patterns specific to an illness. Deep Features: CNNs and other pretrained deep learning models are used to automatically learn complex disease-related features.

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4. System Modeling:
Models for Machine Learning: Traditional classifiers like (SVM) and random forest computing are employed for initial testing. Models for Deep Learning: Complex designs such as Transformer-based models or (CNNs) are used to precisely classify diseases. Strategies for imparting knowledge are implemented to leverage pretrained models to enhance performance.

5. Education and Confirmation:
The representation Training**:** The dataset is divided into training and validation subsets. The template is developed using label data and optimized with algorithms such as Adam or SGD to minimize classification errors effectively. Performance Evaluation**:** Criteria including F1-score, memory, preciseness, and consistency
are employed to gauge the efficiency of the model and ensure its reliability.

6. Disease Identification and Categorization:
New images are classified as either healthy or unhealthy using the trained model, which also identifies the exact type of disease.

7. Deployment of Mobile or Web Applications: An easy-to-use interface allows farmers to upload images and receive real-time illness diagnosis.
Edge devices: (UAVs) or IoT-based Sensors are equipped with lightweight models for in-field illness diagnostics.

8. Real-world Validation or Field Testing
Field experiments are conducted to gauge the model's effectiveness in real-world agricultural environments with varying illumination and weather conditions.

This methodology aims to provide an efficient flexible and user-oriented approach for identifying diseases in wheat and rice crops, aimed at improving diagnostic accuracy and supporting agricultural productivity. Early intervention capacities and support sustainable agricultural practices.

### 1.2 Merit of crop disease detection

**Pre-emptive identification**:
Early detection of diseases allows for timely intervention, preventing further spread and minimizing potential crop losses.

**Enhanced Precision**:
AI learning-based automated solutions offer greater precision and less human error as compared to manual examinations.

Financial efficiency:
Extremely accurate and reduced human error are provided by AI and algorithmic automated systems in comparison to manual inspections.

Time optimization:
Speeds up the process of diagnosing illnesses, enabling quicker intervention and decision-making.

Enhanced crop performance:
Lessens the impact of diseases, ensuring healthier and more fruitful crops.

versatility:
Can be installed over huge agricultural areas using drones, IoT devices, or smartphone apps.

Continuous surveillance:
Allows for continuous crop health administration, enabling farmers a grasp on
helpful information and timely notifications.

Decreased Environmental Impact:
Reduces The usage of negligent pesticides and promotes ecologically Conscientious agriculture practices by focusing primarily on affected areas.

Accessibility: with cell phone or web-application solutions, even small-scale farmers can access state-of-the-art disease detection tools.

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## II. LITRETURE SURVEY

| S. No | Year | Title | Abstract | Methodology | Drawback |
|---|---|---|---|---|---|
| 1 | 2024 | Enhancing Rice Crop Health Assessment: Evaluating Disease Identification with a CNN-RF Hybrid Approach | This study introduces an RF and CNN to improve disease detection. The model, which focuses on three diseases—rust, mildew, and leaf spots—performs better than Using a large collection of captioned rice photos, the paper explains steps that are preprocessing, feature extraction, and classification. The hybrid model uses a random forest for classification and (CNN) for feature extraction to enable early and accurate sickness detection [1]. | The methodology involves collecting and preprocessing a large dataset of images of rice crops, then using Convolutional neural networks for Extracting features along with Random forest for classification. Following training, validation, and testing, the hybrid CNN-RF model's accuracy in detecting illnesses was 93.5%. | Among the drawbacks of the hybrid model are its reliance on large annotated datasets, which are costly and time-consuming to gather, and its high training computing resource needs, which are limited for farmers. |
| 2 | 2024 | AI for Agro-Business in the Identification of Rice Diseases | Agribusiness is dependent on the rice's quality and resistant to disease, and effective techniques are required to boost agricultural productivity. By examining pictures of plant, fields, or seeds, generated (AI) and machine learning (ML) demonstrated remarkable effectiveness in diagnosing diseases. This study examines research conducted over eight of those years on crop pest detection, sapling quality with a focus on rice production, an important crop worldwide. In order to use AI to analyze patterns in the diagnosis of rice diseases, knowledge was gathered from the Scopus and Web of Science databases.<br>For researchers in the discipline, the investigation offers statistics regarding national citation is valuable, worldwide trends, and annual trends [2]. | Using AI and ML draws near, research publications over the prior eight years on rice disease notice, grain quality, and seedling viability are analyzed. Global trends and patterns in the recognition of rice diseases were investigated using data from the Web of Science in addition to Scopus databases. | Negative aspects include the focus on data relating to the recent eight years, which could disregard more important but sooner study findings, and relying on restricted access to paid for sources like Web of Knowledge and Scopus, MED which can omit pertinent research. |
| 3 | 2024 | YOLO-Wheat: A Wheat Disease Detection Algorithm Improved by YOLOv8s. | In this work, YOLO-Wheat, the use of deep learning to detect wheat maladies in sustainable agriculture settings, is proposed. The model uses the C2f-DCN module and the SC Net attention mechanism to improve feature extraction, particularly for small desired outcomes, using a dataset of 3622 imagery of wheat malady. By fine-tuning the detecting head, loss function, and layers for small targets, YOLO-Wheat improved the initially developed model by twelve per cent, achieving a m Adaptive@0.5 of 93.28%. The technique shows notable | Design the following Model: To boost accuracy and endurance, YOLO-Wheat leverages the offset acquisition and feature extraction alongside with the SC Net attention strategy. | Performance under diverse lighting and atmospheric conditions, as well as in real-world deployment scenarios, was not fully evaluated. A comprehensive assessment of the effectiveness of computing for huge-scale applications was not accomplished. |

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| | | | gains in accuracy and robustness for real-world wheat diagnosis, with a 47% performance jump[3]. | | |
| 4 | 2023 | Assessing the Impact of Segmentation on Wheat Stripe Rust Disease Classification Using Computer Vision and Deep Learnin g. | Over nineteenth percent that people ingest are obtained from wheat, a grain that thrives all world. However, because corrode disease can cut output by 30%, it gravely compromises food security and yield. To lessen this loss, wheat frost and related illness types require. Research, Rust with wheat stripes data is segmented using the Basin segmentation techniques. The U2-Net segmented dataset achieved accuracy of classification. This emphasizes how important splitting is for improving the effectiveness of classification, which gives researchers pursuing relevant data [4]. | Using a segmentation framework, three illness types—susceptible, durable, and healthy—are offered for the classification of barley stripe rot. Three segmentation methods—Watershed, GrabCut, or, and U2-Net (a neural network-based method)—are deployed to split the gathered input. After photographs have been fractured the unforeseen portions were eliminated and the region that is captivating is localized. | furthermore poor categorization results from inadequate data collection that could reduce rather than increase accuracy, and the accuracy can only be legitimately improved after categorization if the dataset has been properly assembled before robotic segmentation can be utilized. |
| 5 | 2024 | Improving Wheat Leaf Disease Classification: Evaluating Augmentation Strategies and CNN-Based Models With Limited Dat aset. | This study shows how well Stage GAN and the algorithm ADAS to try to enhance the designation of wheat leaf rot using neural network models like the latest version of Mobile which are crucial for boosting the global supply of food [5]. | Phase 1 included assembling and preliminary processing an array of rye leaf diseases, ranging encompassing both healthy and foliage with rusty stripes and septoria burg. Using the enhanced picture statistics, six robust CNN-based classification algorithms tweaked to identify those illnesses. | Balancing deployment in agriculture proves harder still by the paucity of broad studies on stereotypes, accessibility, and computing-edge inclusion. |
| 6 | 2024 | Automated Wheat Rust Disease Classification Using Convolutional Neural Networks With Transfer Learning | Four trained beforehand deep neural networks of neurons (CNNs)—VGG16, Handy Net, InceptionV3, and InceptionResNetV2—are used in this work to automatically detect wheat infections by transferring knowledge. A dataset spanning three classes—brown rust, yellow rust, and fair wheat leaves. With hundred percentage retention for brown rusting of leaf and 95 percent recall for yellow rusting, the one known as the V exhibited remarkable memory endurance with an impressive. These findings highlight how acquired knowledge boost crop control and guarantee worldwide food security by catching wheat wilt early [6]. | For transfer learning, four equipped CNN models—Mobile Net, InceptionV3, InceptionResNetV2, and VGG16—were utilised. | It is unrelated with regards to wheat ailments and confines one to three specific rust strains. Reliance on the well allocated dataset might hinder on plenty of real-life scenarios. The tactics employed might not be enough to cope with obstacles triggered on by various adverse scenarios in landlocked regions. |
| 7 | 2023 | The Art of Multi-Classification: Detecting Rice Sheath Rot | A devastating disease that mitigates productivity and entails large financial losses broadly is rice sheath decay. It's crucial to reliably assess | In the initial two phases, the methodology leverages SVM for rating and CNN for flavor extraction. It detects the | In the initial two phases, the methodology leverages SVM for rating and CNN for flavor |

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| | | Disease Severity Levels using a Hybrid CNN-SVM Model | the magnitude of problems and discern them early. This study draws on a hybrid therapeutic technique that combines neural networks made up of convolutions (CNN) with (SVM). The technique encompasses a pair of installments: dual classification to assess in five phases and a binary assessment to identify the circumstance. Sheaves of rice rot, the trick outperformed the prior comes with a yield of 95.2%. Though a deeper investigation is to explore the relevance to other plant-borne diseases and substitutes, the blended training shows prospective to aid in identifying a disease [7]. | coating of rice rot via a binary ranking and rates its five factors using dual classification. An assortment of radiographs depicting the sheen of rice rot served to remedy and gauge its usefulness. | extraction. It detects the coating of rice rot via a binary ranking and rates in five factors using dual classification. An assortment of radiographs depicting the sheen of rice rot served to the remedy and gauge its usefulness. |
| 8 | 2023 | Integrating YOLOv5 and Pretrained Models to Enhance Wheat Leaf Rust Disease Recognition | Using the YOLOV5, FOR INSTANCE model and trained beforehand models, this dissertation suggests a method creating use of deep learning for identifying wheat leaf rust ailments. 400 snapshots of wheat were retrieved from secondhand collections to construct the dataset. With higher consequently, the model behaved well when generating wheat leaf helmets.Using VGG16 and VGG19, the foliage leaves were binary deemed as either healthy or rust-infected; whilst VGG19's F1 score was 86.52%, VGG16's was higher at 92.89%. This tactic increases wheat yield and dietary stability by depicting the efficiency of sophisticated machine learning in identifying ailments [8]. | Leaf masks were created via YOLOV5 and optimized hyper-parameters Classification: Using exactness, re and F1 assessments, the VGG16 and VGG19 models sorted between fresh and malignant foliage. | Leaf masks were created via YOLOV5 and optimized hyper-parameters Classification: Using exactness, re and F1 assessments,the models sorted between fresh and malignant foliage. |
| 9 | 2023 | A Deep Learning Approach to Detect and Classify Wheat Leaf Spot Using Faster R-CNN and Support Vector Machine | In order to identify and break down wheat bud spot disease, this investigation correlates with an architecture that combines support vector machines (SVM) with Faster Region-Based neural networks made up of convolutions (R-CNN). Both multi-class (five levels of ailments severity) and unilateral (healthy vs. sick leaves) categories were applied to a raw data. The prediction accuracy of the model was 96.63% for binary sorting and 96.33% for categorization into multiple classes. Investigations show that the model might precisely in detail pinpoint and classify wheat leaf spot maladies, offering advantageous assets for early intervention in grazing [9]. | In a hybrid model, SVM served for classification although R-CNN, slightly faster, was pursued for getting features and region guidance. Both binary (appropriate vs. ill) and multi-class (five were taken levels of epidemics severity) classification were fitted to 10,000 images of rye stalks. | The validity and portability of the model may be driven by the extent of the data set and heterogeneity. Furthermore, the blend of models may be tricky to apply in real time on enormous scales in farming industries due to the complexity of its computations. |

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| 10 | 2023 | EMBEDDED AI FOR WHEAT YELLOW RUST INFECTION TYPE CLASSIFICATION | A mold known as dye rust, which undermines 5.5 million tons of crops broadly each year, could endanger Pakistan's staple crop, wheat. This study leverages information from the National Agricultural Evaluation Centre in Peshawar to identify and classify the five that were rust grade classifications. Xception, Inc and ResNet fifty serve as templates for classification afterwards the U2-was 96%. Oversight, a ResNet-50-powered computationally advanced device is developed, and the outcomes are backed up on accessible to others datasets. By making a precise therapeutic, the tool aims at aiding farmers to raise the sheer quantity and standard of gluten cultivated [10]. | The strategy splits the severity of corn tarnish into a quartet using the ResNet-50 and atypical models, that relies on a local dataset bought through momentum surveys. To help landowners in the field, the most effective variant is installed on a consolidated edge gadget which caters for instantaneous detection. | Regardless of its uses, drone-based recording is plagued by obstacles like motion blur, flight constraint, and weather reliance especially when handling at low angles. For the rendering to be strong, it ought to need a lot of tweaking to handle hazy photos and fluctuations in luminance. |
| 11 | 2023 | CNN-based smart agriculture for detecting wheat leaf damage 2 | This piece of writing lays out an approach utilizing CNN for 94% accurate surveillance and labeling of wheat leaf diseases through leveraging photo augmentation to circumvent overfitting. It is designed for disease detection in contemporaneous fashion, notably in scarce in resources contexts. Sustainable agriculture can be grew and crop loss are curable by the detection of early illnesses [11]. | This work recommends a CNN-based tactics to pinpoint wheat leaf disease, which strikes 94% accuracy by inhibiting overfitting through image augmentation. It was created for real-time application in settings with limited resources with the goal of enhancing early disease diagnosis and reducing crop loss while striving to promote sustainable agriculture. | The present paper sets forth a CNN-based method for 94% pinpointing and categorizing of wheat leaf diseases, notably picture augmentation to prevent overfitting. It is designed to be used in real-time in scarce in resources agricultural settings. nevertheless the study neglected to evaluate performance on larger datasets or in a range of terrains, and the system could fail to spot all wheat diseases. |
| 12 | 2022 | Using the Global Leaf Coverage Terrain Feature Algorithm uncovers significant illness in rice crops. | The intention of this endeavor is to deploy image analysis to pinpoint rice crop ailments. The Gray Level Co-Occurrence Matrix Texture Feature Algorithm serves to process 512x512 depictions to pick out between pleasant and unhealthy grass sections. To cope with the thirty percentage crop loss tracked, their intent is to pinpoint diseases early to avert their spread [12]. | Co-occurrence Matrix Texture Feature Algorithm, crisp pictures of rice leaves are snapped as part of the surgical procedure. For detection, the system separates images into territories that are lethal (patch) and healthy (grass). A dataset of 84 leaf images—42 to simulate and 42 for testing—with an aggregate delay of thirty seconds per sample furnished 100% accuracy. | The small dataset (84 samples) restricts the model's generalizability, and increases the risk of overfitting. Reliance on high-resolution images (512x512) may potentially hinder practical usage in resource-constrained environments. |
| 13 | 2022 | An Examination of Deep Learning Techniques for Rice Crop Pest | For the sake to pinpoint pests and diseases in Pakistani plantings of rice, this study investigates at five deep learning models: Vgg16, Vgg19, the ResNet50 algorithm ResNet50V2, and | The fifth recommendation artificial intelligence models—Vgg16, Vgg19, ResNet50 as its ResNet50V2, and ResNet101V2—are hired to | The enormity and broadness of the dataset might hinder the study's models, which could impact how broadly |

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| | | and Vector Detection. | ResNet101V2. Datasets are consulted in the study: actual data from the field (healthy vs. unhealthy) and produced statistics (grouped into three distinct categories: Healthy, Brown Spot, and Leaf Blast). The photographs were pre-processed to eradicate shadows and backgrounds. ResNet50 is the best with a seventy-five rate of precision on the simulation dataset. ResNet101V2 achieved the best accuracy of 86.79% using the actual data [13]. | spot pests and diseases in rice fields. Both real field data (binary classification) and synthetic datasets (four categories) are incorporated in the study. Prior to being analyzed by the models for designation, images endure pre-processing to rid them of shadows and backdrop. | applicable they are. Furthermore, the pre-processing stage might not completely remove deformities or noise from the photos. Additional data sets and more necessary for superior precision, which hinders the research. |
| 14 | 2021 | CNN-Based Multi-Crop Disease Screening and Grading Protocol. | The present investigation offers a CNN-based technique for detecting infection in paddy and maize crops using the ResNet-152 and Inception-v3 models. The accuracy of the work was 97.81% for maize and 97.48% for rice, with ResNet-152 hitting 99.10% proficiency for the most prevalent rice sicknesses. The technique uses to put things rice illnesses into major and minor affiliations. fortunately the results reveal high detection accuracy and robustness for these crops, how the technique's generalizability and diseases not covered within the datasets has not been checked out, and the datasets employ can hinder the range of diseases covered [14]. | To pinpoint pests in crops, this methodology employs use of discrepancies of the ResNet-152 were and The latest version of In CNN models. The method accomplished good detection accuracy via using obtainable information with distinct disease classifications associated with every crop. | Because it uses publicly accessible datasets, the regimen may be capped by both the extent and complexity of disorders it treats. Furthermore, it is not yet proven that the model can be employed on grow more crops and diseases that lack evidence in the datasets. |
| 15 | 2021 | Screening of Leaf Diseases such as A Review residing in Rice | Numerous kinds of illnesses impact crop quality, even though agriculture—particularly the cultivating of rice in Asian nations—is vital for earning a living. Although the symptoms of many of these diseases are similar, it may be difficult to detect these early using conventional strategies. Initial diagnosis and harm prevention are provided by automated systems that use methods including imagery processing, machine learning, and deep learning. The investigation contrasts the datasets, draws near, and accuracy of many different investigations on rice harvest diseases [15]. | The study investigates an assortment of tactics, such as image manipulation, machine learning, and deep learning, to spot rice disease. It lines up each of these strategies owing to their accuracy, strategies, and datasets from various investigations. | The shortcomings of the avenues under inquiry and their compatibility for usage in genuine agricultural scenes may not be smoothly gauged in the present dissertation. Plus, it may not cope via the shortcomings of trainer variation and database quality. |
| 16 | 2019 | Rice the plant's Disease Discovery and Sorting Through Wavelet-Based Image Extraction | Food production is at jeopardy from rice illnesses is contingent upon early detection. The present endeavor uses a straightforward harmonic transform-based image processing strategy to categorize rice illnesses. The work divides images into sub-bands | The Discrete Wavelet Transform is employed for splitting rice infection images into horizontal, vertical, and diagonal sub-bands for multi-resolution analysis. An Aggregation of Logistic | The preciseness of the recommended technique could stem from lessened because it pertains to methods for image manipulation that are susceptible to shifts in |

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| | | | employing the Discrete Wavelet Transform to restore texture and color knowledge. The Random Subspace Method is subsequently employed to organize those features using a bunch of linear classifiers. With a precision of 95% success rate in classification, the method reliably differentiates amid four crop of rice diseases: brown spot, sheath brown rot, blast, and bacterial blight [16]. | Statistical classifiers with the Accidental subterranean Method serves to further separate the color and texture information that has been retrieved from these sub-bands. The method has an accuracy coefficient of 95% in assessing four rice diseases. | radiation and image quality. The effective application of extracting and classifying features in circumstances with few resources may be impacted by the amount of computational capability needed. |
| 17 | 2019 | A Convolutional Neural Network Based on an Unifying Matrix for Classifying Wheat Leaves Infections in Fine-Grained Images. | In winter wheat leaves with tiny grits disease classification, the MnBB6 using a matrix of convolutional kernels and data augmentation, with 90.1% testing accuracy and 96.5% validation accuracy [17]. | The strategy involves proposing the CNN model, which uses a convolutional kernel matrix to enhance data streams, neurons, and connecting channels at cheap processing cost. Whenever assessed upon images of wheat plant disease, the model performs better than other Net in fine-grained classification tasks. | There may be challenges when scaling the CNN model to more complex datasets or jobs outside of the classification the wheat leaf disease. Furthermore, its practical Even with a modest boost in processor horsepower, deployment on gadgets with scarce assets may be constrained requirements. |
| 18 | 2018 | A Handy App for Segmenting Palay Medical Concerns to Foster Sustainability in Palay Harvest via Photographic Processing and Colour Analysis | The present investigation debuts Pa Life as well as an app utilizing picture processing and pigment analysis to figure out the health of rice. It employs strategies like Color Segmentation, CNN, and Local Binary Pattern Histogram for reliable illness and pest recognition. Pa Life surpassed the 25010 ISO software's functionality standard and passed tests, being paid a "Strongly Acceptable" grade. The app aims at aiding farmers as they oversee rice crops via enhanced agricultural pest and disease detection and providing reliable health assessments [18]. | The methodology employs image processing and pigment analysis for rice health categorization, and techniques including Color Segmentation, Convolutional Neural Network, and Local Binary Pattern Histogram are used for accurate disease and insect identification. The mobile application was evaluated in accordance the programming quality norms laid out by 25010 ISO. | To keep up with changing rice pests and illnesses, the application might need to be updated often. Furthermore, its accuracy could be impacted by modifications to the image quality or the surrounding surroundings. |
| 19 | 2018 | Support Vector Machine-Based Wheat Leaf Screening and Reduction | This work employs machine learning methods like (SVM) and utilizing K-means clustering to spot diseases of the wheat leaves. A method that labels leaves into well characteristics using Lab color room for processing images.Statistical metrics are employed for evaluation in order to ensure accuracy [19]. | Wheat crop images are acquired, pre -processed in Lab colour space, and then clustered using K-means to find out healthy and unhealthy areas. Features are extracted for classification using SVM, and the outcomes are assessed using statistical metrics like mean and standard deviation. | The method's accuracy is dependent on image quality so preprocessing, and it possibly not be a good generalizer to other datasets. Additionally, it can be computationally expensive and perform poorly on unbalanced or restricted disease categories. |

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| 20 | 2016 | An investigation on picking out and taxonomy of rice plant illnesses | The present inquiry reviews at 19 journals on machine learning and image processing ways of ruling out rice illnesses, with emphasis on attributes including data sources size, sick classes, preprocessing, segmentation, classification models, and accuracy. It serves as data for creating devices that identify and group together rice plant illnesses, laying a foundation for further investigations on plant disease identification [20]. | This study looks at a number processing of data and machine learning techniques for diagnosing rice plant illnesses. It analyses 19 studies based on factors such dataset size, ailment classes, preprocessing, segmentation, classifiers, and accuracy in order to guide the design of a disease detection system. | Although several Ways of choosing rice plant illnesses are reviewed, none of them are directly compared or used in the study. Furthermore, there was insufficient discussion of the offered solutions' scalability for large datasets or real-time applications. |

## III. CONCLUSION

Disease registration in both cereal crops proves vital for preserving ethical agricultural methods and striking global adequate nutrition. Utilizing sophisticated tools such as computation of images, machine learning, and profound learning is a viable approach for reliably pinpointing and categorizing agricultural ailments. These technologies assist farmers to evolve quickly that mitigates crop losses, ease economic hardships, and promote green approaches to farming.

This study showed that it is feasible to leverage gadgets in agriculture to combat the issues brought on by plant ailments. Crop pathogen surveillance systems lend scalable, inexpensively, and easily livable solutions that may drastically improve the earnings and resilience of wheat and rice production. As long as remains laboratory work in this field, these advances in technology will nonetheless advance.

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