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Wheat Rust Disease Segmentation from Ground Imagery

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***Abstract*—Wheat rust disease is a major agricultural threat, causing significant yield losses globally. Precision agriculture and autonomous robot systems represent pivotal advancements in modern farming and disease detection, leveraging technology to enhance crop management, optimize resource use, and improve productivity. These systems rely heavily on accurate and comprehensive data to train effectively. However, current datasets often fall short of meeting the specific needs of these advanced agricultural technologies. This paper addresses this gap by introducing a primary contribution in the form of an open-source dataset focused on wheat rust disease segmentation for precision agriculture. Open-source datasets in literature are either general plant disease datasets or wheat disease classification datasets. Our proposed wheat rust segmentation dataset, Focussed Rust Disease Images (FRDI), provides close-up views of disease manifestations on wheat leaves, capturing the natural variability and complexity of diseases in field conditions, thereby meeting the requirements of precision agriculture systems. This facilitates detailed analysis and effective training of deep learning models designed for disease detection and segmentation tasks for real-world agricultural environments. Furthermore, in our work we present an improved wheat rust disease detection and segmentation technique which is based on the concept of co-salient feature extraction for disease identification within complex and cluttered field images. By integrating localized and generic contextual information, our proposed approach effectively identifies key features and intricate patterns associated with wheat rust disease.**

***Index Terms*—Precision agriculture, co-salient feature extraction, semantic segmentation, wheat rust disease detection, and disease segmentation.**

I. Introduction

Precision agriculture represents a significant shift from traditional manual labor-intensive farming practices to modern, technology-driven techniques aimed at optimizing crop production and management. Traditionally, farmers relied on manual observation and uniform application of inputs across entire fields, leading to inefficiencies in resource use and variability in crop yields. Precision agriculture, however, integrates advanced technologies including global positioning systems (GPS), remote sensing, drones, and machine learning algorithms to collect and analyze data with unprecedented accuracy and detail [1], [2].

Autonomous robot-based solutions are considered the next step in the evolution of precision agriculture, leveraging robotics and AI to further optimize farming practices. Precision agriculture and autonomous robot-based methods both aim to enhance farming efficiency and crop management, but they differ significantly in their approaches and data requirements [3], [4]. Precision agriculture requires data at a granular level. It necessitates high-resolution, close-up images taken in real-world field conditions, capturing the natural variability and complexity of crops. Unlike laboratory conditions where data is collected from single, perfectly segmented leaves, precision agriculture requires data that reflects the actual state of crops in the field. On the other hand, autonomous robot-based methods focus on wide-angle view of fields, providing an overview of crop health and spatial patterns. These systems use high-resolution cameras on robots to capture images and videos of entire fields, identifying general health patterns and disease distribution across entire crop fields [5]. While this data is less granular, it is collected frequently to monitor changes over time effectively. However, it may lack the granular detail necessary for precise disease diagnosis and early intervention that precision agriculture provides.

Wheat Rust is one of the most devastating diseases affecting wheat crops worldwide, caused by fungal pathogens of the genus Puccinia. There are three primary types of rust: stem rust, leaf rust, and stripe rust, each attacking different parts of the wheat plant. These diseases reduce crop yields significantly, sometimes by up to 70%, making them a major threat to global food security [6]. Datasets specific to wheat diseases are limited for both precision agriculture and autonomous robot-based systems. The non-availability of open-source datasets hinders the development of robust deep-learning models essential for disease detection in real-world agricultural settings [7]. Most open-source datasets available are either general plant disease datasets or wheat disease classification datasets which are mostly based on single-leaf images showcasing the laboratory conditions.

The open-source segmentation wheat disease datasets available in the literature include work by authors in [8] and our

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previous published dataset of NWRD [9], where the former is a single-leaf rust disease segmentation dataset based on laboratory conditions and the latter is a multi-leaf segmentation dataset with wide-angle view images designed specifically for autonomous robot-based systems. There is no multi-leaf rust disease segmentation dataset with focussed images of diseased leaves in field conditions. We have addressed this research gap in our work by presenting a real-world field dataset of wheat crop especially focussed on the requirements of precision agriculture systems. Acquiring comprehensive datasets is crucial for training and refining machine learning and deep learning models, enabling them to effectively analyze and interpret varied conditions encountered in the field [10].

Overall, this paper presents the following significant contributions to the field:

- Creating and introducing an open-source wheat rust disease segmentation dataset named FRDI for precision agriculture. This dataset provides real-world close-view images of disease manifestations on wheat leaves, facilitating nuanced analysis and training of deep learning models for disease detection and segmentation tasks.
- Given the sporadic nature of disease spread, we employ the co-salient object detection (Co-SOD) paradigm to effectively identify key contextual features and intricate patterns of wheat rust disease within complex and cluttered field images. The co-salient feature extraction utilizes local and global context for the identification of irregular and unpredictable patterns of disease spread.

II. Related Work

This section highlights recent and significant contributions in the field of disease detection, focusing on disease datasets, techniques, and advancements that have shaped current research directions for disease segmentation.

A. Wheat Disease Datasets

This section gives an overview of the open-source wheat disease classification and segmentation datasets that are present in the literature.

1) Wheat Disease Classification Datasets: Several prominent datasets have been developed to facilitate research in wheat disease classification, each with unique properties and applications. The first one is the Kaggle wheat disease dataset [11], which includes high-resolution images of wheat plants affected by various diseases. It is widely used for training and evaluating machine learning models aimed at detecting and classifying wheat diseases. The CGIAR [12] dataset was developed by the Consultative Group for International Agricultural Research, this dataset contains a diverse collection of images depicting different wheat disease symptoms and is a multi-leaf classification dataset. The Wheat Yellow Rust Disease Infection type Classification [13] dataset is a single leaf dataset of wheat rust disease classification, which covers various stages of the progression of wheat diseases and has been presented as a single leaf with a plain background. Another well-known wheat disease classification dataset is WDD2017 [14] which is a wheat disease database containing multiple wheat disease images under field conditions, with classes of wheat diseases including leaf rust, leaf blotch, powdery mildew and smut etc. Similarly, LWDCD2020 [15], Leaf Rust Image Dataset, and New wheat disease dataset [16] are other prominent classification datasets available in the literature. Sample images from some of the most prominent classification datasets have been shown in Figure 1. Some datasets have more than three or four classes, however the figure shows only a few. All these datasets presented above are wheat rust classification datasets. These datasets provide details of the disease state, the type of disease present, and the severity level of the disease. The dataset typically consists of images annotated with labels indicating the presence or absence of specific diseases. Each image is associated with a single class label, representing the type of disease or health status of the wheat plant.

While classification datasets are effective for the broad categorization of wheat disease types, they may not provide the level of detail required for advanced analyses and decision-making in complex applications such as precision agriculture. This is where segmentation datasets, which provide pixel-level annotations and spatial information, play a crucial role in enhancing the precision and effectiveness of machine-learning models in agricultural contexts.

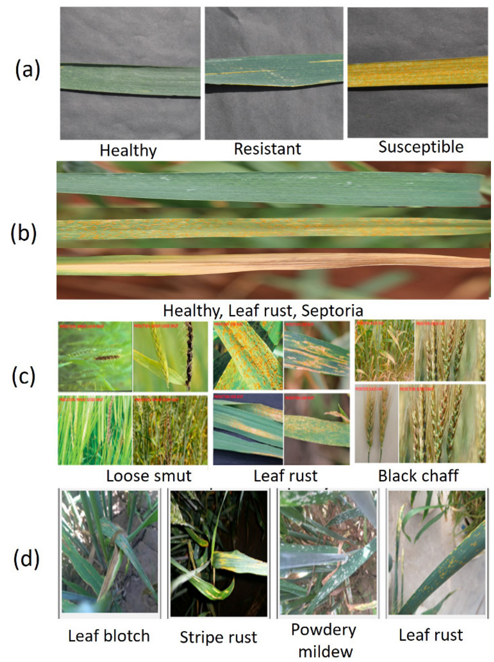

Fig. 1. Open-source wheat rust disease classification datasets. a) sample images from the Wheat yellow rust disease classification dataset with single leaves. b) sample images from the Kaggle Wheat Leaf dataset with single-leaf disease images. c) sample images from the LWDCD2020 dataset with single diseased leaves and crown & root rot disease images. d) sample images from the WDD2017 dataset with multi-leaf images.

2) Wheat Disease Segmentation Datasets: The presence of thoroughly annotated and real-world segmentation datasets is crucial for the effective training of deep learning models. Despite their importance, there is a notable scarcity of in the existing literature. There are only two open-source segmentation datasets related to wheat disease, the Crop Disease Treatment Dataset (CDTS) [8] and the NUST Wheat Rust Disease Dataset (NWRD) [9]. The CDTS dataset focuses on the rust disease spores and spots on each leaf through close-up images. Each image in the dataset features a single leaf, highlighting both diseased and healthy parts, and includes segmentation masks for the background, diseased areas, and healthy sections. However, this dataset shows laboratory conditions with a plain and consistent background of each diseased leaf. The NUST Wheat Rust Disease (NWRD) dataset features slightly wide-angled view images of wheat crops collected from the wheat fields under field conditions [9], which caters to the need for autonomous robot-based systems by providing comprehensive field-level perspectives and contextual awareness. Visual comparison of sample images from both datasets, along with images of our proposed FRDI dataset is shown in Figure 2.

The literature does not highlight any dedicated open-source wheat disease segmentation dataset optimized for precision agriculture, which is crucial for advancing crop health management. Such a dataset is required which features high-resolution, close-view images of wheat crops taken under real-world field conditions. These images would enable detailed analysis and training of machine learning models to accurately identify and delineate disease-affected areas on wheat leaves.

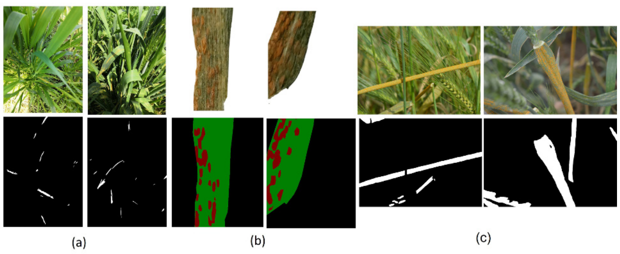

Fig. 2. Open-source wheat rust disease segmentation datasets. a) sample images from the NWRD dataset with multi-leaf disease images showing the wide-angle view of the disease. b) sample images from the CDTS dataset with single-leaf disease images. c) sample images from the proposed FRDI dataset with multi-leaf disease images featuring a close view of the disease.

B. Disease Segmentation Techniques

This section presents the methods and techniques proposed in the literature for crop and fruit disease detection, classification, and segmentation.

Authors in their work have presented the dataset related to peach disease classification and applied deep network models Mask R-CNN and Mask Scoring R-CNN for segmentation of diseased areas of peach fruit. Experiments have been conducted to show that loss function has an impact on the overall accuracy and using the focal loss function has improved peach disease detection results [17].

An improved method called the faster mask regional-convolutional neural network (IFMR-CNN) is proposed by authors to find the affected disease areas in the plants. The model used Mask-RCNN with a ResNet backbone [18]. Work on the detection and segmentation of Northern Leaf Blight (NLB) disease in maize plants has been carried out using the Mask R-CNN and Cascaded Mask R-CNN models. Their results have shown that the ResNet backbone produces the best segmentation results. Similarly authors in [19] introduced an image segmentation algorithm to automate the detection and classification of plant leaf diseases. Additionally, it includes a comprehensive survey of various techniques for classifying diseases, applicable to detecting plant leaf diseases. Authors in their work [20] tackled the challenge of rust segmentation and estimating the disease index for wheat stripe rust. They utilized a combination of CNNs and transformer for rust disease segmentation. The macro disease index was then computed to measure the incidence of the disease at the canopy scale. The authors demonstrated that SegFormer outperformed other segmentation algorithms in segmenting wheat rust on their wheat disease dataset. Authors in [21] worked on the image segmentation problem of plant leaf lesions using the MA-Net architecture for 2019 apple leaf dataset.

Deep convolutional neural networks and encoder-decoder architecture have also been applied for the semantic segmentation of leaf diseases in plant images. Three models, namely LinkNet-34, PSPNet, and SegNet, are utilized for lesion detection. Subsequently, lesion classification is performed using DenseNet-121 and ResNext-101 classifiers [22]. Another study evaluates the performance of the Segment Anything Model (SAM) for the domain of precision agriculture by using the CWFID dataset [23]. The PlantVillage and PlantDoc datasets have been utilized to demonstrate the capability of the YOLOv8 model for disease identification [24]. The authors have shown through results that this model can have applications in precision agriculture as it accurately detects diseased areas.

In agricultural applications, such as wheat disease detection, deep learning techniques have shown remarkable promise. However, the success of these models heavily relies on the quality and quantity of the datasets used for training. For wheat disease detection, this means assembling a comprehensive dataset that includes images of wheat plants under various conditions and having field conditions.

III. Materials and Methods

A. Dataset Acquisition

The wheat crop disease data were collected from wheat fields at the National Agriculture Research Centre (NARC) in Islamabad, Pakistan. NARC spans approximately 1,396 acres and is situated near Rawal Lake, about six kilometers southeast of Islamabad. The wheat crop disease data were collected for the 2022-2023 season, from a single NARC wheat field in which wheat was sown in November 2022 and harvested in May 2023. The collection process covered various stages of wheat rust manifestations on the leaves of the wheat crop which is a multi-strain wheat crop. Images were captured using a high-resolution D3200 DSLR camera. Most of the images present in the data have a resolution of 6016x4000 pixels.

B. Dataset Properties

The proposed FRDI dataset features close-up images captured in field conditions with varying lighting and overlapping leaves, providing detailed insights into rust disease. It exhibits a significant increase in rust patches, showcasing a higher density of rust per image compared to the other multi-leaf segmentation dataset. This richness in detail and variation supports improved disease detection and segmentation, making the FRDI dataset a valuable resource for precision agriculture applications.

1) Real-world dataset: The dataset is a real-world field dataset that accurately reflects field conditions rather than a controlled laboratory environment. The images are collected from different parts of the wheat field, which allows the inclusion of the rust images with different spatial patterns of disease. The dataset primarily includes images of healthy wheat leaves, with a portion of 20% data depicting diseased leaves afflicted by wheat rust disease.

2) Occlusion and blurred images: Images in the dataset have wheat leaves with diseased portions that are occluded and blurred. This means rust disease is prominent in some regions while the healthy leaves or wheat kernels cause occlusion in other diseased areas.

3) High-resolution images: The images of the proposed dataset have been captured by the DSLR camera and are high-resolution images with each image of 6016 x 4000 pixels. These high-resolution images capture various saptial patterns of the disease including high-level and low-level disease features.

4) Clear and Fuzzy view of disease: The dataset contains a predominant number of images depicting healthy wheat leaves, with a smaller proportion showcasing leaves affected by rust disease. Additionally, the dataset includes images of brown leaves resulting from water deficiency rather than disease. Most images focus primarily on the diseased leaves, capturing detailed views of the rust infection. However, some images also feature a mixed view with a blurred background, where both diseased and healthy leaves are visible but not the main focus.

5) Shape complexity: The rust disease in wheat crops surfaces as pores and spores on the leaf, which spread with time and cover the leaves. The shape pattern of the disease is irregular for each leaf and this complexity leads to difficulty in annotating the diseased regions of the image.

6) Diverse dataset: The diverse range of images in the dataset provides valuable contextual information, making it a robust resource for developing and testing segmentation models. This comprehensive dataset enhances the model's ability to generalize across various conditions, featuring a mix of healthy, diseased, and water-deficient leaves. Additionally, images portraying different environmental conditions such as varied lighting, angles, and disease stages further add to the diversity of the dataset.

7) Manual Annotation: The diseased areas in the images do not follow a consistent pattern across the images, therefore all the images have been manually annotated one by one using the Gimp software.

Sample images from the proposed FRDI dataset have been shown in Figure 4.

TABLE I
DISTRIBUTION OF RUST AND NON-RUST PATCHES IN MULTI-LEAF WHEAT RUST SEGMENTATION DATASETS OF NWRD [9] AND OUR PROPOSED FRDI DATASET. THE FRDI DATASET SHOWS A MARKED INCREASE IN RUST PATCHES, ENHANCING THE POTENTIAL FOR EFFECTIVE TRAINING.

	NWRD		**FRDI**	
	Rust	**Non-Rust**	**Rust**	**Non-Rust**
Training	2,153	26,370	7,788	29,782
Validation	230	1,696	344	1,866
Test	684	2,824	769	3,651

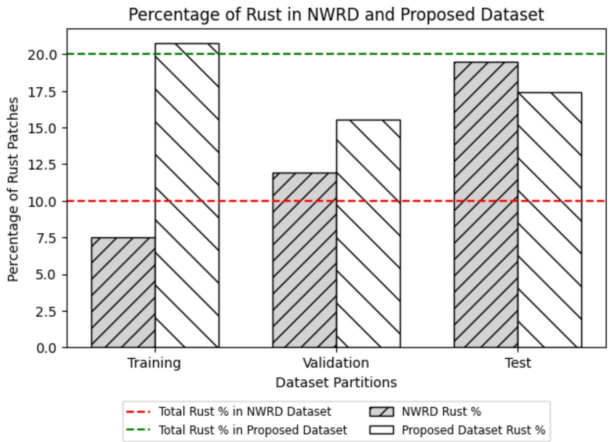

Fig. 3. The FRDI dataset exhibits a significant increase in rust coverage, featuring a higher concentration of rust within each patch and a 10% increase in the overall percentage of rust in the dataset as compared to NWRD dataset.

IV. METHODOLOGY

In this study, we tackled the challenge of automatically detecting wheat rust disease (WRD) in real-world field data, characterized by varying light conditions and complex backgrounds. This section discusses in detail the methodology for wheat rust disease detection and segmentation.

A. Data Preprocessing

The field data that has been collected is carefully annotated and then preprocessed to be fed to the deep learning model for learning. This stage is crucial for enhancing compatibility with complex algorithms and ensuring optimal input for effective feature extraction. The high-resolution images are sliced into patches of size 224x224. Patch-based input is important for

Fig. 4. Sample images and binary masks from the proposed FRDI dataset, captured in field conditions with varying lighting and overlapping leaves. The FRDI dataset features close-up images of rust that capture more disease detail and exhibit a higher rust presence per patch.

deep learning models as this allows for better utilization of hardware resources, enabling more efficient training and inference. The data is then divided for train, validation, and test set in a ratio of 85:5:10. The number of patches generated from our proposed rust segmentation dataset have been given in Table I while Figure 3 presents a comparison of rust and non-rust patch distribution for the multi-leaf segmentation datasets of wheat disease, highlighting an overall rust percentage of 20% in the proposed FRDI dataset which is almost twice as compared to the NWRD dataset which had approx 10% overall rust.

The second preprocessing step carried out in this work for disease detection is to augment the original training dataset and balance the rust and non-rust patches. Various augmentation techniques have been applied to the dataset, resulting in multiple versions of dataset being trained and tested to identify the optimal distribution. Six different augmentations, including horizontal and vertical flips, horizontal and vertical shears, rotation, and contrast and hue adjustments, were performed on the training dataset to achieve the best results. These augmentations help ensure that the model does not become biased towards the majority class of the input data.

B. Rust Disease Segmentation

The rust disease segmentation process was carried out through multiple methods including the semantic segmentation models, salient object detection models, and co-salient feature extraction model.

The UNet segmentation model which is known for its capability of producing high-quality segmentation maps for precise segmentation was utilized to segment the diseased areas of the input images [25]. The U-Net model's performance on our proposed wheat rust segmentation dataset was not satisfactory. Another semantic segmentation model DeepLabv3 was also applied to the proposed dataset for segmentation [26]. This model did not perform very well for disease identification and segmentation. Traditional segmentation models struggle with intricate, small-scale features at the fine-grained level such as those of wheat rust disease in a cluttered background. To overcome this, we explored the salient object detection models which can capture intricate salient features from images and provide better segmentation. The salient object detection model based on the transformer architecture was then applied for rust disease segmentation on the proposed diseased dataset [27]. When attempting to detect early signs of disease in wheat leaves using a standard salient object detection model, the model predominantly identifies the leaf as the salient object within the images and is not able to accurately segment the diseased regions of the leaves. We also used the SegFormer for disease segmentation of wheat rust [28]. Owing to the sporadic nature of rust disease spread, it is quite challenging to detect diseased areas, and therefore we have applied the co-salient object detection (Co-SOD) paradigm which is a specialized field of salient object detection (SOD) for feature extraction from diseased wheat leaves. Our proposed technique is based on identifying common and salient objects across a group of images, leveraging the local and global context for identification and segmentation of diseased regions within leaves. The proposed disease detection architecture has been shown in Figure 5. We utilized the Co-SOD model by authors in [29], which is a comprehensive feature mining technique for performing pixel-level semantic segmentation in intricate scenes of wheat disease. The cosalient feature extraction model takes as input groups of images for feature extraction. As a first step, we use the ViTbase transformer as a classifier to separate rust patches from the input stream of patches produced after augmentations. These rust patches are then grouped into multiple small groups and fed to the co-salient feature extraction model to extract background, foreground, and inter-class similarity features for disease segmentation. Based on the local and global context, the cosaliency model accurately identifies diseased regions from the input images. The produced saliency maps are restitched to be compared to the ground truth masks for the final segmented diseased regions.

V. Experiments

A. Experimental Setup

The training of different models was performed using the Nvidia RTX A5000 machine utilizing the Linux operating

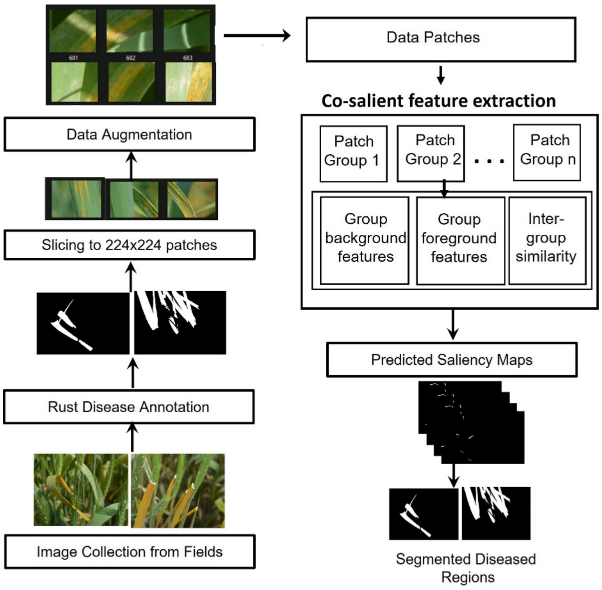

Fig. 5. The proposed wheat rust disease detection and segmentation architecture based on co-salient feature extraction.

system. The PyTorch framework was integrated into the Anaconda environment, and Python (version 3.8) with CUDA (version 11.7) support was used. The hardware configuration comprised an Intel(R) Core i7-9700 CPU @ 3.00 GHz x 8 processor, with 24GB memory.

B. Metrics

This section presents the details of the metrics that have been used for evaluating the rust disease segmentation models.

1) IoU: IoU measures the degree of overlap between the predicted segmentation mask generated by a model and the ground truth mask, which represents the actual infected areas as annotated by experts. It quantifies how accurately the model can identify and delineate rust-affected regions on wheat leaves. A higher IoU value indicates better segmentation performance, reflecting a greater correspondence between the model's predictions and the true locations of rust disease. The IoU is mathematically expressed as:

$$\text{IoU} = \frac{|A_p \cap A_g|}{|A_p \cup A_g|} \tag{1}$$

where A_p represents the predicted segmentation mask area and A_g represents the ground truth mask area.

2) F1-Score: The F1-Score metric combines precision and recall into a single value by calculating their harmonic mean. This score provides a balanced measure that accounts for both false positives and false negatives. The terms involved are defined as follows:

$$\text{F1-Score} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{2}$$

where:

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}} \tag{3}$$

and

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}} \tag{4}$$

Equations (1), (2), (3), (4) define the metrics of IoU, F1 score, precision, and recall respectively that have been used to evaluate and compare the wheat rust disease segmentation models.

C. Training

The wheat rust disease detection was carried out using the semantic segmentation model UNet and DeepLabv3, SOD model, SegFormer model, and Co-SOD model. For UNet training, the input patches of the original dataset of size 224x224 were fed to the model. The NAdam optimizer with an initial learning rate of $1e-5$ was used to train the model. The next training was carried out using the salient object detection model, AbiU-Net [27], which was fine-tuned on the proposed dataset. The training was carried out for 25 epochs, using AdamW optimizer, and a learning rate of $5e-5$. The Segformer model was then trained using transfer learning with a learning rate of $5e-5$ and weight decay of 0.01 on the proposed dataset for disease identification and segmentation. For the training of the proposed disease segmentation technique based on co-salient feature extraction, as a first step, the ViTbase classifier was applied on the input augmented patches of the dataset. The classifier was used to separate rust and nonrust patches from the input. The rust patches were then grouped into multiple groups of 12 patches each, since the Co-SOD model is based on the concept of extracting features from groups of images. Each group of the input patches was then fed to the co-salient feature extractor. The training of co-salient object detection model was carried out using the model proposed by [29] which is pretrained on COCO dataset with CoCA as the validation dataset. The model was then fine-tuned on the FRDI dataset. Adam optimizer with an initial learning rate of $1e-4$, β_1 = 0.9, and β_2 = 0.99 values were used to train the model for 50 epochs.

D. Evaluation and Results

To evaluate all segmentation models, we conducted both qualitative and quantitative assessments. For qualitative analysis, the segmentation results generated by the models are visually compared with the ground truth annotations of the proposed FRDI dataset. This helps to identify how well the model has segmented the rust disease in the images with a complex background, highlighting areas of agreement and discrepancy. For quantitative analysis, the trained models generate predicted segmentation masks for the test set of the proposed dataset. These predictions are then used to calculate the F1-Score and IoU score according to the equations 1, & 2. The feature maps of various layers of the detection model

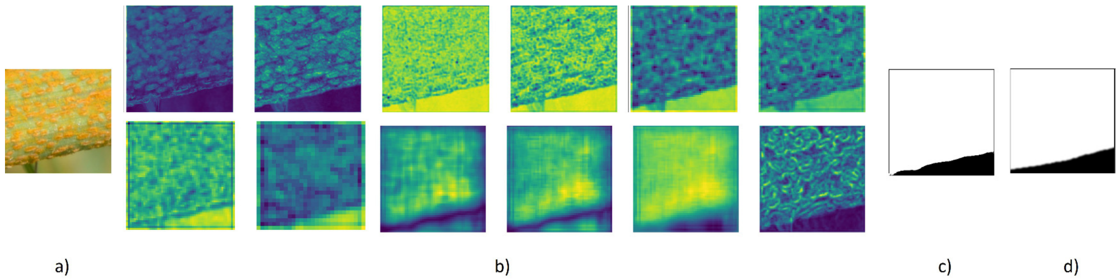

Fig. 6. Feature maps generated from our proposed co-saliency based feature extraction technique for rust disease segmentation. a) input rust patch. b) feature maps of various internal layers. c) final prediction map. d) ground truth patch where the white part shows disease and the black part shows background. The final prediction map closely aligns with the ground truth, demonstrating the effectiveness of the technique.

TABLE II
DISEASE SEGMENTATION RESULTS OF DIFFERENT MODELS ON THE FRDI DATASET. OUR PROPOSED TECHNIQUE PRODUCES THE BEST F1-SCORE AND IOU FOR WHEAT RUST DISEASE SEGMENTATION.

Sr. No.	Model	F1- Score ↑(%)	IoU ↑(%)	Training Time ↓ (mins)
1	U-Net [25]	0.457	0.325	540
2	DeepLabv3 [26]	0.473	0.344	1,560
3	AbiU-Net [27]	0.806	0.211	4,140
4	SegFormer_MiT_B5 [28]	0.627	0.427	2,160
5	**ViT+ DCFM (Proposed)**	**0.831**	**0.713**	**1,150**

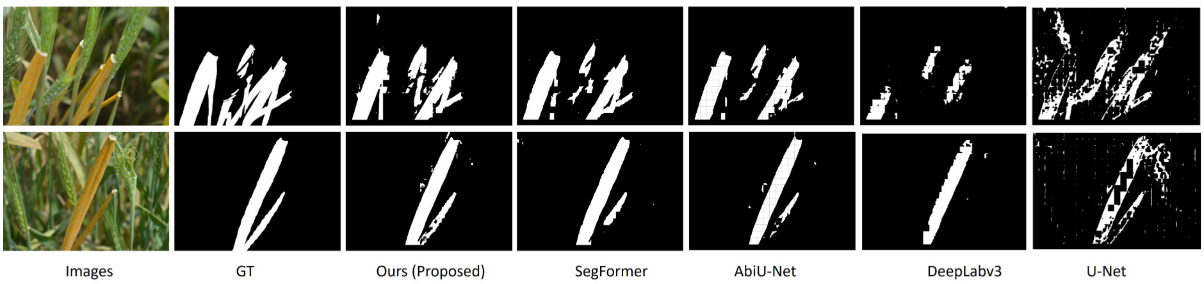

Fig. 7. The qualitative comparison of segmentation models for wheat rust disease segmentation on the proposed FRDI dataset shows that our technique—ViT combined with DCFM—produces the most accurate visual results.

obtained for our proposed technique, which demonstrates disease features at different levels along with the final prediction map showing the result of the disease segmentation, can be seen in Figure 6. The UNet model demonstrated shortest training time but achieved a modest IoU of 0.325. DeepLabv3 produced an IoU of 0.344, slightly better than UNet for disease segmentation. Conversely, the SOD model required the longest training time and yielded intermediate results. The SegFormer model achieved an F1-score of 0.627 and IoU of 0.427. Our proposed segmentation technique, leveraging classifier and co-salient feature extraction, delivered the highest performance for disease segmentation with an F1-score of 0.837 and IoU of 0.724. The quantitative results are presented in Table II while qualitative results are shown in Figure 7.

VI. DISCUSSION

The performance of state-of-the-art models for wheat rust disease segmentation on our proposed segmentation dataset has been presented in Table II. For all the experiments, we used image patches as input so that the models can focus on specific regions, capturing fine-grained details and contextual information more effectively. This approach enhances the model's ability to produce precise segmentation results while mitigating issues related to memory constraints and computational complexity. The performance of the U-Net model for wheat rust segmentation was not satisfactory. Despite its proven capabilities in segmentation, it struggled to accurately segment rust due to the intricate and variable nature of the disease symptoms and the cluttered background. To overcome this, we used the salient object detection (SOD) model, which is designed to identify the most visually prominent features in an image. We anticipated that the SOD model would be better suited to detect the distinct visual characteristics of rust from the dataset. However, this model also did not perform well, as it predominantly identified the leaves as the salient objects rather than the rust-affected areas. Given the irregular and unpredictable pattern of disease spread, we present a technique for rust disease segmentation utilizing the Co-SOD paradigm. The proposed technique leverages contextual information within images to discern subtle and complex patterns of disease. By focusing on the co-salient features, which are the common and salient features across multiple image groups, our technique is better equipped to accurately identify and segment the rust-affected areas, addressing the limitations faced by previous approaches.

VII. Conclusion

The development of precision agriculture datasets, such as the one presented in this paper, is crucial for effective disease detection and early intervention. These datasets enable timely remedial actions and play a pivotal role in advancing agricultural technologies. By providing high-quality, field-specific data, these datasets empower farmers and researchers to harness the full potential of precision agriculture and autonomous systems, ultimately leading to more efficient and sustainable, agricultural practices. Training deep learning models on datasets with a higher incidence of rust-affected images is crucial for robust feature learning. Models trained on such datasets can better detect early signs of rust disease in field conditions, enabling timely intervention and management. Context plays a crucial role in disease detection and experiments have shown that using the co-salient object detection models for contextual feature extraction has considerably enhanced the rust disease detection and segmentation results.

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