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AUTOMATED WHEAT DISEASE DETECTION: A SYSTEMATIC LITERATURE STUDY OF MACHINE LEARNING APPROACHES

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ABSTRACT:
Wheat is one of the primary staple crops in India and also it provides essential nutrients such as iron, calcium, especially riboflavin and thiamine for good health to millions of people. But the pest and diseases severely affect the wheat crop quality and cultivation throughout the world. This paper reviews around 100 research papers and various articles published between 2020 and 2025 that focuses on various machine learning and deep learning techniques such as CNN, SVM, RF, KNN, hybrid models, etc to classify the wheat crop diseases. Common diseases affected by the wheat crop are viral, bacterial, fungal, rust, etc. This survey highlights recent advancements in automation of wheat disease detection, different datasets and performance metrics that offers high accuracy and scalability. It also helps farmers to minimize the yield loss and improve the crop quality and production in efficient manner.
Keywords: Wheat Diseases, Artificial Intelligence, Machine Learning, Deep Learning, Convolutional Neural Networks (CNN), Support Vector Machine (SVM).

INTRODUCTION:
Agriculture is the vital backbone in India and wheat is the second largest crop production in northern and north western part of the country after China. Wheat requires cool climate with moderate rainfall of 75cm to 100cm. India produces around 112 million of wheat per year so it is the second vital staple food in our population. It grows well in black soil of Deccan Plateau and it occupies 13 percent of country's cropped area. The yield production can be reduced due to the diseases caused in the wheat crop [1]. To detect the disease by visiting the land manually is very tedious and time-consuming process. Many researchers have been developed various hybrid machine learning techniques and which are used to detect the crop diseases easier and also strengthen the wheat crop quality [2].
Major diseases caused by the wheat are fungi, viruses, bacteria and nematodes. The major practice to control the disease is crop rotation. The fungi diseases with their pathogens reduce crop yields by damaging the green leaves, prevents sugar and protein that can be needed for growth. Table 1 summarizes the major fungi diseases with scientific names and their symptoms that is caused by the wheat crop [3]. The diseases caused by viruses are more difficult to control because it is invisible to the eye. They damage the plants by blocking its transport mechanism.

S. No	**Disease Name**	**Scientific Name**	**Symptoms**
1	Stem Rust	*Puccinia graminis*	Dark red pustules on stems/leaves
2	Powdery Mildew	*Blumeria graminis*	White powdery patches on leaves/stems
3	Leaf Rust	*Puccinia triticina*	Orange-brown pustules on leaves
4	Septoria Leaf Blotch	*Zymoseptoria tritici*	Brown spots with yellow halos

5	Stripe Rust	*Puccinia striiformis*	Yellow stripes on leaves
6	Fusarium Head Blight	*Fusarium graminearum*	Bleached spikelets, pink mold
7	Loose Smut	*Ustilago tritici*	Black powdery spores replacing grains
8	Karnal Bunt	*Tilletia indica*	Black spore masses in grains, fishy smell

TABLE 1 FUNGAL DISEASES OF WHEAT

Table 2 summarizes the major viral diseases with scientific names and their symptoms that is caused by the wheat crop [3]. The most significant biotic factor of wheat is the bacterial pathogens, important carbohydrate source. The bacterial infection that affects the early growth stage of wheat leads to lack of crop quality.

S. No	Disease Name	Scientific Name	Symptoms
1	Wheat Dwarf	*Wheat Dwarf Virus (WDV)*	Severe dwarfing, yellowing, no heading
2	Wheat Streak Mosaic (WSM)	*Wheat Streak Mosaic Virus (WSMV)*	Yellow streaks, leaf curling, necrosis
3	High Plains Wheat Mosaic	*High Plains Wheat Mosaic Virus (HPWMoV)*	Chlorotic streaks, resetting (tight leaf clusters)
4	Soil-Borne Wheat Mosaic	*Soil-Borne Wheat Mosaic Virus (SBWMV)*	Yellow-green mosaic patterns, stunting
5	Yellow dwarf	*Wheat Yellow Dwarf Virus (WYDV)*	Yellow/red leaf tips, stunted growth

TABLE 2 VIRAL DISEASES OF WHEAT

Table 3 summarizes the major bacterial diseases with scientific names and their symptoms that is caused by the wheat crop [4]. Nematodes are microscopic parasites that can directly damage the seed, root and lower stem of the crop. It is a soil-borne disease it can cause 60-100% of yield loss.

S. No	Disease Name	Scientific Name	Symptoms
1	Bacterial Sheath Rot	*Pseudomonas fuscovaginae)*	Rotting leaf sheaths, slimy discharge
2	Bacterial Leaf Blight	*Pseudomonas syringae*	Water-soaked lesions turning yellow/brown
3	Basal Glume Rot	*Pseudomonas syringae pv. atrofaciens*	Darkened glumes, shriveled grains
4	Bacterial Leaf Streak	*Xanthomonas translucens*	Yellow streaks with sticky exudate

TABLE 3 BACTERIAL DISEASES OF WHEAT

Table 4 summarizes the major nematode diseases with scientific names and their symptoms that is caused by the wheat crop [5].

S. No	Disease Name	Scientific Name	Symptoms
1	Seed Gall Nematode	*Anguina tritici*	Distorted seed heads, galls replacing grains
2	Root Lesion Nematode	*Pratylenchus spp. (P. thornei, P. neglectus)*	Brown root lesions, poor root system

3	Stem Nematode	*Ditylenchus dipsaci*	Swollen stem bases, twisted leaves
4	Stunt Nematode	*Merlinius spp.*	Patchy field growth, uneven plant height
5	Cereal Cyst Nematode	*Heterodera avenae*	Stunted growth, yellowing, reduced tillering

TABLE 4 NAMETODE DISEASES OF WHEAT

Automation of disease identification in wheat can be achieved by using different machine learning techniques with high accuracy and less time. The crop disease was identified either by using wheat plant image datasets or by using text datasets. If the crop was correctly identified then the disease classification and detection was successful [6].

TECHNOLOGIES USED:

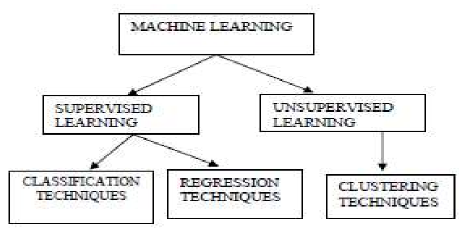
Artificial Intelligence (AI) is a vital powerful tool in agricultural field. The techniques used in AI are machine learning, deep learning, and computer vision. These systems can analyze the images of wheat plants to identify symptoms of disease with high precision. These technologies are being integrated into smartphones, drones, and field robots, enabling real-time monitoring and early intervention, which are critical for effective disease management.

Machine Learning (ML), a branch of Artificial Intelligence, has emerged as a powerful approach to automate and enhance the detection of wheat diseases.

ML algorithms can be trained on large datasets of wheat plant images to recognize complex patterns and symptoms associated with different diseases. By learning from labelled data, these models can classify diseases, assess severity, and even predict outbreaks under certain conditions.

TYPES OF MACHINE LEARNING ALGORITHMS:

Machine learning algorithms are increasingly being used in agriculture to optimize various processes, improve productivity, and enhance sustainability. The below diagram shows different types of machine learning algorithms.



A. Supervised Learning:

Supervised learning involves training a model on labeled data, where the desired output is known. The goal of this learning is to map input data with the output data. Once the training and processing are done, the model is tested by providing a sample test data to check whether it predicts the correct output. Examples of supervised learning algorithms are Simple Linear regression, Decision Tree, Logistic Regression, KNN algorithm, etc.

B. Unsupervised Learning

Unsupervised learning works with unlabeled data. In this, the machine does not require any external supervision to learn from the data. The aim is to find hidden patterns based upon the given input data. In this type, a large amount of data is divided into different clusters.

Examples of Unsupervised learning algorithms are K-means Clustering, Apriori Algorithm, Eclat, etc.

C. Reinforcement Learning

Reinforcement learning is a part of machine learning based on which an agent does work to get maximum reward. In this type of learning the model keeps on learning in the whole process. There is no supervision provided to the agent. Q-Learning algorithm is used in reinforcement learning.

In recent years, Deep Learning, a subset of machine learning, has shown tremendous potential in transforming plant disease detection. Deep learning models, particularly Convolutional Neural Networks (CNN), excel at image recognition tasks and can automatically learn complex patterns from large datasets of wheat plant images. These models can identify subtle visual symptoms of different diseases with high accuracy, often surpassing traditional machine learning approaches that require manual feature extraction.

LITERATURE SURVEY:

This survey describes the work done by different researchers by using different machine learning techniques from 2020- 2025.

A study by Ruksar et al [7] considered a deep learning CNN model to classify the wheat diseases by using image datasets and achieved the accuracy of 93%.

Zi-Heng Feng et al [8] predicts the powdery mildew disease in wheat by using SVM and RF machine learning algorithms and produced 90% accuracy.

Parmar Rinkesh et al [9] stated the management of crop using various machine learning algorithms and achieved 99.7% accuracy.

Sumit Nema et al [10] predicts the wheat disease prevention using machine learning for android application. SVM algorithm was implemented and produced 93% accuracy.

A study by Atila et al [11] proposed the Machine Learning algorithm such as EfficientNet and MobileNetV2 to detect the plant diseases, achieving over 98% accuracy on public datasets. These models reduced the time and require less data, useful for agricultural applications.

Khan et al [12] proposed an ML framework by achieving 99.8% accuracy in classifying brown and yellow rust diseases in wheat using features like Haralick texture and color histograms.

Ünal and Bolat [13] stated the deep feature extraction using VGG-19 combined with SVM, achieving a classification accuracy of 98.63% for septoria and stripe rust diseases in wheat.

Long et al [14] developed CerealConv, a CNN model trained on field and glasshouse images, achieving a 97.05% accuracy in five categories of diseases such as yellow rust and powdery mildew.

Saleem et al [15] stated a multi-scale feature extraction method using ensemble models like Xception, Inception V3, and ResNet 50, reaching a high accuracy of 99.75% in classifying wheat diseases such as loose smut and crown rot.

Ferentinos et al [16] achieved 99.5% high accuracy rate using CNNs, a deep learning technique to detect the disease in multiple crop types.

Sethy et al [17] developed a hybrid deep learning algorithm ResNet50 to detect wheat rust diseases, achieving 98.3% accuracy on a custom dataset to reduce time.

Wang et al [18] introduced a hybrid CNN-Transformer deep learning model for wheat disease detection, combining local feature extraction (CNN) with global attention (Transformer), achieving 97.1% accuracy.

Chen et al [19] developed a MobileNetV3-based wheat disease detection for smartphones, achieving 94.5% accuracy with real-time inference.

Feng Z et al [20] detects Nitrogen deficiency and yellow mosaic disease in wheat crop by using three nonparametric machine learning algorithms such as k-nearest neighbor (KNN), random forest (RF), and Support Vector Machine (SVM) and achieved 96.7% accuracy.

Table 4 summarizes various algorithms and its use cases performed by the researchers in this survey to classify the diseases in wheat crop.

Algorithm	**Authors**	**Use Case**
SVM	Ahmad & Khan (2020), Patel & Joshi (2022)	Early disease classification
Random Forest	Kumar & Patel (2021)	Hyperspectral data classification
k-NN	Zhang & Li (2020)	Baseline comparison

Basic CNN	Wang & Chen (2020)	Rust detection
ResNet-50	Singh & Kaur (2022)	Fusarium head blight
EfficientNet	Chen et al. (2023)	Hyperspectral classification
MobileNet	Gupta & Sharma (2025)	Mobile deployment
Vision Transformer	Liu & Wang (2024)	Captures long-range dependencies
U-Net	Gao et al. (2024)	Pixel-wise disease segmentation
GANs	Jiang & Li (2024)	Data augmentation for rare diseases
YOLOv5	Islam & Rahman (2023)	Drone-based field monitoring
Faster R-CNN	Nguyen & Hoang (2022)	Localized lesion detection

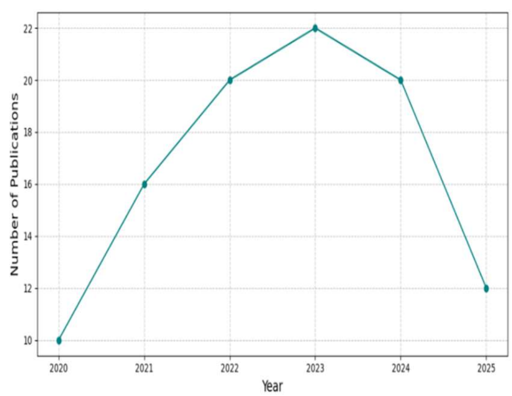
TABLE 4 ALGORITHMS USED

RESULTS AND ANALYSIS:

A. Review Paper Analysis

The growing concern over crop health and food security has led to increased research activity in the field of wheat disease detection. As new technologies such as machine learning, deep learning, and remote sensing have become more accessible, researchers have increasingly focused on developing automated and accurate methods to identify and manage wheat diseases [38].

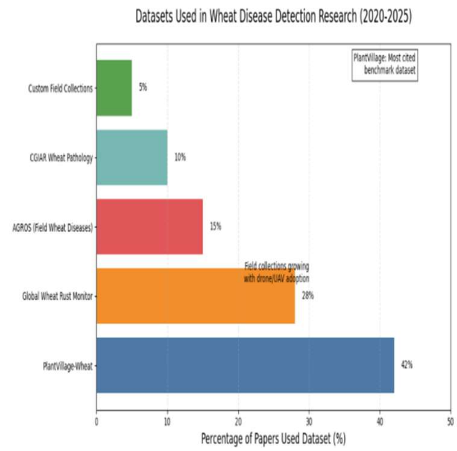
The graph presented illustrates the number of research papers published per year related to wheat disease detection during 2020. This trend reflects the rising interest and investment in this area by the scientific community. A steady or sharp increase in publications over time suggests not only technological advancements but also a growing awareness of the importance of early disease detection in sustainable agriculture [41].



B. Data Set:

Data collection is one of the most vital tasks, used for the foundation for analysing the model validation and development. With the growing adoption of artificial intelligence and machine learning techniques in agriculture, the role of high-quality datasets has become increasingly important. In the context of wheat disease detection, datasets serve as the foundation for training, validating, and testing machine learning and deep learning models that can automatically identify disease symptoms [44].

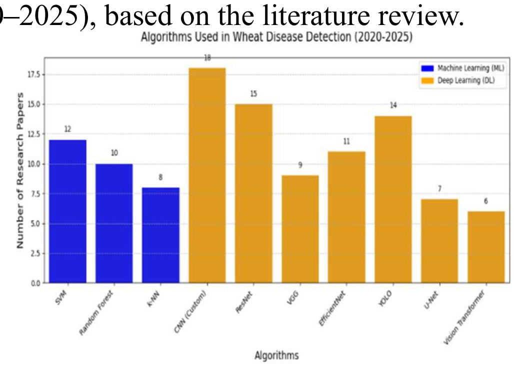
The graph shows the frequency of different datasets used in wheat disease detection studies from 2020 to 2025. These datasets typically consist of annotated images of wheat leaves or spikes, captured under various environmental conditions and showing different types and stages of diseases such as leaf rust, stem rust, powdery mildew, and Septoria.



Global Wheat Rust Monitor (28%) data set is used for especially to find the rust diseases in wheat. Well-known publicly available datasets, like the PlantVillage dataset, have played a key role in advancing research in crop disease detection, although specific datasets tailored to wheat are still being developed and expanded [45]. The quality, size, diversity, and proper annotation of these datasets are crucial, as they directly impact the accuracy and reliability of disease detection systems in real-world applications.

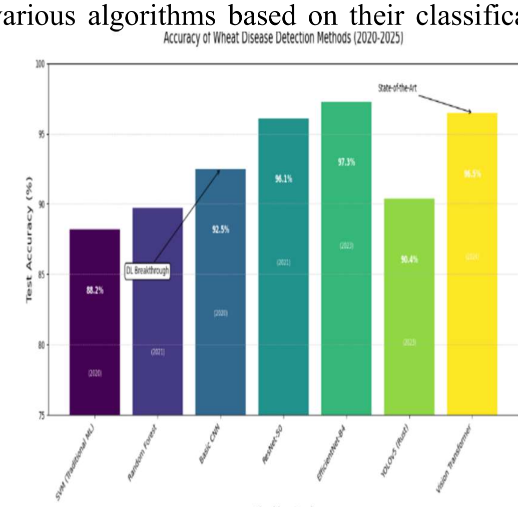
C. Algorithm Analysis:

The graph shows the popularity of machine learning (ML) and deep learning (DL) algorithms used in wheat disease detection (2020–2025), based on the literature review.



D. Accuracy:

Accuracy is more essential for selecting the most effective tools for wheat disease detection by using various Machine Learning and Deep Learning algorithms. The chart presented illustrates a comparative analysis of various algorithms based on their classification accuracy when applied to



wheat disease datasets [48].

This chart highlights the performance differences between traditional machine learning models such as Support Vector Machines (SVM) , Random Forests, and K-Nearest Neighbors (KNN)—and more advanced deep learning models, including Convolutional Neural Networks (CNNs), ResNet, and EfficientNet. The highest potential accuracy performed by the algorithm is EfficientNet-B4 of 97.3% efficiency when compared to other algorithms.

CONCLUSION:

The literature study highlights significant advancements in automating disease identification, offering faster and more accurate diagnostics compared to traditional visual inspection. Machine learning, especially deep learning, has significantly shown remarkable success in wheat disease classification. Deep learning models, particularly CNNs (e.g., ResNet, EfficientNet) and Vision Transformers, have demonstrated remarkable performance (accuracy >95%) in classifying diseases like rust, powdery mildew, and Fusarium head blight. Techniques such as transfer learning, data augmentation (GANs, synthetic datasets), and lightweight models (MobileNet, YOLOv5) have addressed challenges like limited datasets and real-time deployment. Future research should focus on lightweight models, better datasets, and integration with agricultural robotics for practical applications.

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