CROP DISEASE DETECTION USING MACHINE LEARNING

PROJECT REPORT

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE AWARD OF DEGREE OF

MASTERS OF TECHNOLOGY
IN
ARTIFICIAL INTELLIGENCE

Submitted by
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CANDIDATE'S DECLARATION

I, **NITIN SAHU**, Roll No. 2K21/AFI/22 student of M.Tech (Artificial Intelligence), hereby declare that the Project Dissertation titled "**Crop disease detection using Machine Learning**" which is being submitted by me to Delhi Technological University, Delhi, in partial fulfillment of requirements for the degree of Master of Technology in Artificial Intelligence is a legitimate record of my work and is not copied from any source. The work contained in this report has not been submitted at any other University/Institution for the award of any degree.

Place: Delhi
Date: May, 2023

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2K21/AFI/22

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CERTIFICATE

I hereby certify that the project entitled "**Crop disease detection using Machine Learning**" which is submitted by Nitin Sahu, Roll No. 2K21/AFI/22, Department of Computer Science and Engineering, Delhi Technological University, Delhi in partial fulfilment of requirement for the award of the degree of Master of Technology in Artificial Intelligence, is a record of the project work carried out by the student under my supervision. To the best of my knowledge this work has not been submitted in part or full for any degree or diploma to this university or elsewhere.

Place: Delhi
Date: May, 2023

Dr. Aruna Bhat
Associate professor

ABSTRACT

Humans rely on cereals as a major food source, emphasizing the need for increased crop production to sustain the growing population. However, plant diseases significantly impact crop yield and food quality. Wheat, a crucial crop worldwide, is particularly vulnerable to diseases. Early detection and classification of these diseases are vital for effective disease management.

In this study, we conducted a comprehensive literature analysis of wheat diseases from 2017 to 2022. We identified three major types of wheat diseases, namely fungal, bacterial, and insect-related. Additionally, we reviewed 32 studies focused on disease detection and classification using various machine learning and deep learning algorithms.

Our analysis revealed that Stripe Rust garnered the most attention, accounting for 56% of the total studies. Self-acquired datasets were predominantly used, and convolutional neural networks (CNN) and its frameworks were the most prevalent classification techniques, representing 34% of the studies. Accuracy emerged as the dominant performance metric, constituting 65% of the total studies. Notably, the majority of the literature was published in 2019 (25%) and 2020 (25%).

Considering the urgency of crop health and productivity, we propose a hybrid model that combines the strengths of Convolutional Transformer and EfficientNet architectures for reliable wheat disease classification. Our model integrates global contextual information gathering from Convolutional Transformer with the efficiency and accuracy improvements of EfficientNet. To train the model, we preprocess and augment a dataset comprising 14,560 images of Fusarium head blight, Yellow rust, Brown rust, Powdery mildew, and healthy wheat leaves.

With an impressive accuracy of 93.6%, our proposed model offers valuable insights for agricultural disease management, enabling enhanced crop health monitoring and ultimately improving productivity and sustainability. This research contributes to addressing the challenges associated with wheat disease detection and classification, paving the way for more efficient agricultural practices.

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I am extremely grateful to my project guide, **Dr. Aruna Bhat**, Associate Professor, Department of Computer Science and Engineering, Delhi Technological University, Delhi for providing invaluable guidance and being a constant source of inspiration throughout my research. I will always be indebted to her for the extensive support and encouragement she provided.
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LIST OF ABBREVIATION

1. **WSM - Wheat Streak Mosaic**
2. **SR - Stripe Rust**
3. **PM - Powdery Mildew**
4. **StR - Stem Rust**
5. **FHB - Fusarium Head Blight**
6. **LR - Leaf Rust**
7. **BSB - Bacterial spike Blight**
8. **WLS - Wheat Loose Smut**
9. **TS - Tan Spot**
10. **STB - septoria tritici blotch**
11. **FS - Flag Smut**
12. **SB - spot blotch**
13. **SLS - Septoria leaf Spot/Blotch**
14. **CRR - Crown Root and Rot**
15. **CNN - Convolutional Neural Network**
16. **ANN - Artificial Neural Network**
17. **WD - Wheat Disease**
18. **DCNN - Deep CNN**
19. **RCNN - Region based CNN**
20. **SVM - Support Vector Machine**

21. MLP - Multi Perceptron layer

22. PNN - Probabilistic Neural Network

23. PLSR - Partial-Least-Squares Regression

24. DT - Decision Tree

25. RF - Random Forest

26. ML - Machine Learning

27. DL - Deep Learning

28. D&C- Detection and Classification

29. L- Leaves

30. St – Stripe

31. S- Spike

32. KNN- K-Nearest Neighbor

CHAPTER 1

INTRODUCTION

Wheat is one of the most common crops grown in the world [1]. We can say, world's 2nd top crop grown by farmers in their field and also consumed by all over the world as their food diet. The principal crop for an estimated 35% of the world's population is wheat [2]. More than 2/3s of the wheat produced worldwide is consumed for human consumption, with only 1/5th going to animal feed. The world society needs to double the food production by 2050 to feed an expected population size that is predicted to be 9.8 billion [3]. Wheat production also needed to be increased because it is one of the world's most staple and important crops, accounting for 20% of calories and proteins consumed by humans [2,3].

According to estimates, pests and illnesses account for 21.5% of current output losses [4], which is one of the biotic limitations. The most detrimental losses are caused by fungal diseases [5] such as LR [28], FHB, SLB, SR [28], Spot blotch, TS, and PM [29] out of the 31 pests and pathogens that have been reported in wheat. Diseases of wheat can also change the quality and chemical composition of wheat.

To decrease the losses in the wheat production one task is to detect the disease in the plants accurately as early as possible So that the farmers can spray the antifungal chemicals over the wheat plants [24]. The disease in plants used to be detected by the experts or by the farmers himself which is very time consuming and also it can be inaccurate as to which type of disease and what type of cure it is needed. In recent years Computer Vision [6-10] has been widely used in disease detection using wheat plant images. There is many Deep learning [11-15] & Machine learning [16-18] techniques that are used in the early D&C of diseases in wheat plants. These techniques are found more accurate and less time consuming. To apply Deep learning & Machine learning techniques there is always a need for datasets which have a lot of images of wheat plants. There are very few datasets of wheat plants available So, most of the researchers have prepared their own datasets using self-acquisition and image processing [17,19-22].

To achieve accurate classification, we use two cutting-edge deep learning models: Convolutional Transformer [5] and EfficientNet v1 [6] and also Compare the performance of different architecture along with the proposed model..

The Convolutional Transformer model combines the beneficial properties of both CNNs and transformer topologies. The CNN model [2], known for its powerful feature extraction capabilities, is improved with transformer layers to capture long-range dependencies in image information effectively. This modification allows the model to better recognise complicated patterns and differentiate between various forms of wheat diseases [3]. In addition, we use the EfficientNet v1 model, which is well-known for its efficiency and scalability. When compared to typical CNNs [2], the EfficientNet design uses a compound scaling strategy to optimize model depth, width, and resolution, allowing it to achieve greater performance with fewer parameters. We hope to examine EfficientNet v1's suitability for this task by exploring its application in wheat disease classification [4].

We compare the accuracy of the Convolutional Transformer [5] and EfficientNet v1 models [6] using comprehensive experiments and evaluations. Our findings contribute to current attempts to use deep learning techniques [1] for accurate and automated wheat disease classification [4]. The methodology used to train and evaluate the Convolutional Transformer [5] and EfficientNet v1 models is described in the following sections. We also discuss the experimental design, dataset specifics, and performance evaluation criteria employed in this study.

1.1. MOTIVATION

Being born in India we are very familiar with farming and agriculture. Providing employment for more than 60% of the overall population and making up around 17% of the country's GDP, agriculture is a key sector of the Indian economy [23]. Being a great source of income in India there is very low agricultural productivity as the farmers face many challenges like lack of sources in the farming. Due to climate change and cropping patterns there are new pests and diseases which cause 15-25 % loss in Indian agriculture annually [4]. Some of these diseases can be cured if they are detected earlier or on time. Technologies like Computer Vision [6-10] are being used in this case and much work has been done. So, we have tried to summarize all the recent works on Machine learning [16-18] and deep learning [11-15] and also have done many experiments in this field and found good results along with CNN transformer and EfficientNet hybrid model.

1.2 RESEARCH QUESTION

This section consists of the identification of research questions which is defined on the basis of the summarization of the topic so that keywords can be generated and which will be useful for the search of the studies on different platforms. We find out a total of 8 research questions which are defined below on the basis of which the whole thesis will move forward to tell you about WD D&C. The research questions are given below:

RQ1: What are the available literature sources for WD detection and classification?

RQ2: What are the different diseases present in wheat plants?

RQ3: Which datasets are used for wheat disease detection and classification?

RQ4: What different DL or ML techniques are used for disease detection and classification?

RQ5: Which type of images are used to train the models?

RQ6: What methods of image processing were employed to extract more accurate features?

RQ7: How are features extracted from the data using the various feature extraction techniques?

RQ8: What performance metrics are used to describe performance of models?

1.3 RELATED WORK:

1.3.1 Background

Wheat plants [24,26] are grass type plants which have leaves, root, stem, kernels, ear/spike, stripe as its part. The wheat plants were first cultivated around 10000 years ago and the first disease was discovered in 1922. After that many diseases were discovered. All diseases affect different parts of the wheat plants. leaves, stem, roots, spike/ears, kernels all have their specific diseases explained in Table 1. These diseases can be categorized as Fungal [5], bacterial [25, 30], viral [27] etc. on the basis of their causes.

1.3.2. Types of wheat Disease

There are many categories for wheat disease [34,36,57,58] but in this survey we have studied only fungal [5], viral [27] and bacterial [25, 30] diseases. These disease categorizations are on the basis of their symptoms. In this literature survey, we have shown images of all the 18 diseases discussed in the Table 2 and discussed them under the following categories:

1. **Fungal Disease:**

   Some fungus can be good for plants but there are thousands of fungus which affect plants badly and so there is a need to care for fungus disease. Fungi can infect both the upper and lower part of the wheat plant [24]. There are diseases like root rot , dead root and swelling root below the ground and leaf rust [28], powdery mildew are above ground disease. Due to the light weight of fungus spores, they can spread by wind, insects, water, animals and people to infect other wheat plants. Symptoms of a fungus [5] include drying off of seedlings, leaf spot (septoria brown spot), and leaf yellowing.

Table 1. Part of the plant was affected by disease.	
Affected Part of Wheat	**Diseases**
Leaves	Rust [28], powdery mildew [29], bacterial spike [30], mosaic [27], tan spot etc.
Stem and root	Crown root rot [31], fusarium root [31], foot rot [31] etc.
Heads and grain	Loose smut [5], fusarium head blotch (FHB) [5] etc.

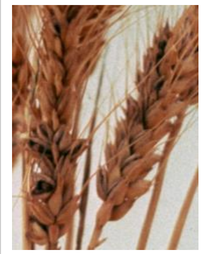
2. Bacterial Diseases:

Just like fungus, all bacteria are not bad for plants but still there are almost 200 types of bacteria which can infect a plant. In warm and humid environments they are more active and can cause more disease to the plants. The bacteria in the plant produce a chemical which is responsible to kill the nearby cells of the plants. Sometimes bacteria stops water and nutrients from reaching other parts of the plants which can lead to dramatic decline in the plants. Other symptoms are dead tissue in the plants [32]. Bacteria can enter in the plants through tiny openings caused due to damage, cuts or naturally [32]. They can spread through insects, splashing water or nearby infected plants. Symptoms of bacterial [25, 30] disease include shepherd's crook stem ends on woody plants, canker, crown gall, and leaf spots with a yellow halo.

3. Viral Disease:

Even All viruses are not bad for plants but most of them destroy field plants. They can be seen and are non-treatable. When a plant is infected by viruses then its leaves become yellow or mosaic patches of yellow, light green or white can be seen. Viruses can not be spreaded by water or wind but insects can spread the diseases as they feed on infected plants and then transmit the disease while feeding again on healthy plants. Other ways of transmitting the viruses are human, plant propagation

Table 2. Images of types of Wheat plant diseases which are described in this paper. (a) Bacterial Black Chaff [33], (b) Bacterial spike blight [35], (c) Leaf rust [34], (d) Septoria tritici blotch [34], (e) Stem rust [34], (f) Kernel bunt [34], (g) Fusarium head blight [34], (h) Flag smut [36], (i) Pink snow mold [36], (j) Powdery mildew[34] (k) Root or foot rot [34], (l) Tan spot [34], (m) Loose smut [34], (n) Spot blotch [36], (o) Fusarium leaf blotch (snow mold) [36], (p) Stripe rust [34], (q) Septoria leaf spot/ blotch [92], (r) wheat streak Mosaic [34].

 (a)	 (b)	 (c)	 (d)	 (e)	 (f)
 (g)	 (h)	 (i)	 (j)	 (k)	 (l)
 (m)	 (n)	 (o)	 (p)	 (q)	 (r)

and infected seeds. Mosaic leaf patterns, crinkled leaves, and yellowed leaves are signs of the viral illness.

CHAPTER 2

LITERATURE SURVEY

The section consists of identification, evaluation (screening) and interpretation of a particular topic area. For this Literature Survey on Wheat Disease (WD) [34,36,57,58] we have followed a sequence of steps depending on different approaches as explained. First on the basis of the research questions defined above we have got the necessary keywords to search related recent literature to our literature survey. Then we have collected the different literature sources from articles, books and this step is called searching. We have collected the research studies from different sources named IEEE, SpringerLink, Elsevier Scopus, MDPI and Google Scholar and every paper's sources are described in Table 3.

The collected research studies have both journal and conference papers. Next, we have defined the Inclusion criteria (IC) and exclusion criteria (EC) to exclude the research studies. In the next section we have defined the research questions as we have discussed above. These research questions are very useful to collect the studies and summarize the review.

2.1 SEARCH STRATEGY

For this Literature Survey on wheat disease detection and classification we have used the keywords related to the topic to search the research papers on google scholar and directly on the journals or conferences website. The main databases used in searching and selection strategies are IEEE, Springer Link, Elsevier Scopus, MDPI and Google Scholar. We have chosen only recent papers belonging to 2017 to 2022 (The number of studies belonging to specific years is shown in Fig. 3 so that we can describe only recent Computer Vision techniques on which we have done our experiments with different architecture and hybrid models. Fig. 1 depicts the useful keywords to find out the research studies and these keywords are also available in the papers.

2.2 STUDY SELECTION AND QUALITY ASSESSMENT:

The research articles related to wheat Disease detection and classification are acquired from different sources which are searched based on the Aim of the papers, abstract of the paper and the keywords taken from the research questions defined above chapter. But there were still many research papers which were not useful on the basis of our research question and there are domains which were repeated in our database. The keywords-based search helped to acquire a total 430 research studies for our systematic literature review. There are some IC and EC that are defined to include or exclude the selected studies for our SLR. Those criteria are used to determine the quality of each study as they are partially or totally related to our motive to write the Systematic Literature Review. Those inclusion and exclusion criteria for our systematic reviews are described below:

2.2.1 Inclusion Criteria:

IC 1: The Aim of the paper is clearly defined.

IC 2: The studies are published after the year 2016.

IC 3: The Aim is relevant to Wheat disease detection and classification using ML or DL.

IC 4: The Results of the studies are clearly specified.

IC 5: The future work and conclusion are consistent with the results.

IC 6: The studies are completely available in digital form.

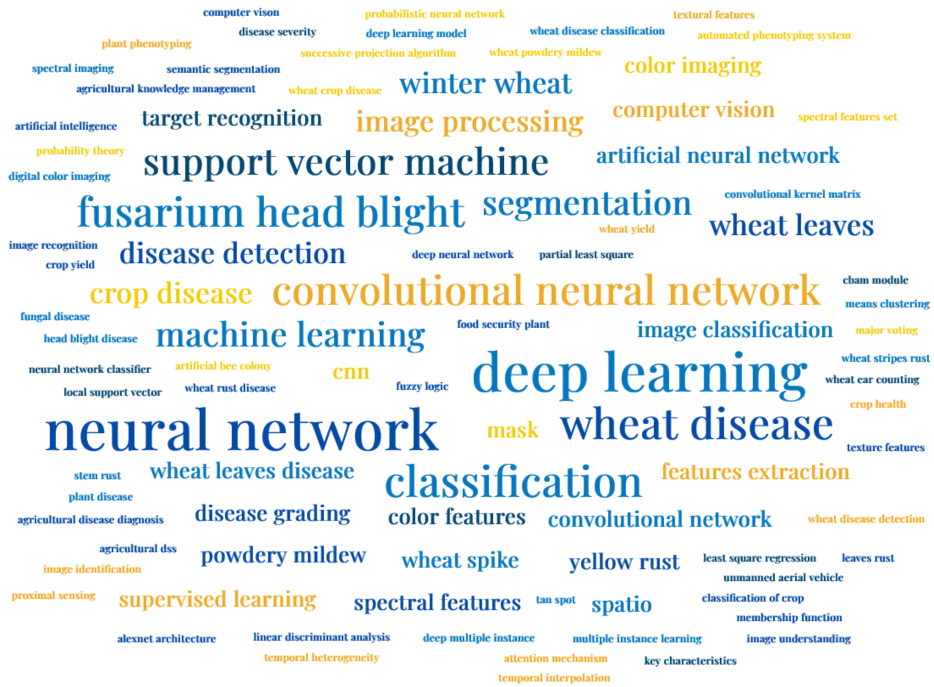


Fig. 1: Keywords present in all literature studies for SLR.

2.2.2 Exclusion Criteria:

EC 1: The research studies have been published before 2017.

EC 2: Publication is already downloaded from other sources.

EC 3: The paper is not completely available on any source.

EC 4: The Research studies whose title and abstract are not relevant to our SLR topic.

Table 3. Years of paper and their literature name used in literature survey.

Selected Literature given reference	**Selected research papers for review**	**Reference**	**Year**
T1	Z. Lin et al.	[38]	2019
T2	Lu, Jiang et al.	[39]	2017

T3	S. Abdollahpour et al.	[40]	2020
T4	T Su et al.	[41]	2019
T5	Zhang X et al.	[12]	2019
T6	Sadeghi-Tehran et al.	[42]	2019
T7	Kumar, D et al.	[43]	2021
T8	Tutygin et al.	[44]	2019
T9	Kumar, M et al.	[20]	2017
T10	Raichaudhuri et al.	[21]	2017
T11	Zhang, Dongyan et al.	[45]	2019
T12	Jiang, Li et al.	[46]	2018
T13	Hussain et al.	[47]	2018
T14	Zhao et al.	[48]	2020
T15	Su, W et al.	[49]	2020
T16	Jahan et al.	[17]	2020
T17	Mi, Z et al.	[13]	2020
T18	Ebronne et al.	[50]	2020
T19	Gaikwad et al.	[22]	2017
T20	Huang et al.	[51]	2020
T21	Haider et al.	[52]	2021
T22	Ennadifi et al.	[7]	2020
T23	Su, W et al.	[8]	2020
T24	Qiu et al.	[53]	2019
T25	Nema et al.	[54]	2018
T26	Goyal et al.	[55]	2018
T27	Aboneh et al.	[9]	2021
T28	Xie et al.	[18]	2022
T29	Huang et al.	[10]	2019
T30	Sood et al.	[14]	2022
T31	Kukreja et al.	[56]	2021
T32	Genaev et al.	[60]	2021

We have answered all the research questions defined by us in the above chapter. Data from selected 32 studies have been extracted and synthesized. A summary of all papers as an excel sheet is prepared and based on that data the answers of the research question are given accordingly in the next section known and Results. For the reference of each paper we used Ti so that we don't need to use the whole paper again and again. The reference for each paper is given in Table 3.

2.3. DISCUSSION OF THE REVIEW

We have selected only 32 research studies which are properly related to wheat disease detection and classification. After this we have studied all 32 papers and summarized the types of wheat disease [34,36,57,58], the dataset availability, the techniques which were used, the features extracted and so on. In this section we will try to discuss the literature summary by providing the answers to the defined question. And we will also compare the results and their working. The answers to the each defined question are defined below:

2.3.1. Research Question

RQ1: What are the available literature sources for WD D&C?

The number of studies belonging to the conference, journal or book article is given in Fig. 4. The literature source and other information related to studies are given in Table 4. Each literature source consists of how many literature sources are given in fig. 5.

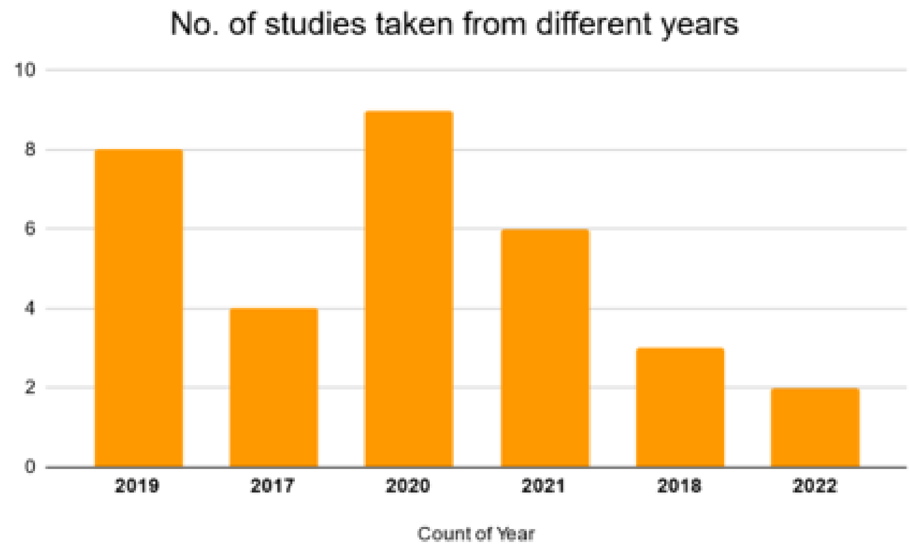


Fig 2. Number of studies in each year.

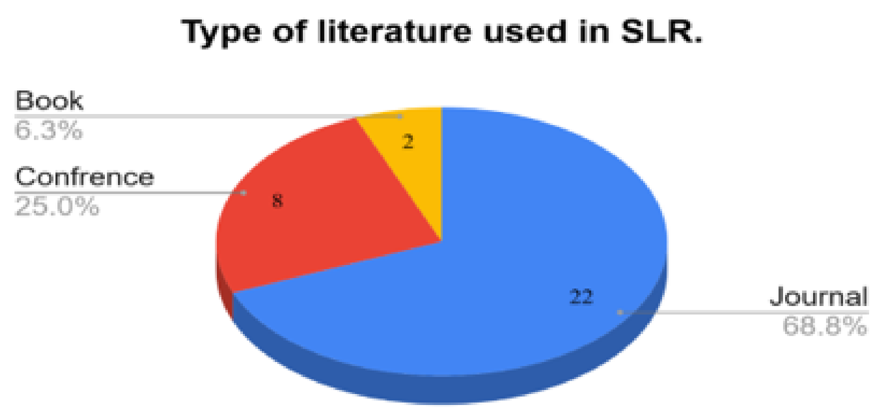


Fig 3. Percentage of studies belongs to the journal, conference and book.

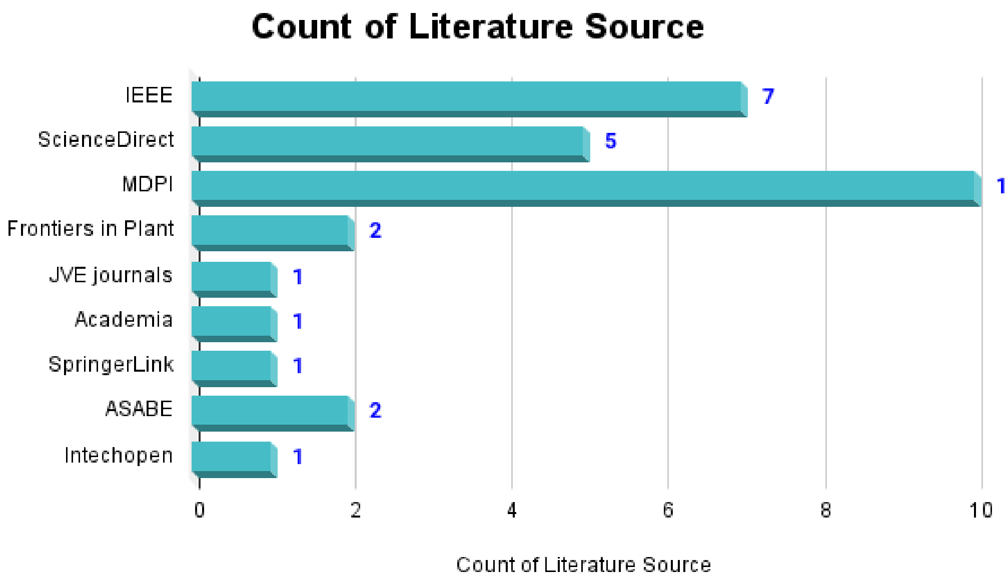


Fig 4. Count of literature Source.

Summary of RQ1:

Among all the selected studies, most of the studies belong to the journal papers (#22), then there are conference papers (#8) and there are articles of some book (#2). Each paper belonging to either journal, conference or book article is given in table 4.

Table 4: Journals/ Conference information

Selected Literature	Literature Source	Publication Name	C-Conference J- Journal B- Book	#Citations
T1	IEEE	IEEE Access	J	42
T2	ScienceDirect	CEA	J	140
T3	ScienceDirect	IPA	J	15
T4		NNW	J	4

T5	MDPI	Remote Sensing	J	96
T6	Frontiers	FPS	J	69
T7	IEEE	ICDASA	C	1
T8	JVE journals	Vibroengineering Procedia	B	1
T9	Academia	IJLTEMAS	J	8
T10	SpringerLink	PICDECT	J	9
T11	MDPI	Remote Sensing	J	12
T12	ScienceDirect	CEA	J	8
T13		ICNGC 2018	C	12
T14	MDPI	Plants	J	68
T15	ASABE	ASABE 2020	C	7
T16	ASABE	ASABE 2020	C	12
T17	Frontiers in Plant Science	TAPS	J	24
T18	ScienceDirect	Biosystems Engineering	J	18
T19	IEEE	ICISIM 2017	C	35
T20	MDPI	Sensors	J	18
T21	IEEE	IEEE Access	J	11
T22	IEEE	ISCV 2020	C	7
T23	MDPI	RemoteSensing	J	34
T24	MDPI	RemoteSensing	J	38
T25	IEEE	ICCSDET 2018	C	3
T26	ScienceDirect	IMU	J	11
T27	MDPI	Technologies	J	6
T28	MDPI	AgriEngineering	J	1
T29	MDPI	Applied Sciences	J	18
T30	Intechopen	FSR	B	
T31	IEEE	ICRITO 2021	C	0
T32	MDPI	Plants	J	6

RQ2: What are the different diseases present in wheat plants?

In the given Fig. 6, we have defined the type of wheat disease [34,36,57,58] present in wheat plants and we have also defined disease above with the introduction section. Now we will like to introduce the symptoms and precaution here in this question.

In each study, which disease is used to classify is given in Table 5.

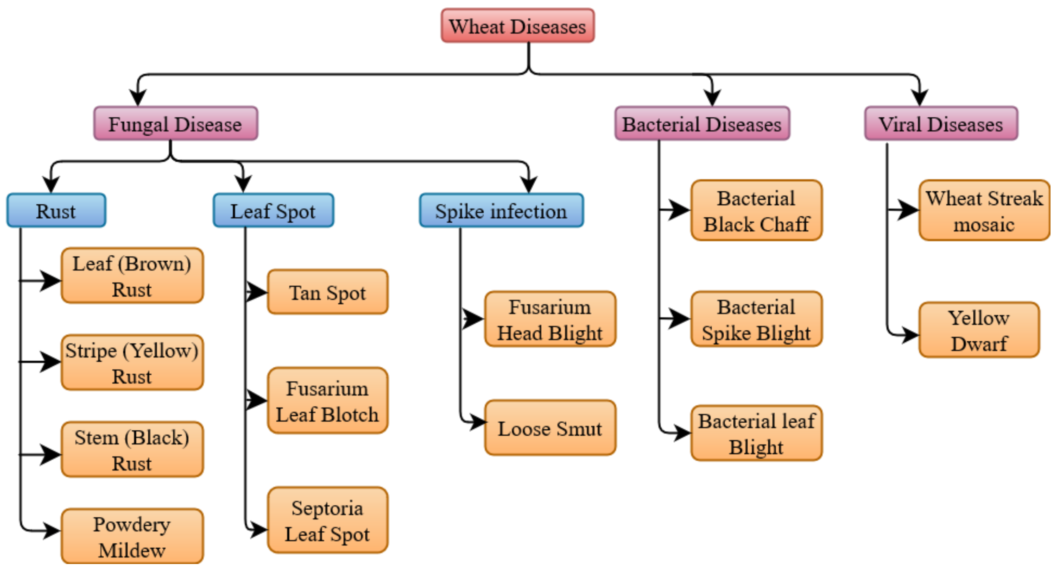


Fig 5. Types of wheat plant disease.

Table 5. Wheat disease type and their symptoms.

Type of Disease	**Selected Literature**	**Symptoms of Disease on wheat plants**	**Percentage (%)**
LR (Brown rust) [34]	T1, T2, T4, T8, T9, T10, T13, T16, T18, T19, T22, T26, T27, T30, T31, T32	Small yellowish-brown pustules can be seen on leaves which causes less tearing of leaf tissue.	50

SR (Yellow rust) [34]	T1, T2, T4, T5, T6, T7, T8, T10,T13, T17, T18, T19, T21, T22, T27, T30, T31, T32	Mainly leaves can be seen affected by this and blister like lesions and yellow in color can be seen stripes. Head tissue can also be seen to be affected by heavy infection.	56.25
StR (Black rust) [34]	T2, T8, T10, T13, T21, T22, T27, T30, T31, T32	The reddish-brown pustules of fungus cause tearing as they burst through the plant's outer layers. Scratches that look like blisters can be seen on the leaves, leaf sheaths, and stems.	31.25
PM [34]	T1, T2, T4, T6, T8, T9, T10, T13, T14, T19, T22, T25, T26, T32	Initially, white to pale yellow powdery colonies can be seen on upper surfaces of leaves, leaf sheaths and on spikes also. With time the fungus changes to a grayish yellow hue.	43.75
Bacterial black chaff [33]	T1, T2, T4, T26	Wheat leaves will develop tan, linear scars from this. The degree of yellowing varies between species and lesions may possess a yellow border.	12.5
BSB [35]	T1, T4, T6, T10	The first sign of this disease is a yellow fluid on the spikes and necks followed by early wrinkles and bent on the leaves.	12.5
Fusarium leaf blotch (Snow mold) [34]	T2,T8	Young sores typically appear as elliptical to oval, grayish green patchy spots appear on leaves especially where the leaf bends.	6.25
WLS [34]	T2, T21, T26	The head of wheat is completely replaced by heavily dark fungal spores and the ear looks like a black powder.	9.37
WSM [34]	T3, T6, T8, T26	Unusual leaf mottling, such as light and dark green or yellow streaks. Leaves are usually seen dwarfed, twisted, or wrinkled.	12.5

FS [36]	T10	On the leaves, there is bent and sagging as well as a grayish black sori (black powdery spores). This may have an impact on the stem, clum and leaves.	3.12
FHB [34]	T11, T12, T15, T19, T20, T24, T23, T26, T29	There are premature bleaching and unfilled heads or spikelets in the wheat plants.	28.12
TS (yellow leaf blotch/ spot) [34]	T16, T19, T25, T26	Tiny tan-brown blotches on the lower leaves that grow into lens-shaped brown flecks up to 12 mm in length.	12.5
STB [34]	T18, T25, T32	Soon after the seedlings emerge, little spots can be seen on the lower leaves and these spots can expand and become light to dark brown blotches with an oval or striped form on the leaves.	9.37
Septoria leaf blotch/ spot	T8, T19, T21, T25, T32	Yellowish or chlorotic specks on leaves, especially those which touch the soil can be seen as first symptoms and these particles grow into uneven, brown to reddish brown lesions.	15.62
SB	T19	Sores typically have an oval or elongated shape and are dark brown in hue. Leaves and spikes can be infected by this.	3.12
Pink snow mold	T25	Gray blotches on the stems and wet spots that effectively convert brown can be seen on the leaves and It can be identified by the mycelium's pink color.	3.12
Karnal bunt [34]	T26	The grain and grain products are stained by masses of powdered spores of fungus Tilletia indica and the grain has a tainted, fishy smell.	3.12
CRR [34]	T26, T28	Infected regions seem discolored, tan, or dark in color, implying dead tissue, and the plant will begin to crumble and die at its maturity.	6.25

Summary of RQ2:

Among different types of diseases, the most research studies are worked on stripe rust (#18) and leaf rust (#16). The least work has been done on Flag smut (#1), Karnal bunt (#1), Pink snow mold (#1), Spot blotch (#1) and many more diseases.

RQ3: Which datasets are used for wheat disease detection and classification?

Datasets are given as input to the model for training so that the model can train itself to classify the wheat diseases [34,36,57,58]. Each study has used some datasets to train their models and to produce results. The datasets we found in the studies which we are reviewing are mostly generated by self-acquisition and there are very few studies which have used standard datasets. Most of the researchers took real time datasets by collecting images of healthy or diseased wheat plants. The images are collected using mobile or digital cameras [20,21,45], UAVs [12] for hyperspectral images and the internet. They have labeled the images wheat plants accordingly. The standard datasets are available publicly but the datasets which are not self-acquired might be publicly available or not. The dataset used in each study is given in Table 6.

Another observation from the research studies is that most of the mentioned datasets are small in size while datasets with large size are very few. If the size of datasets can be increased then the results can be better.

Table 6. Different datasets used in different studies

Selected studies	Dataset (Type)	DataSet (year)	Dataset (size)	Dataset (target)
T1	Self-Acquisition	2017	83260	L
T2	Wheat Disease Dataset 2017 [39]	2017	50000	L , St
T3		2020		L
T4	Self-Acquisition (Shandong Agricultural University).	2019	82344	L
T5	Self-Acquisition	2019		L
T6	Self-Acquisition	2019		L

T7			400	L
T8				
T9	Self-Acquisition	2017		L
T10	Self-Acquisition	2017		L
T11	Self-Acquisition (Anhui Academy of Agricultural Sciences)	2019	1600	plant
T12		2018	80920	L
T13	Self-Acquisition	2018	2207	St, L
T14	Hyperspectral imaging dataset [48]	2020	150	L
T15	Self-Acquisition	2020		S
T16	Self-Acquisition	2020	1400	L
T17	WSR grading Image Dataset [13]	2020	5242	St
T18	Self-Acquisition	2020	630	St, L
T19	Self-Acquisition	2017	120	L
T20	Self-Acquisition	2019	150	L
T21	Self-Acquisition	2020	9340	L, St
T22	Self-Acquisition (Walloon Agricultural Research Center))	2020	1163	L, S, Stem
T23	Self-Acquisition	2020	524	L
T24	Self-Acquisition	2019	1720	L
T25			81	L
T26	LWDCD2020 [55]	2020	12000	L S, Plants
T27	Self-Acquisition (mundi.com)	2021	1500	L, Stem, St
T28	Self-Acquisition	2022	60	Stem
T29	Self-Acquisition	2018	89	Ear/head
T30	CGIAR Dataset [61]		1486	L, Stem, St
T31	CGIAR dataset [61] and Secondary sources		2000	L, Stem, St
T32	wheat fungi diseases (WFD2020) [60]	2020	2414	L, Stem, St, Ear/head

Summary of RQ3 :

There is not so much public standard dataset of wheat plant diseases available online and mostly every research study shows that they have collected by themselves. They have collected either by clicking photos by themselves from some specific research center or they have got a little dataset and after performing preprocessing like data augmentation [62] they have generated more images. In my studies, wheat fungi diseases (WFD2020) [60], large wheat disease classification dataset (LWDCD2020) [55], Wheat Disease Dataset 2017 [39] are some standard datasets of wheat plant disease. The size of datasets is also a major problem as there are very few datasets with large size. A large size dataset performs much better than less size of dataset.

The disease of leaves is mostly explored by the researchers and there are other parts of wheat plants which can be infected from some disease but very less work has been done such as roots and head.

RQ4: What different DL or ML techniques are used for disease detection and classification?

The different ML [16-18] & DL techniques [11-15] is used in the recent 32 studies is given as follows:

ML Algorithm [16] : Support Vector Regression (SVR) [40], Support Vector Machine (SVM) [64], Random Forest (RF) [66], Partial-Least-Squares Regression (PLSR) [50], Decision Tree (DT) [65]

SVM [63]**:** Multi-layer Perceptron (MLP) [40], Probabilistic Neural Network (PNN) [20].

CNN [67] **& its framework:** VGG-16 & VGG-19 [68], AlexNet [69], GoogleNet [70], DenseNet [71], Resnet-50 [72], InceptionV3 [73], EfficientNet [74].

Matrix-based CNN (M-bCNN) [38]

Region-based CNN (RCNN) [75]

Deep CNN (DCNN) [42,53,56]

Hybrid Approach: Convolutional neural network - Local support vector machine (CNN-LSVM) [41], Inception - Resnet model for feature extraction [12, 79], IABC-K-PCNN [45] for segmentation, Particle swarm optimization – SVM (PSO-SVM) [51].

The Different models/ techniques used in each study is given in Table 7. The advantages and disadvantages of each technique is given in Table 8.

Table 7. Different models used in the different studies.

Technique	Variants	Selected studies	Percentage
ML	SVR, SVM, RF, DT, PLSR	T3, T10, T14, T16, T18, T19, T21, T25, T28, T29	31.25
ANN	MLP, PNN, NN	T3, T9, T10, T14, T16, T18	18.75
CNN & its framework	VGG-16, VGG-19, AlexNet, GoogleNet, DenseNet, Resnet-50, InceptionV3, EfficientNet	T2, T13, T16, T17, T21, T26, T27, T30, T32	28.125
M-bCNN	-	T1	3.125
RCNN	-	T7, T15, T22, T23	12.5
DCNN	-	T5, T6, T24, T31	12.5
Hybrid approach	CNN-LSVM, DC-FCNN, PSO-SVM, IABC-K-PCNN	T4, T5, T11, T12, T20	15.625

Table 8. Advantages and disadvantages of different models/ algorithms.

Model/ Algorithm	Advantages	Disadvantages
ML	Very interpretable , simple to built and understand	Simplified assumption leads to underfitting Need to perform Feature engineering explicitly
ANN	Predictions are faster	Simple feedforward network (no feedback loop)

	work best with more data points Information is stored in entire network Works good with incomplete knowledge	Vanishing and exploding gradient problem Behavior of network can't be explained Costly computation
CNN	Less classification time More accurate classification Detects feature by itself	Computation is costly Data training is time taken Large size data is required
M-bCNN	High performance Better classification accuracy	Modest computation increased compared to simple networks.
RCNN	Very high accuracy Each object can be classify and detected Very deep network	Time consuming and very complex computation as it computes feature map for every region Detection is slow
DCNN	Very high accuracy features are automatically extracted	High computational complexity Huge dataset is required

Summary of RQ4 :

Among all the techniques used for the wheat disease detection and classification, the most used techniques are machine learning [16-18] algorithm (#10) followed by CNN & its framework (#9). The least used technique is Mb-CNN (#1), DCNN (#4) and RCNN (#4).

RQ5: Which type of images are used to train the models?

There are many types of images which can be used for classification as the main three types of images are described below which are used in our selected studies.

RGB (Red Green Blue) [76]: It is an image in which the three layers are stacked and these layers are of red, green and blue color. These images can be captured using the camera of any phone or DSLR.

HSI (Hyperspectral Imaging) [10,46,48]: The visualization of hyperspectral data is an image cube, with each image representing one of tens or hundreds of narrow wavelength ranges or spectral bands. HSI enables the evaluation and analysis of spectral properties of regions or objects for use in applications such as crop health screening and environmental degradation tracking.

MSI (Multispectral imaging) [50]: Light from a constrained wavelength range across the electromagnetic spectrum is captured by multispectral imaging. Instruments that are sensitive to certain wavelengths, such as light from frequencies that are undetectable to the human eye, or special cameras that separate various wavelengths using filters are used to acquire multispectral images.

The different types of images used in the different studies is given in Table 9.

Table 9. Different types of images used.

Selected Literature	Type of Wheat Image
T1	RGB
T2	RGB
T4	RGB
T5	HSI
T6	RGB
T7	
T8	RGB
T9	RGB
T10	RGB
T11	RGB to HSI
T12	HSI
T14	HSI
T15	RGB
T16	RGB to HSV
T17	RGB
T18	MSI
T19	RGB
T20	RGB
T21	RGB

T22	RGB
T23	RGB
T24	RGB
T25	RGB
T26	RGB
T27	RGB
T28	RGB to HSV and LAB
T29	HSI
T30	RGB
T31	RGB

Summary of RQ5 :

RGB is widely used for image classification and in this survey RGB images are used in #20 studies and then HSI used in #7 studies while MSI images used in only #1 paper.

RQ6: What methods of image processing were employed to extract more accurate features?

Image Processing techniques [17,19-22] are used to extract important features from the images (Digital images) after applying some operations on those images. The computer takes these images as input and after processing the images gives output which is fed to the Deep learning or machine learning models. Some of the image processing techniques which are used in our selected studies are given below:

Segmentation

Segmentation [77] is used to divide the image in different parts on the basis of region. There are 4 types of image segmentation techniques [77] - Region based, edge detection, clustering based, mask RCNN [7,8,43,49].

Image enhancement techniques

The image enhancement techniques [78] are used to enhance the features of the images so that the feature can be easily extracted. There can be image scaling, image filtering, noise removal, image smoothening, image rotation, image color enhancement, image enlargement [78].

Adjacency Matrix

Adjacency matrix [48] is used to extract features from the images by maintaining a matrix.

Sliding Window approach

Sliding Window approach [12] is a rectangular region used to slide over images to extract the feature of the window only.

PCA

Principal Component Analysis [21,38,50] is a dimensionality reduction which is used as image processing for compression of data as there is a lot of data and sometimes it performs color reduction on images.

Data Augmentation

Data Augmentation [62] technique is used to increase the data instances by altering the existing data. Some techniques can be seen as image rotation, image flipping, image blurring, image shifting, image noising.

Spatial Filtration

Spatial Filtering [60] is used to make changes directly on the pixel value of a digital image. Image smoothening and sharpening on images can be performed on images.

The different image processing techniques [17,19-22] used in different studies are given in Table 10. The image processing technique used percentage is shown in Fig. 7. The advantages and disadvantages of the different image processing techniques used in our studies are given Table 11.

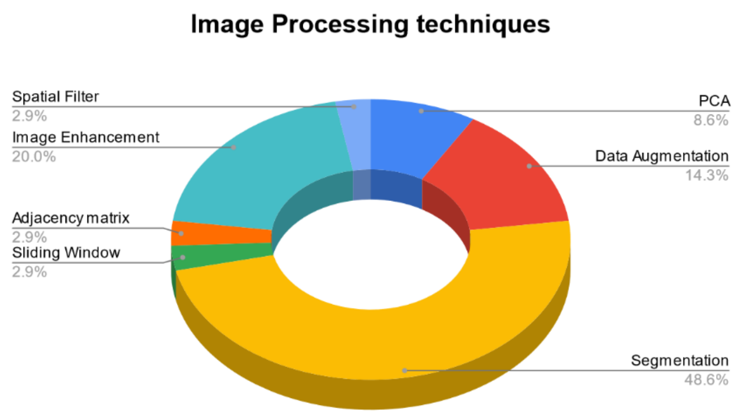


Fig 6. Image processing techniques percentage.

Table 10. Different Image processing techniques used.

Selected studies	Image Processing techniques
T1	PCA
T4	Segmentation
T5	Sliding Window Approach
T6	Segmentation
T7	Segmentation
T8	Adjacency matrix
T9	Segmentation
T10	Segmentation
T11	Segmentation
T13	Image Enhancement
T15	segmentation
T16	segmentation
T17	Image enhancement, Data Augmentation
T18	PCA
T19	Image Enhancement, Segmentation
T20	Segmentation
T21	Image Enhancement, Data Augmentation
T22	Segmentation

T23	Segmentation
T24	Segmentation, Data Augmentation
T25	Segmentation
T26	Image Enhancement, segmentation
T27	Image Enhancement, Data Augmentation
T28	Segmentation
T30	Segmentation
T31	Image Enhancement
T32	Data Augmentation, Spatial Filter

Table 11. Advantages and disadvantages of image processing techniques.

Image processing techniques	Advantages	Disadvantages
Segmentation	Implementation is easy. Detection time will be reduced.	Not suitable for images with smooth edges. Storage and time both are required.
PCA	Minimize the chances of overfitting Remove correlated dimensions	Information (Data) loss Difficult to understand the independent variables
Sliding Window Approach	Gives exact location of an object present in image	Time consuming
Adjacency Matrix	Work good for bright images	Complexity is high
Image Enhancement techniques	Image intensity can be increased. Enhance contrast and sharpness. Most effective for gray scale images	Not easy to understand the color images Original image will be lost
Data Augmentation [62]	Reduces the cost of collection of data and labeling of data. Reduces overfitting.	Complex in some applications. Not easy to get optimal data augmentation strategy.
Spatial filter	Simple concept and noise resistant.	Costly computation

Summary of RQ6 :

From the following image processing techniques [17,19-22] the mostly used technique is Image segmentation (#18) followed by Image enhancement (#7). The least used technique is Sliding window (#1), Spatial filtering (#1) and Adjacency matrix (#1).

RQ7: How are features extracted from the data using the various feature extraction techniques?

Feature extraction [12,79] is an important part of classification. Deep learning models can extract features by itself but Machine Learning algorithms [16] are not able to do so. Before applying Machine Learning algorithms, features need to be extracted first using different techniques. Color, Shape and texture features are extracted when feature extraction techniques are applied. There are many feature extraction techniques used to extract features from images and sometimes Deep Learning models (VGG 16, VGG 19, Alex Net etc.) are also used as feature extraction techniques in many studies. In our SLR, many studies used different feature extraction techniques as can be seen in Table 12. The defined feature extraction techniques are:

GLCM (Grey-Level Co-occurrence Matrix) [80].
CCM (Color Co-occurrences Matrices) [17,20].
PCA (Principal Component Analysis) [21,38,50].
FLDA (Fisher Linear Discriminant Analysis) [10].
LDA (Linear Discriminant Analysis) [10]
Region of interest (ROI) extraction [81].

Table 12. Different techniques for feature extraction from images.

Selected Literature	Feature Extraction Technique
T1	PCA
T8	GLCM/CCM

Table 12. Different techniques for feature extraction from images.

T9	CCM
T10	GLCM
T13	GLCM
T16	CCM
T19	GLCM
T20	GLCM
T26	region of interest (ROI) extraction
T28	region of interest (ROI) Extraction
T29	FLDA, LDA

Summary of RQ7:

Among different feature extraction techniques the widely used technique in our studies is GLCM (#5) and the least used technique is PCA (#1) and LDA (#1).

RQ8: What performance metrics are used to describe performance of models?

To evaluate the performance of the models, different metrics are used to find if the model is performing better or not. These metrics are called performance metrics [82,83]. Depending on different types of models, there are different types of performance metrics available. The performance metrics which are used in our SLR studies is given below:

Accuracy [82,83].
Precision [82,83].
Recall [82,83].
F1-Score
AUC (Area under ROC curve [82].
Error Guess Method (R^2, RMSE) [82].

The performance metrics used in different studies is shown in Table 13 and the count of studies using the specific performance metrics is given in Fig. 8.

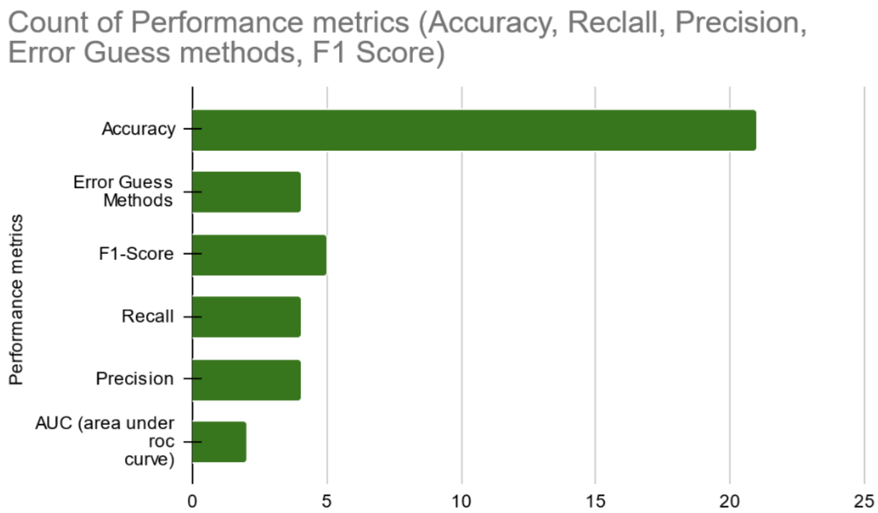


Fig. 7. Count of performance metrics.

Table 13. Different performance metrics to measure the performance of models.

Selected Literature	Performance metrics	Performance score
T1	Accuracy	Mb-CNN:96.5%
T2	Accuracy	VGG-FCN-VD16: 97.95% VGG-FCN-S: 95.12%
T3	Error Guess methods (R^2)	MLP: 92 SVR: 79
	Error Guess methods (RMSE)	MLP: 2.09 SVR: 3.09
T4	Accuracy	CNN-LSVM:93.68%
T5	Accuracy	DCNN:85%
T6	Error Guess methods (R^2)	DCNN:89

	Error Guess methods (RMSE)	DCNN:75
T7	F1-Score	VGG-16: 90.63% VGG-19: 87.25%
	Recall	VGG-16: 89.68% VGG-19: 86.98%
	Precision	VGG-16: 91.62% VGG-19: 84.53%
T11	AUC (area under roc curve)	IABC-K-PCNN:92.5
T12	Accuracy	Hybrid: 74.3%
T13	Accuracy	AlexNet: 84.54%
T14	Accuracy	SVM: 93.33%
T15	F1 Score	RCNN: 74.04%
	Precision	RCNN: 72.10%
	Recall	RCNN: 76.16%
T16	Accuracy	ANN: 83% VGG-16: 98% GoogleNet: 93% SVM: 86%
T17	Accuracy	DenseNet: 97.99%
	Recall	DenseNet: 97.99%
	Precision	DenseNet: 97.99%
	F1-Score	DenseNet: 97.99%
T18	Error Guess methods (R^2)	PLSR: 69 ANN: 72
	Error Guess methods (RMSE)	PLSR: 37.1 ANN: 34.9
T19	Accuracy	SVM: 89% ANN: 80%
T20	Accuracy	PSO-SVM: 95%
T21	Accuracy	Decision Tree: 94.7% Alexnet: 95.10% VGG-16: 96.72% Resnet-50: 97.12%
T22	Accuracy	RCNN: 97.88%
T23	Accuracy	RCNN: 98%
T24	Error guess methods (R^2)	DCNN: 0.80

	Error guess methods (RMSE)	DCNN: 1.17
T25	Area Under Curve	Histogram
T26	Accuracy	VGG-16: 90.87% Resnet50: 81.97% Proposed Model: 97.88%
T27	Accuracy	VGG-16: 96% VGG-19: 99% InceptionV3 : 95% Resnet-50 : 81%
T28	Accuracy	SVM: 82%
	F1-Score	SVM: 89%
T29	Accuracy	SVM: 88.60%
T30	Accuracy	VGG16: 99.54%
T31	Accuracy	DCNN: 97%
T32	Accuracy	EfficientNet: 94.20%

Summary of RQ8:

Among all the performance metrics, most of the studies used Accuracy (#21) to evaluate the performance. The performance metric which is used in very few studies is AOC (#1).

In the next section we have done discussion on the results belonging to the defined research question. The results are mentioned in the above section. The description of results included points are mainly focused on the (i) Methodology used in the classification and detection of the wheat disease, (ii) Type of datasets and improvement can be made to the datasets, (iii) The challenges the researchers faced.

2.4. OUTCOMES OF THE LITERATURE SURVEY

The overall results of all the papers in our SLR is discussed in the above section in the form of question and answer and the overall summary is reflected in the Table. 14. The overall results of all SLR can be discussed in three section as below:

Table 14. Overall Summary

Subject	**Summary**
Wheat disease	Most frequent: Rust Least frequent: Flag smut, Karnal bunt, Pink snow mold, Spot blotch
Standard Datasets	Wheat fungi diseases (WFD2020), LWDCD2020, Wheat Disease Dataset 2017, CGIAR dataset
Most frequent ML Models	SVM
Most frequent DL models	CNN & its framework, ANN [63], Hybrid approach
Image processing techniques	Most frequent: Segmentation Least frequent: spatial filtering, adjacency matrix
Most frequent feature extraction technique	GLCM

CHAPTER 3

EXPERIMENTAL METHODOLOGY

The very basic methodology followed for any crop disease detection is shown in the Fig. In this chapter we have defined all the required steps in the basic methodology step by step.

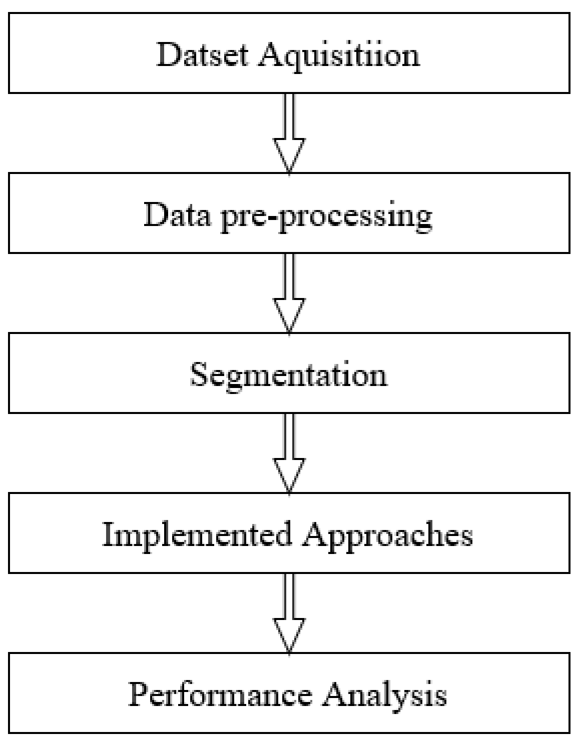


Fig.8. Basic Methodology for crop Disease detection

3.1. DATASET ACQUISITION:

Each algorithm needs a labeled dataset which is used to learn while training. The datasets are divided in two parts in some ratio and then first and bigger part is used for the training of the model and the 2nd part is used for the testing of the model and to get performance measurement of the model. Each study used a dataset for learning and performance of the model using accuracy or other performance metrics. There are some standard datasets like large wheat disease classification dataset (LWDCD2020), wheat fungi diseases (WFD2020), CGIAR Dataset, Wheat Disease Dataset 2017. There is one more option that is the researchers can use their own dataset which they can acquired by self-acquisition of images. There are very few public standard wheat disease datasets available and due to which most of the researchers have collected their own datasets by self-acquisition.

3.1.1. Dataset splitting:

It is crucial to divide the available dataset into two distinct subsets, the training set and the testing set, when using ML algorithms. This division makes sure that the model's performance can be assessed on hypothetical data, which aids in determining how generalizable it is. The testing set is used to evaluate the model's performance after it has been trained on the training set.

3.1.2. Different methods of dataset splitting:

1. **Holdout Validation**: The simplest way to separate a dataset is by holdout validation. It includes partitioning the dataset into the training set and the testing set at random. The testing set typically makes up the remaining data, with the training set often comprising between 70 and 80 percent of the total. The training set is used to develop the model, and the testing set is used to assess it. Holdout validation is simple to build, however depending on the precise split of data, its speed may differ.

2. **Cross-Validation**: Cross-validation is a more reliable method that mitigates the limitations of holdout validation. It involves dividing the dataset into k equally-sized folds. The model is trained k times, with each iteration using k-1 folds for training and the remaining fold for testing. The performance measures from each fold are then averaged to obtain an overall assessment of the model's performance. Common variations of cross-validation include k-fold cross-validation, stratified k-fold cross-validation, and leave-one-out cross-validation.
3. **Leave-One-Out Cross-Validation (LOOCV)**: LOOCV is a special case of cross-validation where each data point is used as the testing set once, while the remaining data points form the training set. Consequently, the number of folds equals the number of data points. LOOCV provides an unbiased estimate of the model's performance, but it can be computationally expensive, especially with large datasets.
4. **Stratified Sampling**: Stratified sampling is particularly useful when working with imbalanced datasets where some classes or target variables are underrepresented. It ensures that the distribution of classes remains intact in both the training and testing sets. The dataset is split while preserving the original class proportions, ensuring that the model is trained on a representative sample of the data and evaluated on a balanced test set.
5. **Time Series Split**: Time series data often exhibits temporal dependencies, making random shuffling or splitting unsuitable. In time series splitting, the dataset is divided into consecutive and non-overlapping blocks. The model is trained on data from earlier time periods and tested on data from later time periods, resembling real-world scenarios where predictions are made on unseen future data. Rolling window and expanding window are commonly used time series cross-validation methods.

3.2. DATA PRE-PROCESSING:

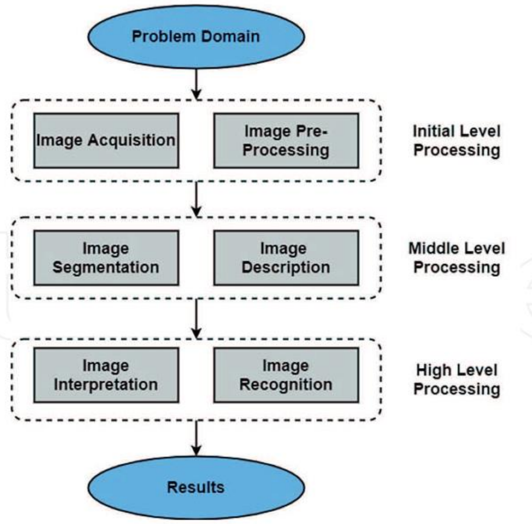


Fig.9. Steps in Image Processing.

Data pre-processing, in deep learning refers to the set of operations and transformations applied to raw data before it is fed into a deep learning model. It involves cleaning, transforming, and organizing the data to ensure its suitability for effective training and accurate predictions.

The purpose of preprocessing is to prepare the data in a way that enhances the model's performance and improves its ability to extract meaningful patterns and relationships. By performing appropriate preprocessing steps, we can address various challenges associated with raw data, such as noise, missing values, varying scales, and inconsistent formats.

Preprocessing is a critical step in deep learning as it significantly impacts the model's ability to learn and make accurate predictions. The choice of preprocessing techniques depends on the features of the data and the specific requirements of the deep learning task. Through appropriate preprocessing, we can improve the quality, consistency, and usability of the data, leading to better model performance and more reliable insights.

Common preprocessing steps in deep learning include:

3.2.1. Segmentation

Segmentation in image processing involves dividing an image into distinct regions based on specific criteria. There are two main types of segmentation:

1. **Semantic Segmentation**: It involves assigning each pixel in an image to a specific class or category, such as person, car, or background. It focuses on capturing the high-level semantics and understanding the content of the image at a pixel level. CNN architectures for semantic segmentation typically employ encoder-decoder structures with skip connections to capture both local and global context information.

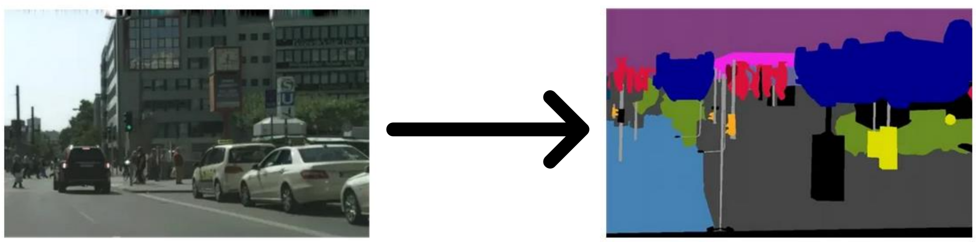


Fig. 10. Semantic Segmentation

2. **Instance Segmentation**: It goes beyond semantic segmentation by not only assigning a class label to each pixel but also differentiating individual instances of objects. It aims to identify and delineate each object instance separately. Instance segmentation models typically generate pixel-level masks or bounding boxes around individual objects within the image.

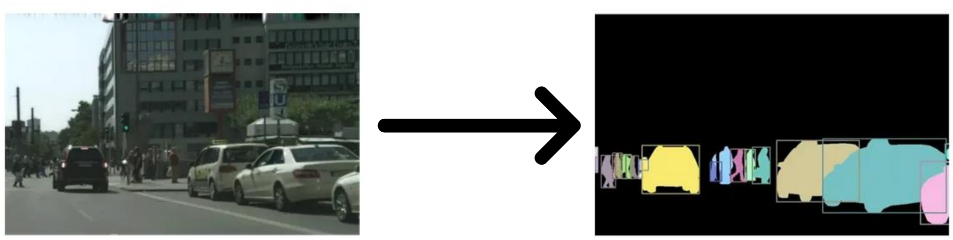


Fig. 11. Instance Segmentation

3.2.2. Image enhancement techniques

In deep learning, It involve methods to improve the quality and visibility of images. They include contrast enhancement, sharpening, denoising, super-resolution, color enhancement, and image restoration. These techniques leverage deep learning models to enhance specific visual features, reduce noise, and restore degraded images. They play a crucial role in improving image quality and making images more suitable for analysis and interpretation. These are used to enhance the features of the images so that the feature can be easily extracted. There can be image scaling, image filtering, noise removal, image smoothening, image rotation, image color enhancement, image enlargement.

3.2.3. Sliding Window approach

It is a rectangular region used to slide over images to extract the feature of the window only.

3.2.4. PCA

Principal Component Analysis is a dimensionality reduction which is used as image processing for compression of data as there is a lot of data and sometimes it performs color reduction on images.

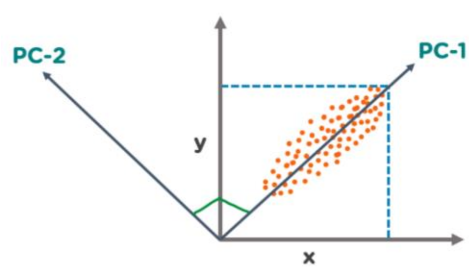


Fig. 12. Principal Component Analysis

3.2.5. Data Augmentation

Data Augmentation technique is used to increase the data instances by altering the existing data. Some techniques can be seen as image rotation, image flipping, image blurring, image shifting, image noising.

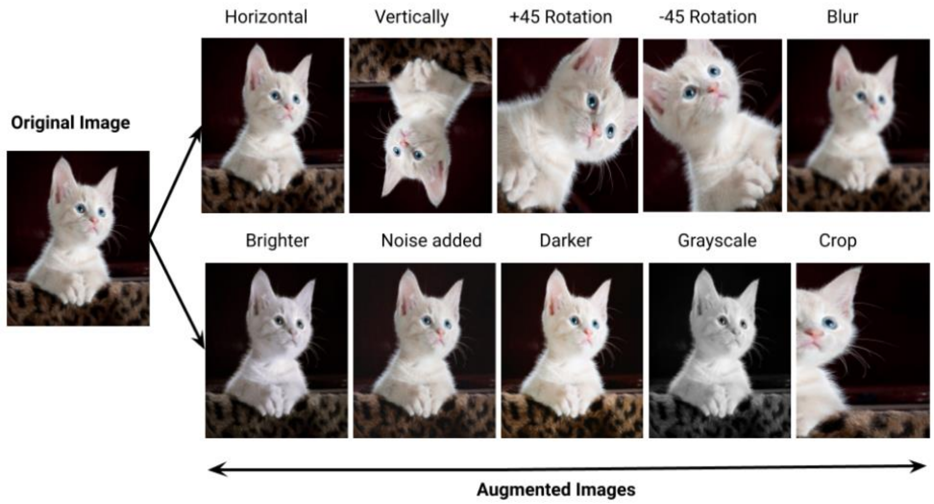


Fig. 13. Data Augmentation example.

3.2.6. Spatial Filtration

Spatial Filtering is used to make changes directly on the pixel value of a digital image. Image smoothening and sharpening on images can be performed on images.

3.3. IMPLEMENTED APPROACHES:

Machine learning [16-18] techniques have been widely used in past decades in various sectors and still are capable of being used in different applications. In Wheat disease detection and classification also, Machine learning has shown incredible results but recently the rise of Deep learning [11-15] has overcome different flaws of Machine learning techniques [16-18]. From these literature studies we somehow managed to explore different ML & DL techniques recently used for D&C of different wheat diseases. In some research studies deep learning & machine learning both are used together as a hybrid approach and shown good results.

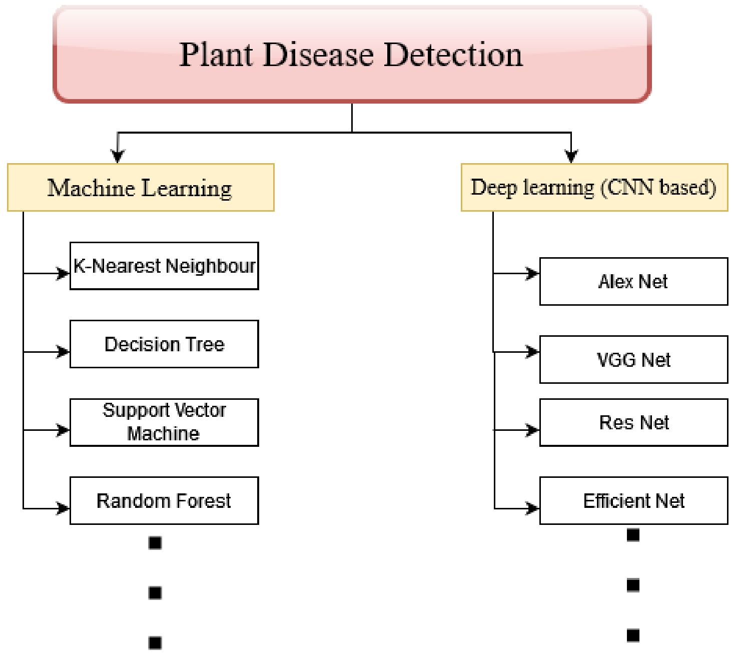


Fig. 14. Approaches for crop disease detection

3.3.1. Machine learning

Supervised algorithms [84] of ML [16-18] are widely used for wheat disease detection and classification. The algorithms like SVM [64], RF [66], DT [65], KNN [85], Naive Bayes classifier [86] can classify the WD but SVM and RF outperform all the above algorithm and widely used to classify the wheat disease using feature selection-based methods. ANN [63] is also an ML algorithm which can classify wheat disease with better performance. Probabilistic neural network [20] and multilayer perceptron [40] is also useful in wheat disease detection and classification.

SVM [64]: It is a supervised ML algorithm used for classification and regression tasks. It works by finding an optimal hyperplane that separates different classes in the data. The algorithm aims to maximize the margin between the classes, effectively finding the best decision boundary. SVM also uses a technique called the kernel trick to handle non-linearly separable data.

RF [66]: Multiple DT are combined in this ensemble learning technique to produce predictions. By training each tree on various random subsets of the training data and random subsets of the features, it builds a collection of DT. Each tree in the forest independently predicts something during prediction, and the outcome is decided by a majority vote or by average the results from all the trees. High-dimensional data can be handled by RF effectively, and it is less prone to overfitting.

DT [65]: For classification and regression applications, it is a straightforward and understandable supervised learning technique. Each internal node represents a feature, each branch represents a choice depending on that feature, and each leaf node indicates the result or class label. This diagram resembles a flowchart. To maximise information gain or reduce impurity, the tree is built by repeatedly separating the data based on the chosen attributes. DTs can handle category and numerical data and are interpretable.

KNN [85]: It is a non-parametric approach used for regression and classification problems. By taking into account its k nearest neighbours in the training dataset, it assigns new data points to classes or predicts values. For classification or regression, the class or value is chosen by majority vote among the K closest neighbours. KNN is a straightforward and adaptable method, but the choice of K can have an impact, and computing power is needed to calculate the distances between data points.

Naive Bayes Classifier [86]: A probabilistic algorithm used for classification problems is called Naive Bayes. It is based on the Bayes theorem and makes the "naive" assumption that each attribute is independent of the others. Based on the probabilities of each feature happening in that class, the algorithm determines the likelihood that a data point belongs to a particular class. High-dimensional data can be effectively handled using Naive Bayes, which is computationally efficient. However, in some circumstances, its premise of feature independence may not be true.

3.3.2. Deep learning

In DL [11-15] the specific feature extraction [12, 79] is done as part of learning so, it does not need to extract features previously. DL is an evaluation of machine learning [16-18] or we can say it is a subset of ML. Deep learning also has cons like overfitting [87] and needing a much bigger dataset. These problems in deep learning can be removed using dropout [88] and regularization [87]. There are many deep learning architectures which are pre-trained models but not necessarily pre-trained on the same dataset. This is also called transfer learning [89] as the weights of these pretrained models are utilized for the classification. The deep learning architecture which are used in the studied literatures are VGGNet (VGG-16 and VGG-19) [68], AlexNet [69], GoogleNet [70], InceptionV3 [73], EfficientNet [74], ResNet-50 [72].

A pre-trained network used in DL called transfer learning is used as a jumping-off point to learn new tasks. To train a network, initializing weights with transfer learning is quicker and simpler than doing it at random. The features that have been learned can be swiftly applied to a new task with just a limited collection of training photos. These architectures are the different frameworks of the Convolutional Neural network [7,38,42,55,56,67]. Some architectures are explained below:

DL has seen significant advancements in various domains, including computer vision (CV), natural language processing(NLP), speech recognition, and many others. Some popular deep learning models include:

CNNs: CNNs are primarily used for image analysis and computer vision tasks. They employ convolutional layers that learn local patterns and spatial hierarchies in the data, enabling effective feature extraction and image classification.

At the core of CNNs are convolutional layers, which leverage the concept of convolution—a mathematical operation that applies a filter or kernel to the input data. The convolutional layers capture local patterns and spatial hierarchies by convolving these filters across the input data, extracting meaningful features. Each filter detects specific patterns, such as edges, corners, or textures, allowing the network to learn increasingly complex and abstract representations as information flows through the layers.

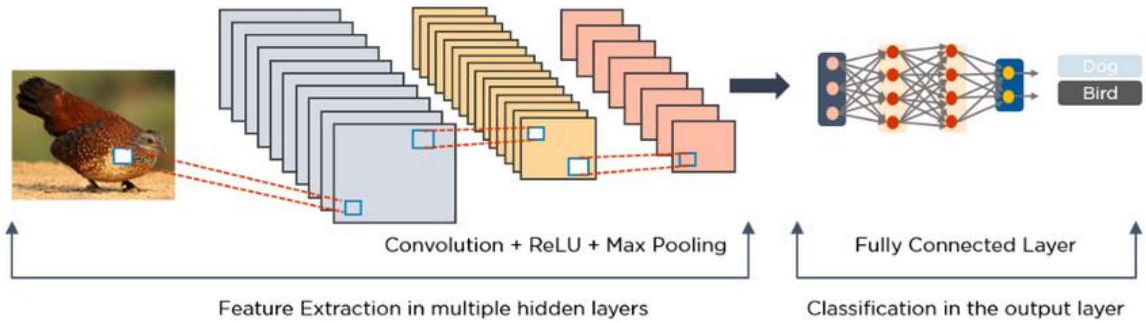


Fig. 15. CNN Layers

The key components of a CNN architecture include:

1. Convolutional Layers: These layers perform the convolution operation, applying filters to the input data. The output of each filter is a feature map, representing the presence of a particular feature or pattern in the input.
2. Pooling Layers: Reducing the spatial dimensionality of the feature maps through layer pooling allows for the consolidation of the acquired knowledge. Max pooling, which chooses the highest value inside a sliding window, and average pooling, which determines the average value, are examples of common pooling processes.

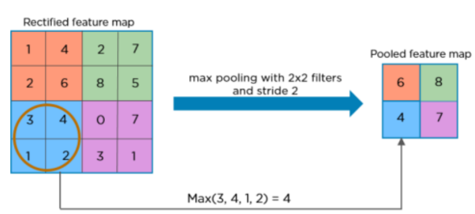


Fig. 16. Max-Pooling layer.

3. Activation Functions: Activation functions introduce non-linearity into the network, allowing it to learn complex relationships. Popular activation functions in CNNs include Rectified Linear Unit (ReLU), which sets negative values to zero, and variants like Leaky ReLU and Parametric ReLU.

Fig. 17. ReLU Activation Function graph.

4. Fully Connected Layers: These layers allow the network to make predictions by linking every neuron in the layer below to every neuron in the layer above. In order to process the extracted features, fully connected layers are often added following convolutional and pooling layers.

During the training process, CNNs optimize their parameters (weights and biases) using backpropagation and gradient descent. By comparing the predicted output with the true labels, the network adjusts its parameters to minimize the defined loss function, iteratively improving its ability to make accurate predictions.

Some pretrained models of deep learning are defined below:

Alex Net:

It is a pre-trained model with 8 layers of the CNN with 5 convolutional layers and 3 dense layers [69]. It was first introduced in 2012 at ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [90] and GPUs and activation functions like ReLU were used in this model. AlexNet [69] is pretrained on millions of the images of the database named as ImageNet. It is able to classify images in almost 1000 categories.

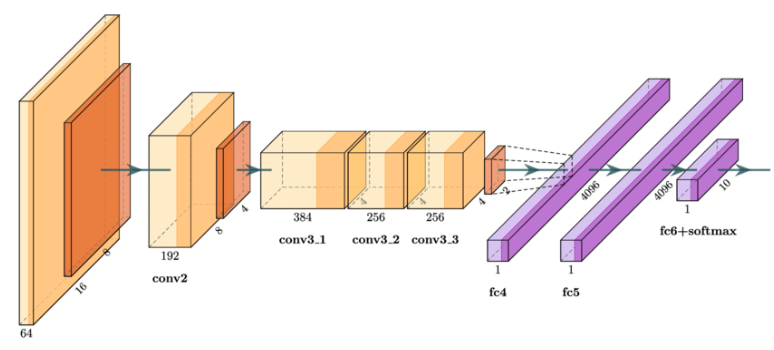


Fig. 18. Alex Net Architecture

VGGNet:

It is also a standard convolutional neural network (CNN) [7,38,42,55,56,67] with convolutional [67], pooling [67], and fully connected layers. VGG-16 and VGG-19 [68] are its types based on the number of layers. VGG is an abbreviation for visual geometry group, and the numbers 16 and 19 represent the number of layers.

VGG-16 was introduced in 2014 at ILSVRC [90] and achieved almost 92.7% accuracy on ImageNet [90] Dataset. It takes input images of size 224 x 224 and there are 13 convolutional layers followed by 3 fully connected layers in VGG-16. It uses smaller kernels of size 3 x 3 rather than using larger kernels.

VGG-19 is very similar to VGG-16, with the exception of having 19 layers, 16 convolutional layers, and 3 fully connected layers. Both VGG-16 and VGG-19 are still very famous architecture and extract very deep features from the images.

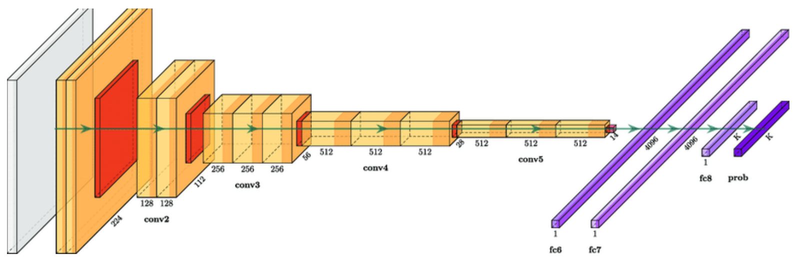


Fig. 19. VGG16 Architecture.

ResNet:

It stands for Residual Network which was first introduced to ILSVRC [90] in 2015 and Resnet [72] was the winner of the competition with minimum error rate of 3.57%. In previous architecture if the number of layers were increased then it can cause the problem of vanishing or exploding gradient descent [91]. So, to solve this problem skip connection was introduced in this architecture. Resnet was first with a very deep neural network with up to 150+layers. There are many variants of the Resnet depending on the number of layers and ResNet-50 is one shorter version of ResNet with 50 layers.

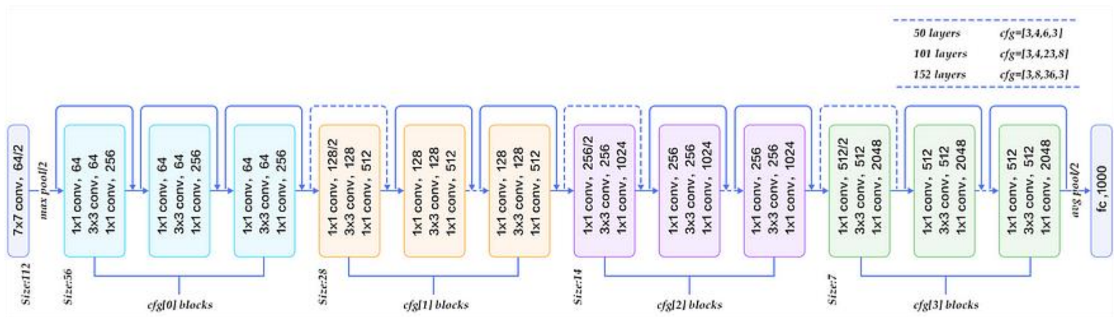


Fig. 20. ResNet Architecture

Google Net:

It is also known as InceptionV1 which was first introduced at ILSVRC14 in 2014 to solve computer Vision [6-10] tasks. It is trained on the dataset of ImageNet [90] as well as on places365 dataset which classifies images into 365 different places categories. It consists of 22 convolutional layers.

InceptionV3 is an advanced version of GoogleNet [70] and introduced in the same paper of GoogleNet. It is a CNN which is 48 layers deep and trained on the dataset of imageNet [90]. The image size which is given as input is 299 x 299 while the googleNet is given 224x224 size of images as input.

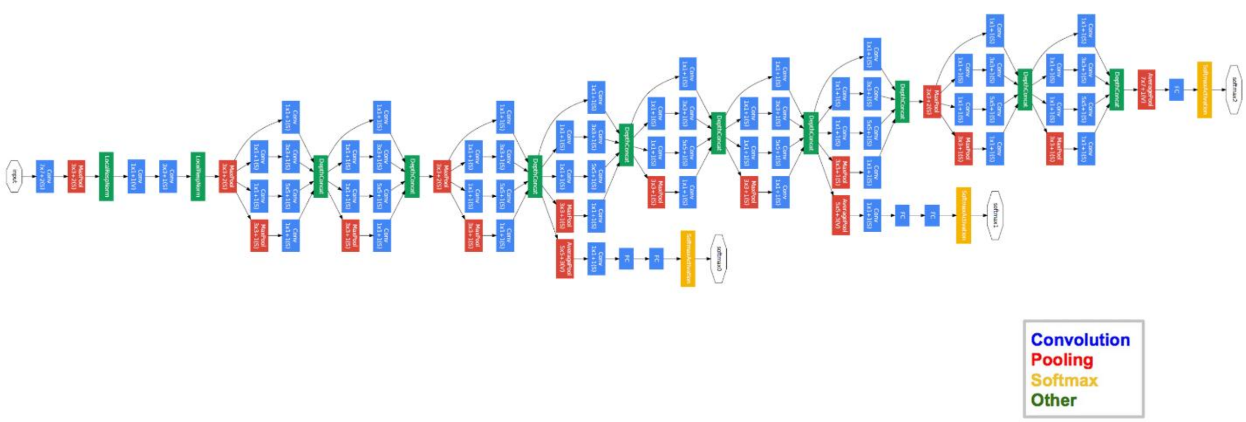


Fig. 21. GoogleNet Architecture

Efficient Net:

Efficient Net is a state-of-the-art CNN architecture designed to achieve high accuracy with computational efficiency. It achieves this by using a compound scaling method that uniformly scales the network's depth, width, and resolution. This ensures that the network's components grow together and maintain a balance between accuracy and efficiency. EfficientNet also incorporates efficient building blocks like depth-wise separable convolutions and squeeze-and-excitation blocks to further reduce computational costs while maintaining strong representation learning. Overall, EfficientNet has gained popularity for its ability to achieve impressive performance on various computer vision tasks while minimizing computational resources.

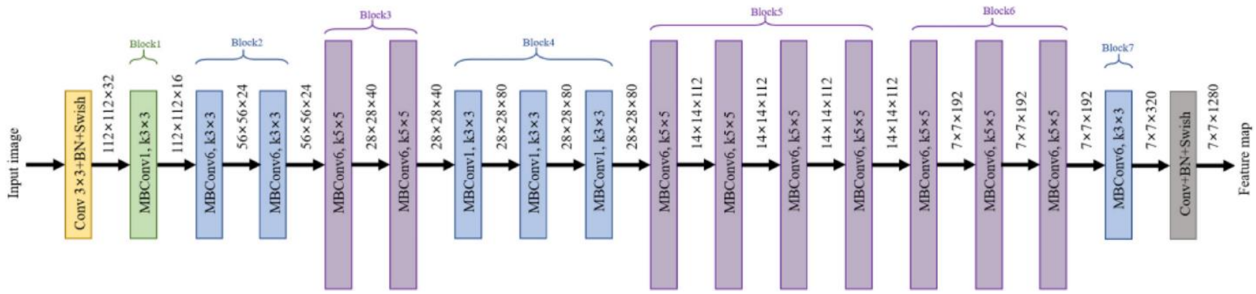


Fig. 22. Efficient Net Architecture

Transformer:

The Transformer is a DL model architecture that revolutionized NLP tasks, such as machine translation and language understanding. It introduced the concept of self-attention mechanisms, allowing for efficient capture of contextual relationships in input sequences.

An encoder and a decoder make up the Transformer. While the decoder processes and produces the output sequence, the encoder processes and produces the input sequence. Multi-head self-attention mechanisms and positionally completely connected feed-forward neural networks make up each encoder and decoder layer.

The self-attention mechanism are use to enable the model to focus on different parts of the input sequence during processing, capturing dependencies and relationships between words or tokens. This attention mechanism replaces the need for recurrent connections, making the model more parallelizable and efficient.

In terms of a hybrid model with convolutional networks, the Transformer can be combined with convolutional neural networks (CNNs) to leverage their strength in capturing local patterns and spatial relationships. This hybrid model is commonly used for tasks that require both sequential and spatial information, such as image captioning or visual question answering.

In this hybrid architecture, the CNN is typically used as the encoder, extracting high-level features from the input image. The Transformer decoder then takes these visual features and generates the output sequence, conditioned on the visual context.

By combining CNNs and Transformers, the hybrid model benefits from the convolutional networks' ability to capture local patterns and the self-attention mechanisms of the Transformer to capture long-range dependencies and contextual relationships. This allows the model to effectively process and generate sequences based on both spatial and sequential information.

Overall, the Transformer is a powerful architecture in deep learning, particularly for natural language processing tasks. When combined with convolutional networks in a hybrid model, it can leverage the strengths of both architectures, enabling effective processing of sequential and spatial information for tasks that require a combination of these modalities.

3.4. PERFORMANCE ANALYSIS:

Different performance metrics are used for performance analysis of models in deep learning. Here are some commonly used metrics and their brief definitions:

1. Accuracy**:** It calculates the percentage of examples that are correctly categorized relative to all instances. It gives a broad summary of how well the model predicts the future.
2. Precision: Out of all the projected positive instances, it calculates the percentage of genuine positive predictions. It emphasizes the model's capacity to prevent false positives by concentrating on the accuracy of positive predictions.

3. Recall: The proportion of true positive predictions out of all real positive cases is measured by the true positive rate, also known as sensitivity. It evaluates the model's capacity to find all pertinent positive examples.
4. F1 Score: In a single metric, it combines recall and precision. It provides a fair evaluation of a model's performance on both positive and negative occurrences because it is the harmonic mean of precision and recall.
5. Specificity: It also goes by the name true negative rate and calculates what percentage of all real negative cases are true negative forecasts. It assesses how well the model can detect unfavorable occurrences.
6. Area Under the Curve (AUC): It stands for the receiver operating characteristic (ROC) curve's area under the curve. It gives an overall assessment of the model's capacity to distinguish between instances that are positive and those that are negative across different probability thresholds.
7. R-squared (R2): It is determined how much of the target variable's volatility the model can accommodate. Better fits are indicated by higher numbers, which also demonstrate how well the model fits the data. All squared residuals are summed up to form SST, and all squared residuals are summed up to form SSR.

Confusion Matrix: A confusion matrix is a table that summarizes the performance of a classification model by showing the counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions. It provides detailed information about the model's classification accuracy and errors, allowing for the calculation of various performance metrics such as accuracy, precision, recall, and specificity.

3.5. PROPOSED HYBRID MODEL:

This section describes the methodology used for image categorization of wheat Diseases. The suggested methodology includes dataset collecting, preprocessing, and augmentation techniques, as well as a hybrid model composed of Convolutional Transformer [5] and EfficientNet V1 [6] architectures. The flow chart for all the steps of proposed methodology is shown in Fig. 2.

Table 15. Number of images in each category

Wheat Disease	Total Images	Train Images	Test Images
FHB	2,870	2,296	574
BR	3,230	2,584	646
YR	3,190	2,552	638
PM	2,910	2,328	582
Healthy	2,360	1,888	472
Total	14,560	11,648	2,912

3.5.1. Dataset:

Our collection contains 14,560 photos of wheat leaves that are categorized as FHB, YR, BR, PM, and healthy leaves as shown in Fig. 1. The number of images for corresponding wheat disease is shown in Table 1. The dataset was compiled from many sources to ensure a full representation of various wheat illnesses and healthy samples.

3.5.2. Data pre-processing and Augmentation

We used image segmentation [18] as a preprocessing step to isolate and extract the regions of interest [21], specifically the disease-infected areas, from the wheat leaf pictures. This segmentation procedure improves the model's capacity to concentrate on disease-specific features during classification. To supplement the dataset, data augmentation techniques [7] such as random rotations, flips, and zooming were used. By creating extra variations of the original dataset, these strategies aid in strengthening the model's robustness [19] and generalization.

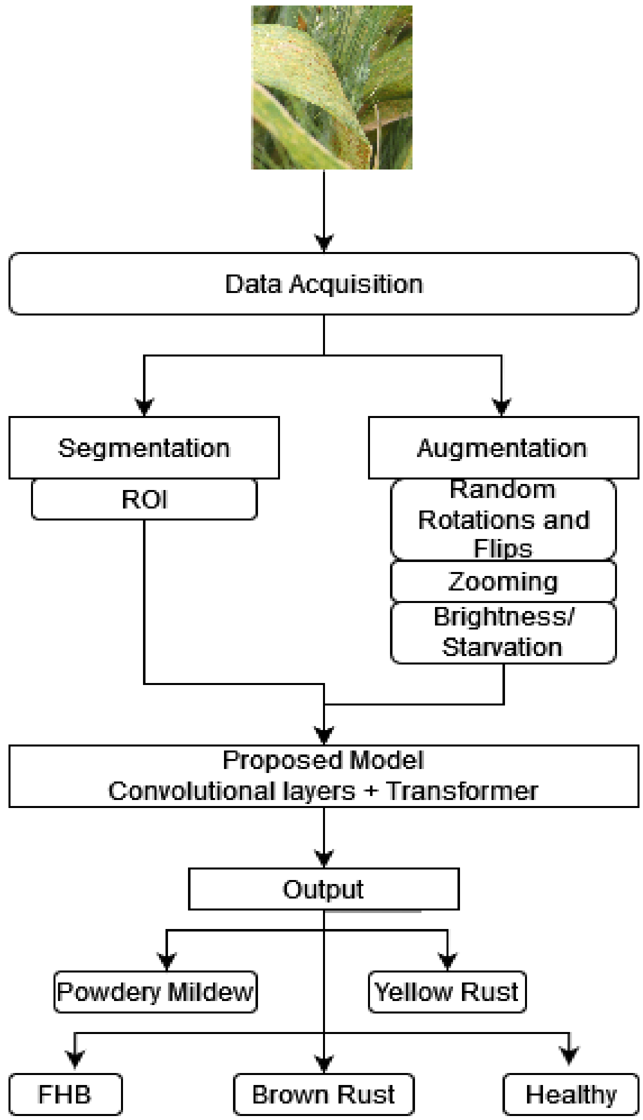


Fig. 23. Proposed Methodology

3.5.3. Proposed model

The proposed approach for wheat disease classification is a hybrid technique that incorporates the topologies of the Convolutional Transformer and EfficientNet V1. The Convolutional Transformer [5] uses the capabilities of transformers [20], a type of model commonly used in natural language processing, to capture long-range dependencies and global contextual information in input images. The model can effectively learn spatial relationships and capture detailed patterns within wheat leaf images by adding transformers into the convolutional architecture.

The backbone network is Convolutional Transformer, which extracts high-level information from preprocessed and

enriched wheat leaf pictures using convolutional layers. These characteristics are then sent to the EfficientNet V1 component, which refines the representations through the use of efficient depth-wise convolutions and squeeze-and-excitation modules. EfficientNet V1 [6] is well-known for its outstanding accuracy and efficiency, making it a good candidate for fine-tuning feature representations obtained from Convolutional Transformer.

The hybrid model combines the capabilities of both architectures, leveraging Convolutional Transformer's robust feature extraction capacity and EfficientNet V1's efficiency. This fusion allows for the precise and discriminative classification of various wheat diseases [3], resulting in useful insights for disease identification and control in the agricultural area.

Our suggested model obtains a thorough knowledge of the wheat leaf images while keeping computational efficiency by integrating the characteristics of Convolutional Transformer and EfficientNet V1. This hybrid architecture accurately classifies input photos into five categories: FHB, YR, BR, PM, and healthy leaves.

Our model's input consists of preprocessed and augmented wheat leaf photos that have undergone segmentation [18] and data augmentation procedures [7]. The projected class label corresponding to the discovered wheat disease category is the model's output. This information is extremely useful for disease identification and management in agriculture.

CHAPTER 4

RESULT ANALYSIS

In the above results analysis section, we have summarized the work in the field of wheat disease detection and classification. Now we have some points for the researchers to do work in the future and we have also done some experimental research due to which we gor the best results and explained after the research gap.

4.1. RESEARCH GAP

- ✓ Most of the researchers have worked on fungal disease like Yellow rust [28], Brown rust [28], Powdery mildew [29] and Fusarium head blight (FHB) but very less work has been done on bacterial [25] disease and viral [27] diseases like Karnal bunt and Root rot.
- ✓ Lack of public standard datasets is a big issue and most of the researchers have collected datasets by themselves and so every work is implemented on very small datasets. There is a need to work on creating large publicly available datasets for different wheat diseases so that researchers can work on that dataset and can provide better results.

- ✓ It is observed that deep learning models work well on the images of wheat disease captured using Mobile or Digital cameras.
- ✓ Most of the datasets are related to some specific region or area which can be a problem like different regions have different weather and environment and can cause different problems in wheat plants.
- ✓ In most of the research studies different Machine learning [16-18] techniques were used and a rise of deep learning techniques can also be seen but in Deep learning ANN is widely used and very few works have been done using different CNN frameworks. The future work are encouraged to use different architectures of Deep learning like Resnet [72], InceptionNet, SegNet, GoogleNet[70], AlexNet [69], VGGNet [68], LetNet, ZFNet, EfficientNet[74] Squeezenet, GAN, and hybrid approaches for Wheat disease detection and classification.

4.2. RESULTS FROM IMPLEMENTATION

The proposed methodology produced remarkable results, with a classification accuracy of 93.6% in the five wheat disease categories. To assure the reliability of the results, rigorous evaluation, including cross-validation and performance metric computations, was carried out. The high accuracy illustrates the hybrid Convolutional Transformer and EfficientNet V1 [6] model's ability in effectively identifying and categorizing various wheat illnesses. In summary, the suggested methodology for wheat disease classification employs a systematic approach that includes dataset collecting, preprocessing, and augmentation approaches, as well as a hybrid model based on the Convolutional Transformer and EfficientNet V1 architectures. Our methodology presents an enhanced solution for accurate and effective image classification in the context of wheat illnesses by utilizing the power of transformers [20] and combining it with efficient feature extraction. These findings add to crop health monitoring by allowing for timely disease identification and assisting farmers in disease control.

CHAPTER 5

CONCLUSION

In this paper, we have conducted a systematic literature review in the agriculture domain, specifically focusing on the detection and classification of wheat diseases using machine learning and deep learning techniques. Our review encompassed 32 research papers published between 2017 and 2022, investigating various methodologies for wheat disease detection.

By defining eight research questions, we examined the significance of each research work and identified key areas of focus, including different machine learning and deep learning techniques, utilized datasets, image processing techniques, and feature extraction methods. Most of the research studies employed machine learning techniques and neural network algorithms, while the exploration of different convolutional neural network (CNN) architectures remains an area for further investigation.

Our analysis revealed a considerable emphasis on rust diseases, while bacterial and viral wheat diseases have received relatively less attention. This observation highlights the need for future research efforts to address these overlooked areas. We have summarized the findings and outlined potential future work in the aforementioned sections, with the intention of guiding researchers towards new advancements in wheat disease detection and classification.

On a different note, we conclude our implementation section, where we proposed a hybrid model combining Convolutional Transformer and EfficientNet V1 architectures for accurate wheat disease classification. Our model effectively leverages the strengths of both approaches by incorporating global contextual information from the Convolutional Transformer and efficient feature extraction capabilities of EfficientNet V1. By preprocessing and augmenting our dataset of 14,560 wheat leaf images comprising Fusarium head blight (FHB), Yellow rust (YR), Brown rust (BR), Powdery mildew (PM), and healthy leaves, our suggested model achieved an impressive accuracy rate of 93.6%.

This hybrid model significantly contributes to crop health monitoring, providing crucial insights for disease control in agriculture. By enabling quick and precise disease identification, our methodology facilitates effective decision-making and targeted treatments. Ultimately, the implementation of our model holds the potential to enhance crop output and sustainability. By capitalizing on the strengths of the Convolutional Transformer and EfficientNet, our hybrid design yields state-of-the-art performance in wheat disease classification.

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LIST OF PUBLICATIONS

COMMUNICATED (In Scopus Journal)

[1] “Wheat Disease Detection and Classification Using Machine learning & Deep Learning: A Systematic Literature Review”, SN Computer Science, Impact factor 1.07.

ACCEPTED (In IEEE Scopus Indexed Conference)

[2] N. Sahu and A. Bhat, “A Survey: Machine Learning and Deep Learning in Wheat Disease Detection and Classification”, communicated and accepted at 7th IEEE International Conference on Intelligent Computing and Control Systems (ICICCS 2023).

[3] N. Sahu and A. Bhat, “Hybrid Convolutional Transformer and EfficientNet Model for Accurate Wheat Disease Classification”, communicated and accepted at 5th IEEE International Conference on Advances in Computing, Communication Control and Networking (ICAC3N-22).

Journal Communication Mails for paper [1].

SN Computer Science - Submission Confirmation Wheat Disease Detection and Classification Using Machine learning & Deep Learning: A Systematic Literature Review for co-author - [EMID:1ecd98c6e1b0bfd8] Inbox ×

SN Computer Science - Editorial Office <em@editorialmanager.com> Thu, Feb 2, 12:22 AM

to me

Re: "Wheat Disease Detection and Classification Using Machine learning & Deep Learning: A Systematic Literature Review"
Full author list: Nitin Sahu; Aruna Bhat

Dear Mr. Nitin Sahu,

We have just received the submission entitled: "Wheat Disease Detection and Classification Using Machine learning & Deep Learning: A Systematic Literature Review" for possible publication in SN Computer Science, and you are listed as one of the co-authors.

The manuscript has been submitted to the journal by Dr. Aruna Bhat who will be able to track the status of the paper through his/her login.

If you have any objections, please contact the editorial office as soon as possible. If we do not hear back from you, we will assume you agree with your co-authorship.

Thank you very much.

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Letter of Acceptance

TO

Nitin Sahu, Dr. Aruna Bhat
Department of Computer Science & Engineering, Delhi Technological University, Delhi, India.

Paper ID- ICICCS144

Subject: Acceptance to the International Conference on Intelligent Computing and Control Systems [ICICCS 2023], May 17-19, 2023, Madurai, India.

Dear Author,

We are happy to inform you that your paper titled **"A Survey: Machine Learning and Deep Learning in Wheat Disease Detection and Classification"** has been accepted for the oral presentation at the 7th International Conference on Intelligent Computing and Control Systems [ICICCS 2023] to be held on **17 – 19, May 2023** at Vaigai College of Engineering, Madurai, Tamil Nadu, India.

With the evident of its previous publications, ICICCS 2023 is also dedicated for the publication in **IEEE Xplore Digital library**. As a result of the peer review process, the technical conference program committee is pleased to inform you that your paper is shortlisted and accepted for the presentation in conference event and formally accepted for inclusion in IEEE Xplore. We appreciate if you could submit the final version of manuscript at your earliest convenience, in order to ensure a novel and timely publication of your research paper.

Once again, on behalf of the conference committee we extend our warm gratitude to welcome you at our conference.

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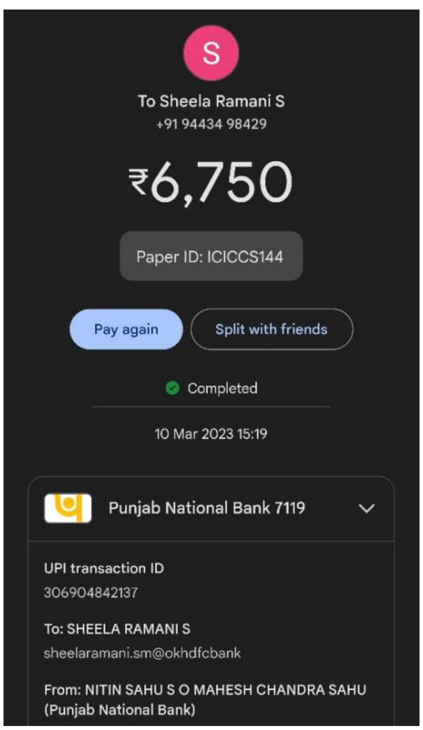

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Dear Nitin Sahu,
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Greetings from ICAC3N-23 ...!!!

Congratulations....!!!!!

On behalf of the 5th ICAC3N-23 Program Committee, we are delighted to inform you that the submission of "Paper ID- 338 " titled " Hybrid Convolutional Transformer and EfficientNet Model for Accurate Wheat Disease Classification " has been accepted for presentation and further publication with IEEE at the ICAC3N- 23 subject to incorporate the reviewers and editors comments in your final paper. All accepted papers will be submitted to IEEE for inclusion into conference proceedings to be published on IEEE Xplore Digital Library.

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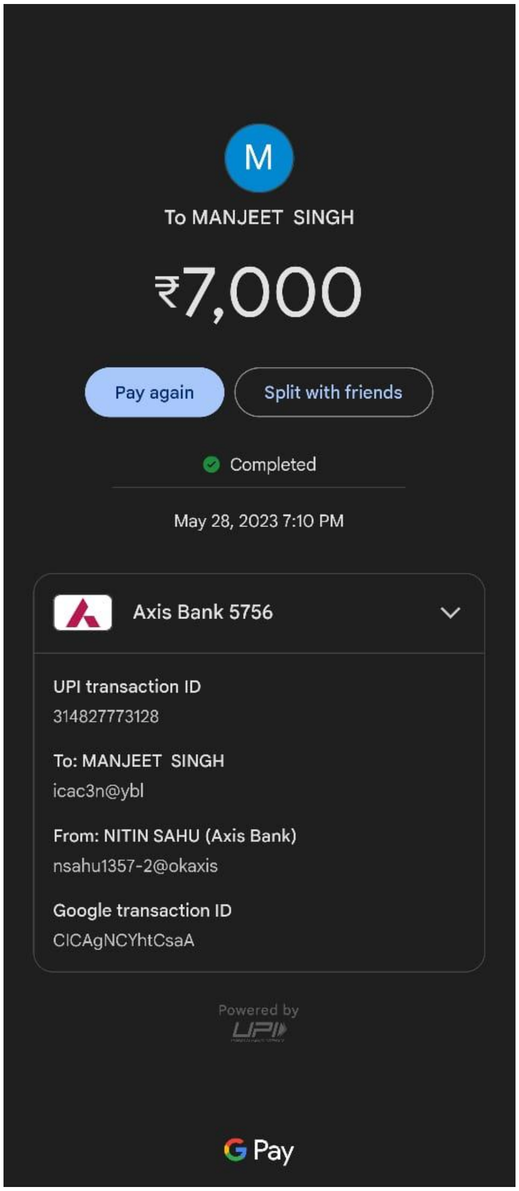

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