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# Digitally-Enabled Crop Disorder Management Process Based on Farmer Empowerment for Improved Outcomes: A Case Study from Sri Lanka

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**Abstract:** We have developed a system facilitated by a mobile artefact to effectively identify crop disorder incidents and manage them using recommended control measures. This work overcomes the limitations of the existing attempts by using digital technology to empower farmers to identify crop disorders rather than replace them with automated techniques. Our approach empowers farmers by providing the information in context for them to identify crop disorders. The developed solution can identify most of the crop disorders instantaneously, irrespective of the crop or other factors that make crop disorder identification complicated. For the rest, it provides a mechanism to carry out a manual identification with the help of subject experts. The solution was deployed among paddy farmers in Sri Lanka to understand how well this could assist them in identifying and managing crop disorders. The system was able to identify 70.8% of the crop disorder incidents reported by the farmers and provided them with the relevant control measures. Farmers' perceptions of various usability aspects of the solution revealed that the application of agrochemicals and expenses associated with agrochemicals were significantly reduced. It was also observed that the yield quality and quantity and overall revenue have increased compared to the previous seasons.

**Keywords:** pest and disease incidents; agriculture sustainability; smart farming; farmer empowerment; ICTs for sustainability

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## 1. Introduction

The agricultural sector has always been an influential economic force in Sri Lanka, making notable contributions to the nation's economy, food security, and workforce [1]. According to World Bank, 23.7% of the total workforce in Sri Lanka was employed in the agricultural sector in 2020 [2]. Moreover, in 2019, the sector contributed to 7.4% of the country's gross domestic product (GDP). However, in recent times, there has been a substantial reduction in the contribution of agricultural production to Sri Lanka's national GDP, which accounted for 20% of GDP in 2000 and declined to 7.4% in 2019 [2,3]. Overall, such negative outcomes have resulted due to many reasons. One major reason was due to the reduced interest of farmers in farming concerning the unstable situation in the context of Sri Lankan agriculture. This includes unstable and lack of support available for farmers to access needful information (e.g., recommended farming practices, cultivation techniques, management aspect of crop losses, etc.), frequent changes in agricultural policies concerning imports and exports, lower profits, and fluctuations in market prices and production quantities [4–6].

In the Sri Lankan agriculture context, farmers often get assistance from an agricultural extension service to support their day-to-day farming activities. An agricultural extension service is a scheme initiated by the government and plays an essential role in distributing agricultural knowledge and recommended farming practices to farmers through farmer education [7]. However, the current agricultural extension service in Sri Lanka fails to provide the necessary support to farmers in a timely manner due to varied reasons [8]. These reasons include changes in government policies and strategies and marketing reforms in the agriculture sector, non-extension duties carried out by extension agents, a lack of qualified and experienced extension agents, the unwillingness of extension agents to work in rural areas, serving/handling a large number of farmer groups, and an insufficient number of extension agents to maintain direct contact with farmers [8]. For example, in Sri Lanka, the extension service has nearly 900 agricultural extension agents working to support more than two million farmers [9]. However, given the limited facilities, it is nearly impossible to fulfil the assigned tasks by extension agents, and there is limited time to provide core extension services. Further, the agriculture extension service has not provided a dynamic structure to facilitate effective knowledge dissemination among farming communities. Therefore, farmers' problems are not conveyed effectively to the extension service, and solutions are not effectively passed on to farmers [10].

In agriculture, it is important for extension agents to assist farmers in making correct decisions on time by providing required information. Failure to provide the required information in a timely manner may severely affect the overall agriculture process [9]. These effects are already being felt in Sri Lanka, where farmers have relied on unreliable sources such as peer farmers, input suppliers, agrochemical dealers, and sometimes themselves to obtain needful information. The problem with unreliable sources is that the information received from each individual is subjective and may lead to bias, resulting in farmers making incorrect decisions instead of recommended ones, especially in a situation similar to managing crop disorder incidents [11,12]. In general, crop losses occur due to many reasons. This includes extreme climatic variations (e.g., drought, flooding, heavy rainfall), changes in soil conditions, machinery use, wildlife damage, crop disorder incidents (e.g., disease and pest outbreaks), nutrient deficiencies, and damage caused by heavy agrochemical usage [13]. In the Sri Lankan context, the overall crop losses incurred during cultivation, harvest, and post-harvest was estimated at Rs.18 billion annually [11]. Of these losses, 30% of the crops were damaged due to crop disorder incidents and wildlife damage, and 30% were due to losses due to misuse of agrochemicals, post-harvest losses, and unfavourable climate conditions, resulting in only about 40% of crops being utilized for consumption. Furthermore, it is also found that crop disorder incidents have significantly contributed to a vast amount of crop losses in the early stage of agricultural production [14,15].

In order to eliminate crop disorders from the field, farmers employing recommended control measures in a timely manner is a mandatory activity. However, the delayed or sometimes the lack of response from extension agents limits farmers' ability to undertake timely remedial action and leads them to seek information from unreliable sources, notably agrochemical dealers. This inconsistency is not new in Sri Lanka and has dramatically worsened over the past years. Farmers who use unreliable sources are often advised to employ chemical control methods due to their high potential to eliminate crop disorders [16]. Similarly, the farmers' need, combined with agrochemical dealers' business strategies such as low prices and sales promotion activities, also encourages farmers to become dependent on agrochemicals rather than employing environmentally friendly control methods [17]. As a result, farmers have become completely dependent on agrochemicals to control crop disorder incidents. The extreme dependency on agrochemicals has imposed significant disruptions to agriculture production, fluctuations in production quantities and qualities, environmental damages and critical health and financial risks to the farmers [14,18].

Due to these reasons, agricultural systems should be developed in such a way that farmers can effectively manage crop disorder incidents and control them to not grow up to a stage whereby they cause substantial damage to the crops. In general, the overall crop disorder management process is carried out in two stages: crop disorder identification and employing recommended control measures. Therefore, reliable identification of crop disorders is a requirement to employ necessary control measures. However, crop disorder management is a complicated process with various challenges that requires a more in-depth investigation. These challenges are identified and explained in Section 2.3. Upon reviewing the literature, we identified that there is currently a lack of interventions being reported in the literature to support farmers to manage crop disorder incidents effectively and in a timely manner. The overall results obtained from such reported works are inconclusive and with several limitations due to not addressing the challenges associated with the crop disorder management process. These limitations are detailed in Section 2.4. Henceforth, this study aims to figure out an effective approach to identify crop disorder incidents by addressing the challenges identified and assist farmers in employing recommended control measures in a timely manner. Finally, the study also aims to identify usability responses of the farming community towards the proposed intervention.

## 2. Background

This section begins with assessing current crop disorder management practices in Sri Lanka, especially the usage of agrochemicals, followed by an understanding of the consequences of agrochemicals concerning economic, human health and environmental aspects. In addition, this section also discusses the challenges associated with the crop disorder identification process and the existing attempts that have been reported in the literature, along with their limitations.

### *2.1. Crop Disorder Management in Sri Lanka*

The present crop disorder management process that is practised by farmers in Sri Lanka consists of three stages: monitoring the field for the presence of any abnormal symptoms, identifying crop disorders if symptoms are present, and employing suitable control measures [19].

In the first stage, farmers perform continuous monitoring in the field to find out any presence of abnormal symptoms in the crops. To do this, farmers walk along predetermined routes or regularly scout through the field [19]. Sometimes, farmers use different types of traps to understand the presence of fast-moving insect pests in the field [20]. In the second stage, farmers attempt to identify relevant crop disorders based on their identified symptoms in the first stage. Farmers use their experience and the input they receive from external sources to identify the correct crop disorder. The sources used by farmers to aid their decision-making process can be grouped into reliable and unreliable sources. Farmers initially seek advice from reliable sources such as agriculture extension agents or agriculture researchers through discussions on the phone. In practice, extension agents are responsible for serving a large number of farming communities, and this situation draws them away from responding on time to farmers' calls or queries in the event of crop disorder incidents. Moreover, agricultural extension agents are reluctant to provide advice verbally without conducting a visual assessment of the symptoms of, or damage to, the plant [21]. Instead, they visit farms to make recommendations to farmers after observing the whole scene. It may take several days for the agents to visit the farms, depending on their workload and engagement with other activities and the distance to the farms. On the other hand, if farmers do not receive a response from reliable sources, they turn to unreliable sources such as agrochemical dealers, peer farmers, and their own experience (i.e., past experience with managing crop disorder incidents) to obtain relevant information. Finally, during the third stage, farmers again rely on their experience or other external sources to get information about the control measures and employ those to manage crop disorders and the related damage [12,22].

### *2.2. Impacts on Agriculture, Economic, Human Health and Environmental Sustainability*

The use of agrochemicals in Sri Lankan agriculture originated in the early 1950s, and the quantities used grew by nearly 110 times between 1970 and 1995 [23]. In addition, farmers in Sri Lanka use stronger agrochemical concentrations in an increased number of applications, and they mix various agrochemicals to improve resistance properties [24]. A study conducted among the upcountry farmers of Sri Lanka found that nearly 45% of farmers used higher agrochemical dosage levels than the prescribed quantity and at a higher frequency to ensure more reliable crop productivity results [25]. It was also found that farmers in the Vavuniya district in Sri Lanka have applied large amounts of agrochemicals for vegetable cultivation due to the susceptible behaviour of the crops to different crop disorder incidents [26]. Moreover, the study revealed that nearly 60% of farmers applied concentrations of agrochemicals that were 40% higher than the prescribed dosage level because they thought they would achieve a higher economic return by minimizing crop damages. Some farmers believed that agrochemicals were less productive and hence overused them, which led to environmental pollution, health problems, crop damages, and lower agricultural production [26]. In addition, as a precaution, farmers engaged in overdosage and frequent agrochemical application even before any crop disorder symptoms arose.

The health effects resulting from the application of agrochemicals form a significant health risk in most developing countries, and this problem shows no indication of decreasing [27]. Various field studies in Sri Lanka have shown that farmers have high morbidity rates due to the heavy usage of agrochemicals, with symptoms including headaches, feelings of being faint, nausea, and diarrhoea [28,29]. In general, the effects of agrochemicals develop in the human body in the short term and the long term [30]. Short-term symptoms, such as rashes and feeling faint, appear shortly after spraying. The delayed health hazards of agrochemical usage include cancer, kidney ailments, and vision problems. For example, a study carried out in Sri Lanka found that farmers using agrochemicals were at a higher risk of chronic renal failure [31]. Furthermore, agrochemical poisoning is a major reason that accounts for 60% of the suicide deaths in Sri Lanka [32].

From an environmental perspective, it has been estimated that more than 50% of agrochemicals used on crops miss their target and fall onto the surface of the soil [33]. Agrochemicals can easily mix with soil and water, and some chemicals can persist in the soil for many years. They can also be toxic to other living beings, such as birds, fish, beneficial insects, and non-target plants [14]. For example, the run-off of agrochemicals into water areas can affect aquatic animals by polluting groundwater and surface water sources. A study carried out in the Nuwara Eliya district of Sri Lanka revealed that milk samples collected from livestock consisted of different chemical components due to the feed for the livestock had traces of agrochemicals [34]. Furthermore, in Sri Lanka, it has been the long-held practice of farmers to apply agrochemicals in the first appearance of crop disorders due to the fear of potential crop losses, even though it is not required. Unnecessary application of agrochemicals affects the quantity and quality of the harvest, resulting in low prices for the products and a lower income for the farm household [35].

On the other hand, the indirect costs of agrochemical usage are high due to the damage that occurs in relation to agricultural production, such as costs relating to hospitalization, doctor consultations, specific dietary requirements, and hired labour due to the difficulties of farmers working during sick days. According to a study, in 2000, the estimated hospital-related cost of farmers' susceptibility to agrochemicals in Sri Lanka was on average equal to about a month's profit (USD 30) [36]. Furthermore, in developing countries, the economic consequence of agrochemicals specific to non-target species has been valued at approximately $8 billion per year [35].

As evident through the above findings, the present situation in Sri Lanka specific to crop disorder management has imposed so many challenges in achieving sustainable economic, social, and environmental development of the country. Developing an effective crop disorder management process will help farmers respond to crop disorder incidents more effectively and achieve healthy living conditions of communities, a non-toxic environment, stable income opportunities for farmers, increased agricultural productivity, reduced losses and cost, and many others.

### 2.3. Challenges of the Crop Disorder Management Process

To manage crop disorder incidents in the field, reliable identification of relevant crop disorders is crucial. At the first instance, we, as a research team, conducted a thorough study of the crop disorder identification process by continuously interacting with subject experts. Elaborating on the discussions with the subject experts, we carried out a causal analysis to identify different entities involved in the crop disorder identification process and associated relationships between the entities. The resulting causal map is presented in Figure 1. The causal map also helped us visualize an overall picture of the problem domain and assisted in identifying the relevant challenges.

According to the identified causal map in Figure 1, a crop becomes prone to different crop disorders due to the influence of causal agents such as fungal, viral, bacterial organisms (collectively called pathogens), animal pests, and other reasons such as chemical toxicity, weeds, and mechanical damage. Similarly, crop disorders can be grouped as diseases, pests, nutrient deficiencies, and disorders due to extreme climatic conditions, usage of machinery and chemical toxicities. From the identified causal map, it is evident that a given crop disorder manifests different symptoms depending on the growth stage of the crop, crop variety, the development stage of the crop disorder, and where it is located in the crop. In addition to the nature of the problem domain identified from the causal map, the following challenges were also identified as part of the study that makes the crop disorder identification a more complex process:

- According to the causal map identified, obtaining symptoms-related observations present in the crops is crucial for the reliable identification of crop disorders. In practice, farmers are the main observers who sight the symptoms-related observations in the crops at the first instance. Hence, obtaining information about the exact depiction of the field observations from farmers is necessary. Uncertainties associated with the field observations may lead to incorrect identification of crop disorders. Furthermore, even with relevant field observations, identifying the right crop disorder is challenging because different crop disorders manifest different symptoms, and the crop disorder has to be identified from larger possibilities of crop disorders [37].
- The similarity of the symptoms between different crop disorders makes the identification even harder [38]. That means, regardless of the causal agents, some crop disorders exhibit common symptoms. This is illustrated in the identified causal map, where Pest 1 exhibits Symptom 2, and Symptom 2 is also common to Disease 2. In the real world, as an example, yellowing of leaves is a common symptom found in many crop disorders and is caused by different causal agents, such as fungal, bacterial, viral, and nutrient deficiency [39]. Hence, in such cases, the common symptom would not help to identify the right crop disorder due to its common presence among different crop disorders.
- The number of causal agents that can infect a plant and cause crop disorders is usually higher in practice. Therefore, one important challenge to be addressed is the ability of the solution to identify all possible crop disorders specific to a crop.
- Sometimes, multiple crop disorders may manifest concurrently on the plant result in complications in crop disorder identification [38,40,41]. This situation arises because when one causal agent weakens a crop's immune system, different crop disorders can easily infect that crop.
- As identified in the given causal map, in practice, symptoms with respect to a crop disorder may appear on different parts of the crop, such as the flower, leaf, stem, and many others, and similarly, the symptoms also vary according to the crop's growth stage and development stage of the crop disorder. Therefore, crop disorder identification should be intended to identify crop disorders from symptoms that appear on any part of the crop, any growth stage of the crop, and the development stage of the crop disorder.
- In some instances, crop disorder identification is carried out based on the scent feature of the symptom [42], and this challenge also needs to be addressed.

- Advising farmers with recommended and time-specific responses about the control measures concerning the crop, human health, and environmental safety aspects is also a challenge, as discussed in Section 2.2.

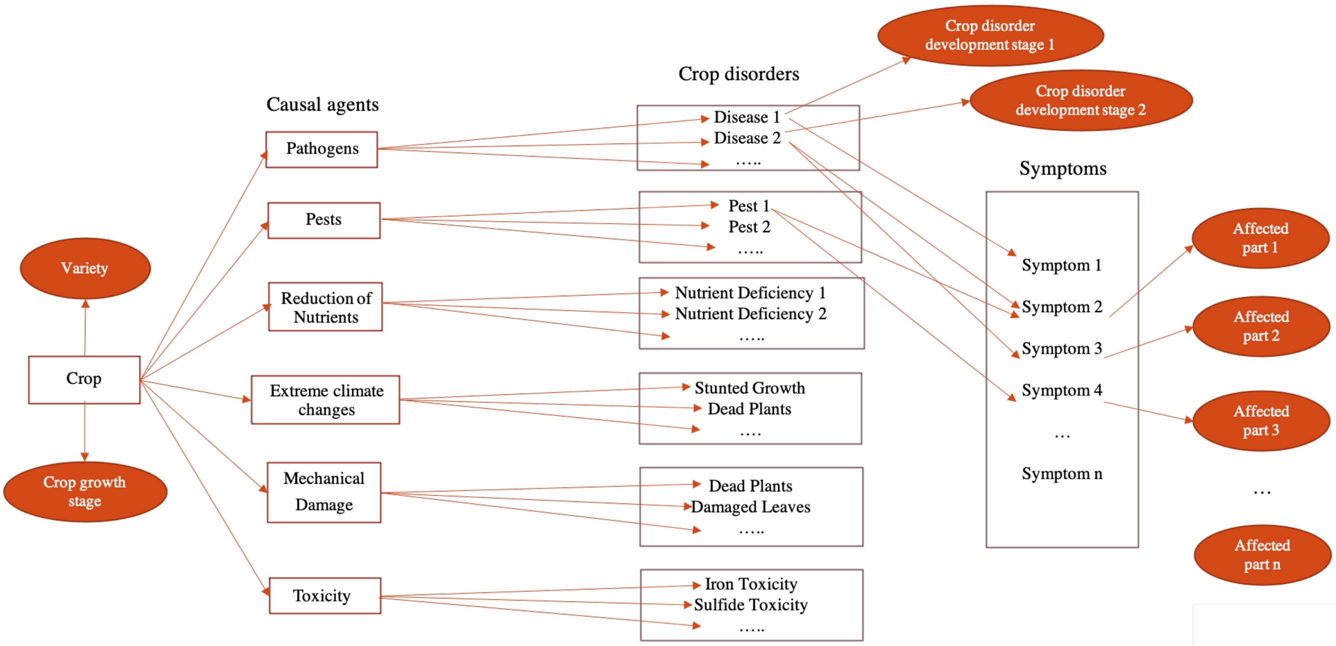



**Figure 1.** Causal map.

### *2.4. Limitations of Existing Attempts in Crop Disorder Management*

Several attempts have been reported in the literature to provide limited support in identifying crop disorder incidents and, in turn, to help farmers employ recommended control measures. These attempts provided limited support and were not considered as reliable solutions mainly due to not addressing the above challenges as identified. As discussed, obtaining correct field observations from farmers is the initial and critical step in the crop disorder identification process; accordingly, part of the reported approaches in the literature was mainly based on farmers transmitting field observations in the crops as images to laboratories for manual identification by the subject experts [43,44]. This approach is not effective because the process of crop disorder identification becomes challenging when these images do not depict the actual conditions in the field or time delays in processing a large volume of crop disorder incidents reported by farmers. As an alternative, in some instances, the subject experts visit the farm fields and prescribe the recommended control measures to farmers based on the field conditions [45]. In practice, this is a slow process that might cause delays, thereby hindering farmers' ability to take timely preventive measures. Given this scenario, it is important to develop strategies to identify crop disorder incidents rapidly and reliably.

With the advancements in ICTs, in recent times, researchers have focused on developing rigorous image processing and machine learning models to rapidly identify crop disorders from the images obtained from the farmers. Accordingly, a common approach that was emerged within the research community was to carry out the crop disorder identification in two steps: (1) symptom identification and (2) crop disorder identification. Here, the output of step 1 was used as the input to step 2 to identify relevant crop disorders. However, the reported approaches in the literature we reviewed so far used images that depict the field observations as the primary input to carry out the crop disorder identification process. The image processing techniques such as smoothing, colour transformation, and segmentation of images were used to identify symptom features from those images, and machine learning-based models were used to identify crop disorders based on the identified symptom features. Table 1 presents a few of such approaches reported in the literature.

**Table 1.** Techniques reported in the literature to identify the presence of crop disorders in plants.

| Study | Input Used | Problem Identified | Symptom Identification | Crop Disorder Identification |
|---|---|---|---|---|
| [46] | Images | Pomegranate diseases (Bacterial Blight and Wilt Complex) | SVM-based classifier to recognize the symptoms from the images using the colour and texture of the affected area on leaves. | A back propagation-based neural network was developed to identify different types of pomegranate diseases from the identified symptoms. |
| [47] | Images | Spot-based diseases on leaves | Image processing-based colour transform approach was used to highlight disease spots on monocot and dicot plant leaves. | Disease spots were classified based on their shapes by applying an image threshold technique called OTSU threshold. |
| [48] | Images | Fungal diseases in arable crops | A remote sensing system was developed and carried by tractors or robots to capture images. Hyperspectral reflection and multiple spectral imaging techniques were used to highlight symptoms. | A neural network-based model was developed to predict the presence of diseases or plant stresses from the collected images. |
| [49] | Images | Lemon citrus canker disease | A k-means clustering method was used to segment the region of concern, and a grey-level co-occurrence matrix was used to decide on the features. | An SVM-based classifier was used to detect images with canker leaf disease. |
| [50] | Images | Whitefly detection | Image pre-processing techniques such as smoothing and colour transformation were used to highlight the symptoms. | A machine learning-based classifier was developed to classify the images to identify the presence of whitefly. |
| [51] | Images | Olive leaf spot disease | Image pre-processing techniques such as smoothing and colour transformation were used to highlight the symptoms. | Fuzzy c-mean clustering and k-means clustering were used in the region of interest in the images to determine the defect and the classification of the detected disease. |

Upon reviewing these approaches, we found that these approaches have focused on identifying a specific crop disorder or a subset of crop disorders instead of all possibilities linked to a crop, and this is too limited in practice [52]. Similarly, as crop disorder manifests different symptoms depending on the growth stage of the crop, the development stage of the crop disorder, and where it is located on the crop, the reported approaches were focused on identifying crop disorders only based on a specific part of the crop. Notably, such attempts have not considered different parts or growth stage of the crop and the development stage of the crop disorders. Further, from a technical perspective, preparing and collecting samples concerning the symptoms of a crop disorder in different parts of the crop is challenging in terms of effort and cost [53]. From a different perspective, image-based techniques and machine learning-based models become obsolete when identifying crop disorders with the symptoms in those crop disorders look similar when concurrent crop disorders present at the same time or identifying crop disorders based on the scent feature of the symptom. As one example, the authors in a study observed that the symptoms used to identify different crop disorders in soybean seeds look very similar, and their model could not distinguish them [54]. From the approaches presented in Table 1, it is not evident whether these aspects have been considered in the reported solutions.

From an extrinsic point of view, identifying crop disorders using images has several challenges in terms of the accuracy of the identification. According to the authors in a study, the image processing technique can be defined as manipulating the inherently multidimensional signals [55,56]. The activities involved in image processing include transmission, enhancement, restoration, and recognition. However, many challenges associated with these activities remain unresolved. In enhancing an image, one aims to process an image to improve its quality due to many possible degradations such as low contrast, noisy behaviour, and blurriness. Over time, many algorithms have been proposed by researchers to eliminate these degradations. However, the major challenge is to eliminate degradations without damaging the multidimensional signals [56]. This situation becomes even worse when the image is severely degraded. For example, the application of noise-reduction algorithms is typically used when smoothing an image, but this can also blur the edges of the image.

Another limitation associated with the approaches reported in the literature is the difficulties in making them operate under different practical settings. A model is currently developed, trained, and evaluated on a dataset that is divided into training and validation datasets. Therefore, the training and validation datasets will have the same characteristics, as both are sampled from the same dataset with common imaging conditions. However, in practice, the actual images may appear different from those used in the training and validation stages. For example, the actual image may vary in angles, zoom level, light conditions, scales, content configurations, and camera settings instead of the configurations used while developing the model. A study showed that the difference in the properties of a dataset would significantly reduce the accuracy of image recognition algorithms [54]. Thus, even with the use of more sophisticated techniques, image processing techniques still cannot be used in many situations and are error-prone to many factors, as mentioned. Besides, in the reported studies, the farmers' abilities in terms of their experience were wholly disregarded. As correct identification of field observations is the crucial step in the crop disorder identification process, and the farmers are the ones who see such observations in the field initially, disregarding this aspect and fully relying only on images in the crop disorder identification process may extensively affect the correctness of the solutions. This is mainly due to the challenges associated with the problem domain and the practical limitations of image processing-based techniques, which in turn affects crop disorder identification. Henceforth, there is a need to figure out an effective approach to identifying crop disorder incidents from field observations by addressing the underpinned challenges.

## 3. Research Approach

The recent studies conducted on assessing the usage of smartphones by the farmers revealed that the application of mobile technology could be a potential tool to assist farmers in making optimal and quick decisions [57–61]. Moreover, inspired by the rapid growth of mobile phone usage in Sri Lanka, including farming communities, a mobile-based artefact was selected as the proposed artefact in this study to support farmers in effectively managing crop disorder incidents [62]. However, when designing an artefact, investigating and exploring different methodologies and selecting the most suitable one is an essential step to shape up the proposed artefact, and this adds value to the work in many ways [63]. Notably, it makes researchers aware of certain dos and do nots in research and the different techniques that can be used to collect and analyse data and evaluate the results. Accordingly, this study consisted of a number of research challenges from the perspective of researchers. The identified research challenges are:

- During the initial stage of the experiments, the farmers could not interpret the challenges they face precisely, resulting in requirements evolving iteratively.
- The crop disorder management process is a complicated topic, thus leading to more detailed sub-problems.
- The solutions proposed in the literature were designed and evaluated in limited practical scenarios, and a need has emerged to design a solution with wider applicability.
- Researchers require continuous interactions with farmers, agriculture extension agents, entomologists, and pathologists while researching the problem domain, building and evaluating the artefacts.

In the literature, problems with the above characteristics are known as wicked problems [64]. Finding a solution to such problems requires active interactions between researchers and end-users to understand the problem within its environment better. Therefore, researchers should select the research methodology based on its ability to solve wicked problems, support users' active collaboration, and encourage the development of an ICT-based intervention with an iterative nature. According to a research study, Action Design Research (ADR) attempts to solve wicked problems encountered in a specific organizational setting by intervening, constructing, and evaluating an artefact that addresses a class of problems typified by a situation [65,66]. Accordingly, this research employs ADR as the research methodology based on its benefits and flexibility concerning the characteristics of the problem domain. As the first step, an international collaborative research team was formed, which consisted of subject experts, including ICT scientists, agriculture extension agents, agriculture entomologists, pathologists, and socio-economists. Then, the research begins with a preliminary investigation and articulation of the problem, followed by iterative and cyclic design and development of the proposed artefact, and then reflection and research synthesis. The research design with respect to crop selection, study area, participants and sampling method used in this study is described below.

### *3.1. Crop Selection*

Crops were chosen mainly based on subject experts' opinions, focusing on those with the extensive application of agrochemicals. Even though high agrochemical usage can be seen in many food crops, specific factors such as the deployment convenience of the proposed intervention and closer distribution of farms in the identified study locations were considered to decide upon the study crop. Accordingly, the study was initially designed for paddy. Paddy production is the main cultivation in Sri Lanka, and farmers face crop losses at various stages of paddy cultivation [67]. Moreover, paddy is cultivated by the highest percentage of the farmers in Sri Lanka, which will pave the way to find participants for this study easily [68].

### *3.2. Study Location*

The selection of the study locations was based on climate vulnerability, agrochemical usage, and the extent of cultivation. Three Sri Lankan districts, namely Polonnaruwa, Kurunegala, and Matara, were selected as study locations to deploy the artefact among paddy farmers. Each district consists of multiple agrarian service centres (ASCs) that provide extension services to farmers with the support of extension agents. Farmers were attached to each ASC depending on the location of their farm fields. Thus, two ASCs from each selected district were chosen in consultation with subject experts and agriculture extension agents concerning the extent of cultivation carried out by the farmers.

### *3.3. Sampling Technique and Participants*

Given that a list of farmers can be obtained from relevant ASCs, the information about the farmers who use smartphones or are exposed to mobile phone usage was not available; thus, the non-probability sampling method was chosen as a sampling method to choose participants who use smartphones and willingness to support this exercise. On the other hand, probability sampling could not be applied because it was difficult for the research team to give farmers an equal chance of being selected within the total population. From a theoretical perspective, all farmers were potential respondents; however, it was difficult to identify the appropriate participants. Therefore, the snowball sampling technique was used to determine the number of required participants. In this technique, the study begins with only a few farmers who then ask other farmers to join the sample group.

In terms of the participants, it was essential to select progressive farmers who had experience with and exposure to ICT-based tools and who can support this exercise. In general, a large sample size ensures higher accuracy of results and a better balance between the proportion in the sample and the population [69]. However, some crucial factors can restrict the findings as a result of the sample size, such as time and resource constraints [70]. For these reasons, researchers may conduct research that is on a small scale and that consists of a sample size of 30–250 participants [69]. Accordingly, with the available resources, the research team selected 60 paddy farmers from each district (a farmer may belong to any of the district's ASCs); thus, the entire sample consisted of 180 paddy farmers. In Sri Lanka, farmers cultivate paddy during two monsoon seasons, called Maha (September to March) and Yala (May to August) [71]. For this research study, the Maha season of 2019/2020 was the period in which the solution was deployed among the farmers for practical use.

## 4. Evolution of the Artefact

Designing a solution to address the challenges identified in the crop disorder management process as discussed in Section 2.3, at the same time, meeting the exact requirements of farmers is a complicated task. However, putting the expectations of farmers first will assure that these needs are fulfilled. Based on the findings and the nature of the study, a list of requirements was identified as follows that need in-depth review to design a robust solution:

- Concerning the complications identified in the crop disorder identification process, field observations such as the growth stage of the crop, affected part, and the symptoms present in the crop must be appropriately captured from farmers to find out the correct crop disorders. Henceforth, a way to capture the field observations must be investigated in the first instance, followed by crop disorder identification.
- Sometimes, due to the complicated behaviours associated with crop disorders and relevant field observations, the involvement of subject experts may be required to identify crop disorders manually. This will certainly result in loss of full automation; however, this may be necessary for the reliable identification of crop disorders.
- Farmers must be advised of the cause of the damage and the recommended control measures to be taken in a timely manner.

Based on the requirements captured, a conceptual solution linked to the crop disorder management process was developed. This is presented in Figure 2. The conceptual solution consists of three components, namely, symptom identification (A), crop disorder identification (B), and recommending control measures back to farmers (C). The identified components were further investigated to identify specific information needs, and these are detailed in the following sections. Moreover, the study was designed to incorporate the information about the fully developed crop disorders initially; however, the proposed conceptual model could also be extended to include the information about the crop disorders that are in different development stages. Notably, the identified requirements were also used to populate a list of interface requirements for the end-users considering the usability of the solution.

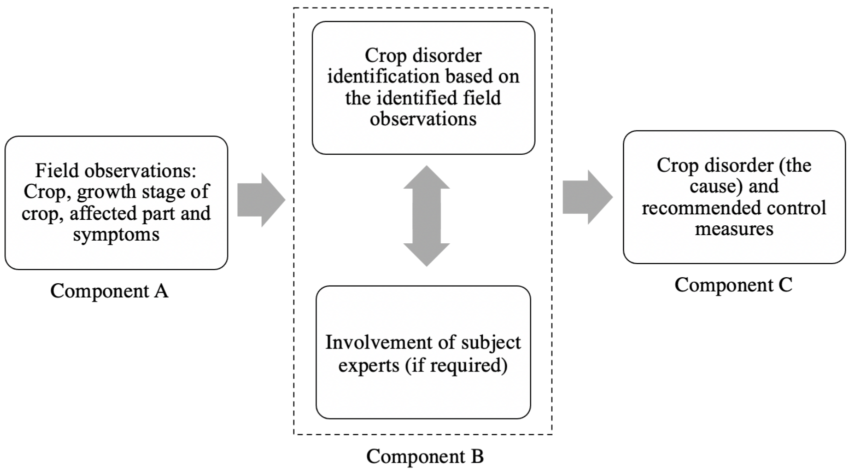



**Figure 2.** Conceptual solution proposed for crop disorder management process.

### *4.1. Component A: Symptom Identification*

As identified from the causal map depicted in Figure 1, a crop disorder specific to a crop may manifest different symptoms depending on the growth stage of the crop, the development stage of the crop disorder, and where it is located in the crop, and these symptoms have their own specific characteristics. For example, fully-developed rice blast disease in paddy (the crop is in the vegetative growth stage) expresses lesions with whitish centres with red margin on the leaves. Likewise, fully-developed bacteria leaf blight disease in paddy (the crop is in the vegetative growth stage) expresses a mix of yellow and orange colour lesions. Here, we introduce the concept of symptom class in streamlining the symptom identification process. The symptom classes can be defined based upon the characteristics of the symptoms of each crop disorder. Even though the appearance of the above two symptoms is different, these two symptoms hold a common characteristic: lesion type symptoms. Hence, these two symptoms can be grouped as elements of a symptom class. We define this class as lesion. Another example is that the paddy exposed to nitrogen deficiency manifests a symptom similar to folded leaves. At the same time, due to calcium deficiency, the crop manifests curled leaves. Thus, the symptoms of folded leaves and curled leaves can be grouped as elements of another symptom class. We define this class as distorted leaves.

Sometimes, symptom classes may also hold some features attached to those. For example, the lesions of rice blast disease are spindle-shaped ones with a random appearance on the leaves. Similarly, the lesions of bacterial leaf blight disease are stripe-shaped ones with their appearance in the tip of the leaves. Based on this, we found that lesion-type symptoms exhibit a set of feature attributes such as the shape of the lesion, the lesion's distribution pattern, and the colour of the lesion. Accordingly, the symptom class lesion that was defined earlier was extended to hold the above specific feature attributes. As an example, the symptom class lesion of rice blast disease will have the values of the feature attributes being, shape: spindled-shaped, distribution pattern: random distribution, and color: whitish centres with red margin. Similarly, the symptom class lesion of bacterial leaf blight disease will have the values of the feature attributes being, shape: stripe-shaped, distribution pattern: tips of the leaves, and color: mix of yellow and orange. On the other hand, there are also symptom classes that do not hold any specific feature attributes. For example, the symptom class distorted leaves holds different elements within that symptom class such as folded leaves, curled leaves, elongated leaves and many others and notably, these distortion-type symptoms do not manifest any feature attributes. Thus, feature attributes are not required to be defined for this symptom class. Conclusively, feature attributes are defined for a symptom class if that class manifests multiple features only (more than one feature attributes). The visualization of the above findings is given in Figure 3, and the image depicts a few of the symptoms that can be seen in paddy and how these symptoms are related to different symptom classes.

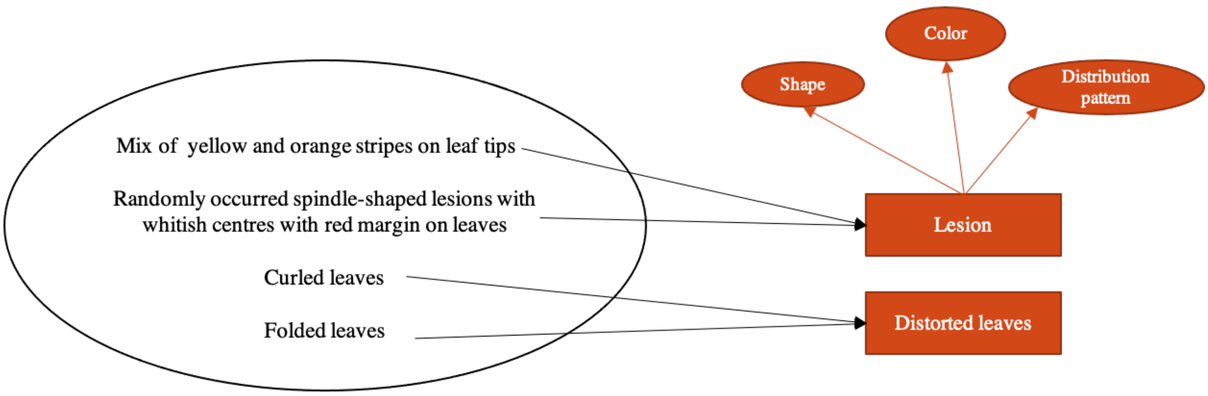



**Figure 3.** Association between symptoms and symptom classes for real-world scenarios.

We then generalized the relationship between symptoms and symptom classes as presented in Figure 4. The generalized outcome represents the symptoms and the symptom classes of fully-developed crop disorders, which appears in a particular growth stage of a crop. In the given Figure 4, $s_1, s_2, \ldots, s_n$ represents symptoms and each symptom belongs to a corresponding symptom class. Further, in the figure, it is also shown as the symptom $s_1$

belongs to *Symptom class 1*, and *Symptom class 1* consists of two feature attributes: *Attribute a* and *Attribute b*. Similarly, $s_2$ belongs to *Symptom class 2*, and this symptom class does not have any feature attributes. Accordingly, we identified the possible symptom classes specific to paddy and the associated feature attributes of the symptom classes (if they exist). This is followed by the symptoms manifested by the possible crop disorders in paddy that were identified and assigned to the relevant symptom classes. Finally, the symptoms identified within the symptom classes were given identifiers in such a way to identify the symptoms within the symptom classes uniquely concerning different crop disorders. Table 2 lists the possible symptom classes identified for paddy, along with the associated feature attributes and possible elements of each symptom class.

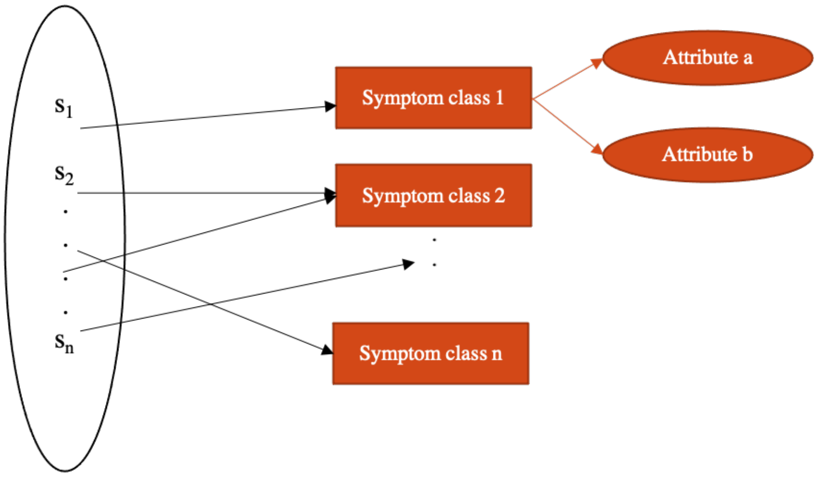



**Figure 4.** Association between Symptoms–Symptom classes.

**Table 2.** Possible symptom classes, the feature attributes and the relevant symptoms identified for paddy.

| Symptom Classes | Symptoms |
|---|---|
| A. Abnormal color | Yellowish green appearance (A1), Yellow appearance (A2), Brown appearance (A3), Black appearance (A4), Light Brown appearance (A5), Grey appearance (A6), White appearance (A7), Green appearance (A8) |
| B. Abnormal growth of plant | Stunted/short (B1), Bigger than normal (B2) |
| C. Cut stems/leaves | Irregular cut (C1), Cut at nodes (C2), Cut at 45 degree (C3), Cut at right angles (C4), Cut at seedlings (C5) |
| D. Bacteria ooze | Bacteria ooze come out (D1) |
| E. Dead plants | Fully dead plants (E1), Partially dead (E2) |
| F. Discolouration on seeds | Brown appearance (F1), Yellow appearance (F2), White appearance (F3), Black appearance (F4) |
| G. Abnormal grain production | Empty grains (G1), Partially filled grains (G2), Failed to produce grains (G3), Low quality grains (G4), Reduced grains (G5) |
| H. Fungal growth | Observable and sooty mold is present (H1), Observable and sooty mould is not present (H2) |
| I. Abnormal root growth | Enlarged (I1), Reduced (I2), Damaged roots (I3), Galls on roots (I4) |
| J. Appearance of excess instances | Spore instance (J1), Presence of velvety smut balls on spikelets (J2), Active burrows (J3), Footprints of rice field rats (J4), White powdery fungal growth (J5) |
| K. Webbing | White coloured presence of webbing (K1) |
| L. Distorted leaves | Elongated (L1), Dropping (L2), Thin/narrow leaves (L3), Hollow tube look (L4), Curled (L5), Wider/big leaves (L6), Folded (L7), Dry leaves (L8), Crinkled leaves (L9), Tiny holes (L10) |

**Table 2.** *Cont.*

| Symptom Classes | | Symptoms |
|---|---|---|
| M. Lesion | M1. Color | Brown appearance (M1-1), Yellow-Orange appearance (M1-2), White appearance (M1-3), Whitish to grey centres with red to brownish border (M1-4) |
| | M2. Shape | Spindle-shaped (M2-1), Linear (M2-2), Spots (M2-3), Circular Irregular or oblong patch (M2-4), Oval (M2-5), Streaks (M2-6), Stripes (M2-7) |
| | M3. Distribution pattern | Tips of the part (M3-1), Side of the part (M3-2), Middle part (M3-3), Parallel to vein (M3-4), Uppermost part (M3-5), Random (M3-6) |
| O. Wilting | | Observable and plant can be easily pulled out (O1), Observable and plant cannot be easily pulled out (O2) |
| P. Tillering | | Excessive (P1), Reduced (P2), Re-tillering (P3) |
| Q. Chlorosis | | Severely occurred (Q1), Moderately occurred (Q2), Randomly Occurred (Q3) |
| R. Dead hearts | | Severely occurred (R1), Moderately occurred (R2), Randomly Occurred (R3) |
| … | | … |

### *4.2. Component B: Crop Disorder Identification*

Concerning the progress made so far, the following activities were carried out to model the crop disorder identification process. According to the generalized relationship derived through Figure 4, one crop disorder may be linked to many symptom classes. At the same time, one symptom class will become relevant to many crop disorders. Moreover, crop disorders also manifest different symptoms depending on specific factors such as the growth stage of the crop, development stage of the crop disorder and affected part; henceforth, these factors were considered whilst developing the model. Accordingly, a model was constructed as given in Table 3 that represents the mapping of crop disorders that are specific to a particular growth stage of the crop against the symptom classes. The information about the affected part of the crop is included as a column dimension in the proposed model, and the crop disorders that are in different development stages will be incorporated as new rows. The proposed model, therefore, can be considered as a crop disorder search space of a crop that is in a specific crop growth stage. Similarly, different search spaces can be produced based on different growth stages of the crop. Notably, to narrow down the size of the crop disorder search space, information such as the crop, growth stage of the crop, and affected part will be used.

**Table 3.** Generalised structure of the crop disorder search space for a crop in a specific crop growth stage.

| Crop Disorder | Affected Part | Symptom Class 1 | Symptom Class 2 | Symptom Class 3 | | …… |
|---|---|---|---|---|---|---|
| | | | | Attribute 1 | …… | |
| Crop disorder 1 | Affected part 1 | | | | | |
| Crop disorder 2 | Affected part 2 | | | | | |
| … | … | | | | | |
| … | … | | | | | |
| Crop disorder n | … | | | | | |

Based on the generalized structure derived, the crop disorder search spaces that are specific to paddy (for different growth stages of paddy) were constructed with actual values for rows being possible crop disorders and columns being the affected part and the symptom classes as identified. If a crop disorder gets related to a symptom class, then the suitable symptom from that symptom class gets mapped to that crop disorder. This is because a crop disorder has symptoms only with respect to some symptom classes. On the other hand, if a crop disorder does not manifest any symptoms from a symptom class, then the cell value will be kept blank. For simplicity, a crop disorder search space that depicts the mapping between the crop disorders of paddy that is in the vegetative growth stage and only the relevant symptoms of the symptom classes is presented in Table 4. Here, if a symptom of a symptom class is linked to a crop disorder, then this information is represented in the given Table as *symptom class -> symptom*.

**Table 4.** Crop disorder search space for sample crop disorders in paddy that is in the crop growth stage of vegetative.

| Crop Disorder | Affected Part | Relevant Symptoms from the Identified Symptom Classes |
|---|---|---|
| Rice blast | Leaves | {E ->E2}, {M ->M1-4, M2-1, M3-6} |
| Thrips | Leaves | {E ->E2}, {L->L4}, {M ->M1-3, M2-6, M3-4} |
| Stem borer | Stem | {L->L10}, {K ->K1}, {N ->N1}, {Q ->Q1} |
| Bacterial leaf blight | Leaves | {D ->D1}, {M ->M1-2, M2-7, M3-1}, {N ->N1} |
| … | … | … |

Although a crop disorder may be attached to many symptom classes in the populated crop disorder search space, it is also found that one symptom or a combination of some symptoms from different symptom classes would provide a unique search space particular to a crop disorder. For example, rice blast disease in paddy manifests spindled-shape lesions with whitish to grey centres and red to brownish margins; this symptom is unique to rice blast disease and can be used to distinguish it from other crop disorders. Hence, it is not necessary to consider all the symptoms relevant to the combination of the symptom classes; instead, the unique symptoms of specific symptom classes would be sufficient to determine the cause of crop disorder. Accordingly, such symptoms with a unique search space are presented in Table 5 as bold text. As a result, the effort required to identify the crop disorders from larger possibilities was drastically minimized. In order to carry out the search operation in the crop disorder search space, information such as the crop, growth stage of the crop, affected part, and suitable symptoms that provide a unique search space must be captured from farmers. To obtain the symptoms that provide a unique search space from farmers, the relevant unique symptoms of different crop disorders were combined to a textual representation and presented through the mobile artefact. These combined representations were considered as the *identifiers* of the corresponding crop disorders. The resulted crop disorder identifiers of paddy, which is in the vegetative growth stage, are presented in Table 6. Similarly, if the symptoms of a crop disorder does not have any unique search space, then the cell value of the *identifier* of that crop disorder will be kept blank. With the proposed approach, the overall process of identifying crop disorders was simplified as the correct selection of the disorder identifier based on the field observations will spontaneously result in the relevant cause of crop disorder.

**Table 5.** Symptoms that are with unique search space specific to sample crop disorders.

| Crop Disorder | Affected Part | Relevant Symptoms from the Identified Symptom Classes |
|---|---|---|
| Rice blast | Leaves | {E ->E2}, **{M ->M1-4, M2-1, M3-6}** |
| Thrips | Leaves | {E ->E2}, **{L->L4}, {M ->M1-3, M2-6, M3-4}** |
| Stem borer | Stem | {L->L10}, {K ->K1}, {N ->N1}, {Q ->Q1} |
| Bacterial leaf blight | Leaves | {D ->D1}, **{M ->M1-2, M2-7, M3-1}**, {N ->N1} |
| … | … | … |

**Table 6.** Sample crop disorders with the corresponding unique identifiers.

| Crop Disorder | Affected Part | Relevant Symptoms from the Identified Symptom Classes | Disorder Identifier |
|---|---|---|---|
| Rice blast | Leaves | {E ->E2}, **{M ->M1-4, M2-1, M3-6}** | Spindle-shaped lesions with whitish to gray centers and red to brownish margin on leaves |
| Thrips | Leaves | {E ->E2}, **{L: L4}**, **{M ->M1-3, M2-6, M3-4}** | Leaves curled to the middle with white streaks parallel to vein |
| Stem borer | Stem | {L->L10}, {K ->K1}, {N ->N1}, {Q ->Q1} | N/A |
| Bacterial leaf blight | Leaves | {D ->D1}, **{M ->M1-2, M2-7, M3-1}**, {N ->N1} | Yellow-Orange color stripes on leaf blades or leaf tips |
| ... | ... | ... | ... |

From a technical perspective, empowering farmers to report the correct disorder identifier based on their field observations and finding out the relevant crop disorders largely addresses the overall challenges identified concerning crop disorder identification, as discussed in Section 2.2. However, on the other hand, if no relevant disorder identifier is chosen when comparing with the field observations, the instant identification of the crop disorders becomes impossible. Thus, the manual involvement of the subject experts such as extension agents, agriculture researchers, entomologists and pathologists was sought to figure out the exact cause by interacting with the farmers. Again, with this scenario, the proposed model can be a useful tool to assist the subject experts to initiate relevant discussions with farmers or to instantly eliminate the irrelevant possibilities as the knowledge required to identify relevant crop disorders from field observations is appropriately structured. The overall search logic that was used to reduce the crop disorder search space is depicted in Figure 5. Sometimes, there can be situations where more than one part of the crop gets affected or concurrent crop disorders present in the crop; if that is so, then the relevant choices must be selected concerning the severity of the visibility. In addition, the proposed model also carries some advantages specific to scalability aspects, as with this model, information such as the symptoms, symptom classes, and disorder identifiers of new crop disorders can be easily incorporated. Moreover, with the proposed model, the manual identification of crop disorders can also be automated as the information is stored in a structured manner results in timely identification of crop disorders.

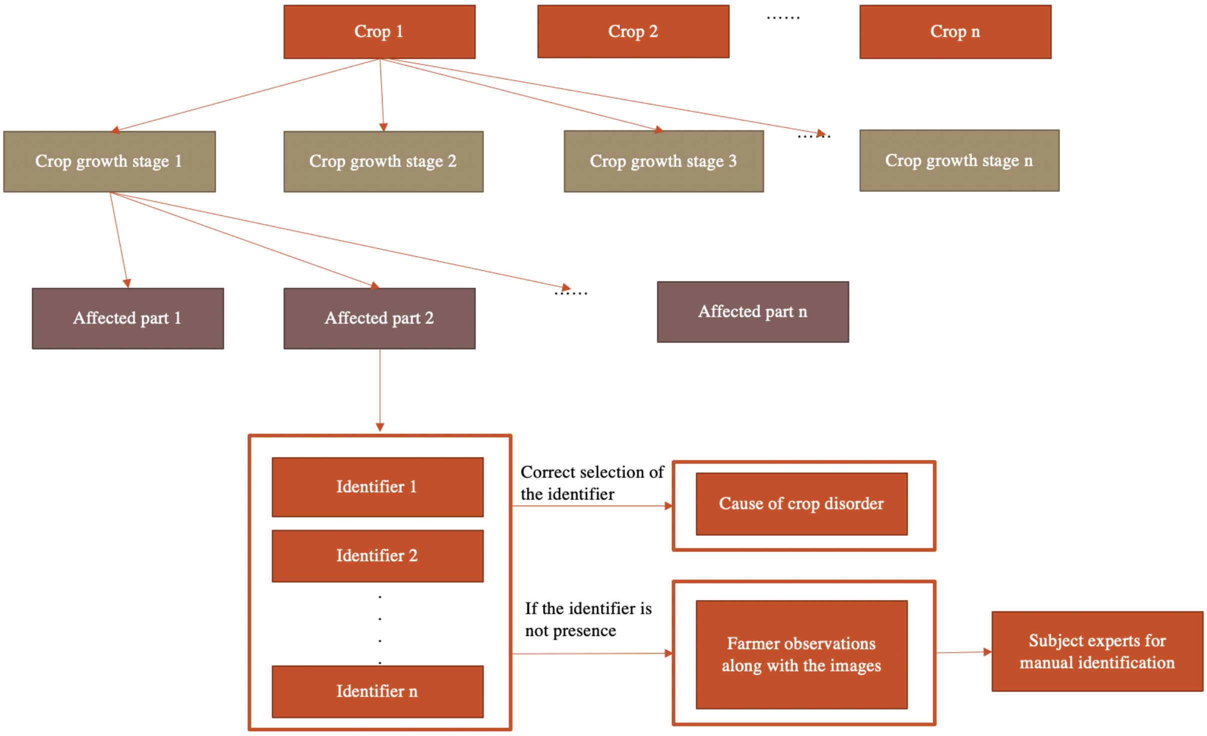



**Figure 5.** Search logic used to identify crop disorders from crop disorder search space.

### 4.3. Component C: Recommendation of Control Measures

The next step was to link recommended control measures to relevant crop disorders considering the current limitations associated with agrochemical handling of farmers, as discussed in Section 2.2. As a possible solution, the knowledge relevant to different control measures, namely, cultural, biological, mechanical, and chemical, and the corresponding application instructions were appropriately structured in a way that assists farmers in prompt decision-making. Further, to prevent the field from likely crop disorders in future, preventive control measures are also needed. Thus, the information about various preventive control measures of crop disorders was also included while structuring the remedial actions. Providing farmers with such enriched information helps them adhere to recommended control measures to manage crop disorders and, at the same time, help to safeguard the crops from likely crop disorders in the future. Table 7 abstracts different types of control measures and the associated recommendations considered with each type in the proposed artefact.

**Table 7.** Recommendations considered in the proposed artefact.

| Control Measure Types | Recommendations Considered |
|---|---|
| Cultural method | Adjust planting location, adjust timing intervals between activities, crop rotation, watering and fertilizing, growing competitive plants, and change cultivation techniques |
| Physical method | Place barriers and traps, physically remove affected plants, vacuum, heat treatments, and mowing |
| Biological method | Use of predators, parasites or microbial pathogens, encourage natural enemies by planting specific plants |
| Chemical method | Use of toxic-chemical substances along with the recommended dosage level, chemical handling and application instructions |

### 4.4. Artefact Development

The application of mobile-based artefact in the crop disorder management process is relatively a new concept to farmers. Hence, it was identified that the mobile interfaces should be appropriately designed with much care. Based on the design requirements identified for each component of the conceptual solution, the proposed model was mapped to separate mobile interfaces. The use cases, user actions and the corresponding system responses were also considered while developing mobile interfaces. Then, the mobile interfaces were shared within the research team for the purpose of assessing those concerning the elements included in the interfaces and their placement on the screen, colour selection, missing functionality, and overall simplicity. The initial mobile interfaces gave the research team an idea of how information flows within the proposed system, which enables them to make the best use of the available screen area and effectively capture user input. Throughout this research study, the team members of the research team were actively collaborated and participated in all the research activities, resulting in the requirements being fully captured and implemented during the initial development of the mobile interfaces itself, and there were no significant modifications suggested to the developed mobile interfaces. The part of the finalized mobile interfaces and the navigation flow between the mobile interfaces were categorized into three groups according to their functionalities and presented in Figures 6 and 7. The arrows in the figures represent the chronological order of the screens.

The mobile interfaces as presented in Figure 6 represent the highlighted feature of the proposed model and depict the information flow linked to capture the field observations from farmers. Initially, the user is presented with a list of crops and the varieties available (based on the geographical region) and the selected season as given in Screen 1 of Figure 6. Farmers can select any preferred crop and variety to grow. However, in this study, the choices related to paddy will be only shown. Based on the chosen crop and crop variety, the system generates a series of inbuilt selections as part of the crop disorder identification process. Accordingly, these inbuilt selections were identified as the growth stage of the plant, the affected part of the plant, and the observed disorder identifier (see Screens 2, 3, and 4 of Figure 6). Here, the choice that a mobile interface farmer selects would generate the dynamic outcome in the following mobile interfaces. The choices given to these selections by farmers are used to find out the relevant crop disorder in the crop disorder search space. Moreover, the choices for the selection of disorder identifiers make it more convenient for the user in selecting the right choice, as these choices represent a unique and consistent depiction of crop disorders present on the crop (see Screen 4 of Figure 6). Since these disorder identifiers are already linked to corresponding crop disorders and control measures, the correct selection of the disorder identifier from the list as in Screen 3 of Figure 6 exposes the user to know the cause of the problem and relevant control measures. The format of the control measures related to the identified crop disorder is presented in Screen 5 of Figure 6. The information such as a short description about the crop disorder and relevant control measures, including cultural, biological, mechanical and chemical, along with the relevant application instructions and preventive control measures, was included as part of the response back to farmers. In addition, farmers were also compelled to attach images of their field observations irrespective of relevant selection of disorder identifier for the evaluation purposes to understand up to what extent farmers can interpret the provided information with their field observation as depicted in Screen 1 of Figure 7.

On the other hand, the mobile interfaces that are presented in Figure 7 represent the information flow related to the manual identification of the crop disorder incidents by the subject experts. Suppose the user does not find a suitable choice out of the populated disorder identifiers (see Screen 4 of Figure 6) or difficulties in interpreting the provided information with their field observations; in that case, the farmer can manually feed the information relevant to their observations to the system through the given input fields as in Screen 1 of Figure 6. Here, farmers were asked to attach images of their field observations in addition to their field observation. As the next step, the reported incidents will be presented to the subject experts through a mobile artefact as in Screen 2 of Figure 7.

To assist subject experts in their decision-making, information such as crop and variety, the growth stage of the crop, affected part, observations related to the symptoms and images will be made available to them as a result of the user actions (see Screen 3 of Figure 7). Accordingly, the subject experts can decide on the relevant crop disorder based on the available information or interact with farmers to understand more about the field situation to get more clarity and to reduce the possibilities of misidentifying the crop disorder. To facilitate subject experts to interact with farmers, a two-way communication channel similar to an instant messaging system was developed as part of the functionality in the proposed solution. Accordingly, the subject experts can decide on the possible causes of crop disorders based on the responses provided by farmers via eliminating irrelevant possibilities (see Screen 4 of Figure 7). Finally, upon subject experts confirming the relevant crop disorders, the farmers will get the corresponding control measures similar to as in Screen 5 of Figure 6. The information presented in the proposed artefact also translated to the local language to support the language needs of the farmers concerning their literacy aspects.

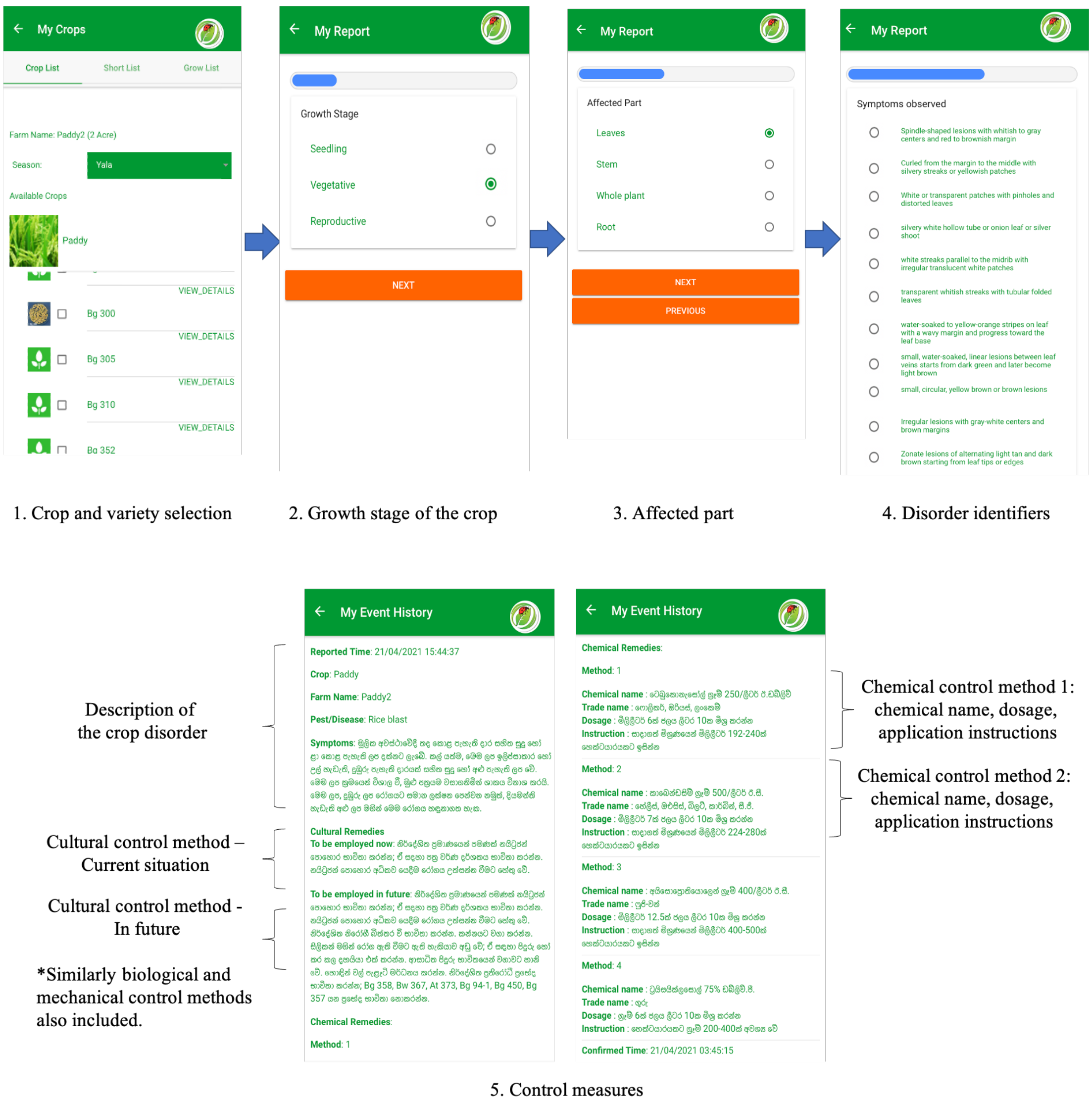
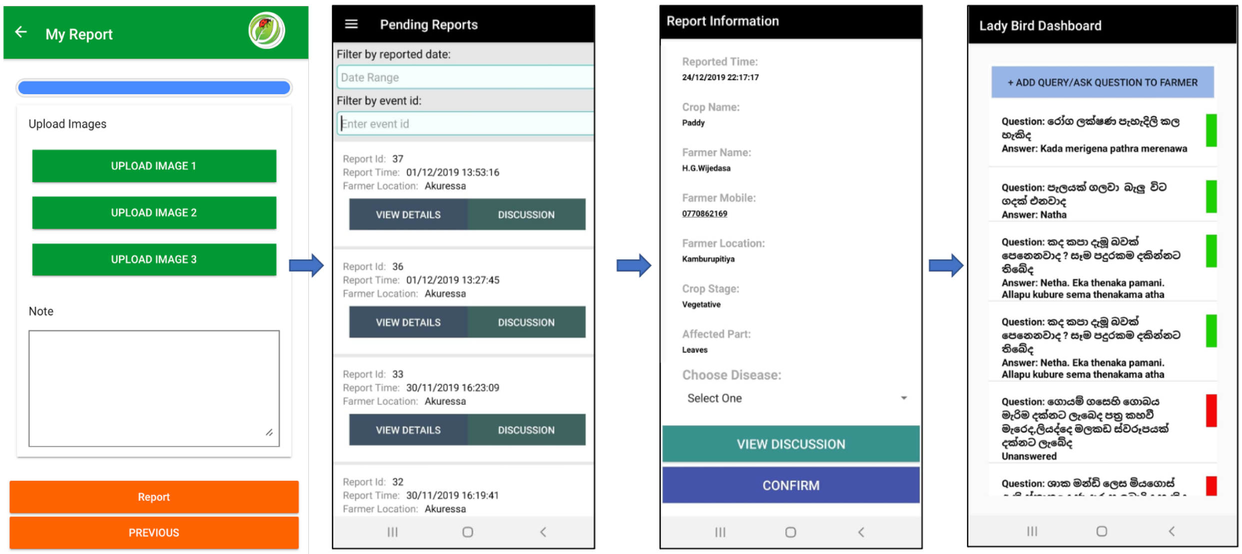



**Figure 6.** Information flow related to reporting crop disorder incidents and obtaining relevant control measures.




1. Image attachment and a note section | 2. Crop disorder reports | 3. Description of the reported crop disorder incident | 4. Two-way interaction between subject experts and farmers

**Figure 7.** Information flow related to manual identification of crop disorders by subject experts.

## 5. Results and Discussion

Providing farmers with information that assists them in making correct decisions is a crucial task. Therefore, the information presented through the proposed artefact must be clear enough for them to make correct decisions. However, the usability of the proposed artefact mainly depends on the extent to which farmers can interpret the provided information and select the correct choice of disorder identifier. In order to understand this measure, the opinions of subject experts towards their assessment of the reported incidents were collected and compared against the relevant output from the proposed model according to the chosen disorder identifiers by farmers. The primary purpose of this experiment was to determine how well the proposed model could replace the subject experts' abilities and assist farmers in identifying correct crop disorder incidents. Accordingly, of the total 74 reported incidents, 48 incidents were reported, with the relevant disorder identifiers being chosen by the farmers. The remaining incidents were reported without any disorder identifiers being selected. The major factor that limits the farmers from selecting the suitable disorder identifier was the difficulties in interpreting the provided information in text format and compare that with the field observations. Thus, the correctness of farmer selection was assessed only with the remaining 48 incidents. Of the 48 incidents, 14 incidents were reported by farmers with the wrong disorder identifiers being selected, resulted in a mismatch when compared with the choices made by the subject experts. Hence, the ability of farmers in selecting correct disorder identifiers was calculated as 70.8%.

Furthermore, to understand the usability aspects and the opinions towards the proposed artefact, a post-evaluation study was conducted among the participants. The post-evaluation survey was designed based on a set of qualitative indicators. The identified qualitative indicators are presented in Table 8, followed by the analysis of the results. The overall analysis of the results collected from farmers based on the above indicators (A-M) is presented in Figure 8. The farmers have claimed that they could access relevant information specific to recommended control measures such as different types of control measures, input requirements, and the appropriate application instructions on time without further delays as depicted under charts A and B of Figure 8. The timely delivery of such information encouraged the farmers to manage crop disorders on time and, at the same time, reduced the chances of being dependent on unreliable sources. Further, farmers also realized the importance of adhering to the recommended practices and, in return, reduce crop damages, increase income, and improve human and environmental safety.

This is evident through charts C and E of Figure 8. The farmers' opinions on yield increase and yield quality consist of mixed thoughts as depicted under charts F and G of Figure 8, and part of the farmers claimed that the overall yield quantity and quality have increased compared to their previous cultivation due to the reduced crop disorder incidents and reduced number of agrochemical applications. Further, some farmers have claimed that the increased yield quantity and quality depends on several other factors such as seed quality, suitable climatic conditions, timely application of fertilizers and many others, and they believe that the combination of the above factors collectively contributes to increasing the yield quantity and quality.

**Table 8.** Qualitative indicators used.

| **Qualitative Indicators of the Proposed Intervention** |
| --- |
| A. Obtaining the required responses in a timely manner and assisting in prompt decision-making |
| B. Assistance provided in the selection of recommended agrochemicals, dosage level and employment instructions |
| C. Applicability of the provided information in practice |
| D. Reduction in the number of agrochemical applications compared with previous seasons |
| E. Knowledge enhancement on IPM approaches |
| F. Increased crop yield compared with previous seasons |
| G. Increased yield quality compared with previous seasons |
| H. Reduction in the cost of agrochemicals |
| I. Increased profits as a result of reduced agrochemicals usage |
| J. Assistance provided in planning future activities to safeguard crops from potential crop disorders |
| K. Adaptation to the proposed intervention and willingness to share with others |
| L L. Perception of the application in terms of user-friendliness |
| M. Overall perception—use of the proposed intervention in managing crop disorder incidents |

Similarly, farmers' opinions regarding the expenses related to agrochemicals revealed that the overall expenses have significantly reduced compared to the previous cultivation seasons. This has resulted due to the reduced application of agrochemicals as depicted through charts D, H, and I of Figure 8. On the other hand, some farmers have mentioned that the expenses related to agrochemicals continue to be the same, and they did not see any significant changes. This is due to the potential fear of farmers concerning the crop losses, which pursued them to employ agrochemicals. Notably, having seen the positive outcomes and benefits of the proposed artefact, farmers pointed out that the proposed artefact can be considered as a potential tool that assists them in prompt decision-making in managing crop disorder incidents. Moreover, farmers also believe that the proposed artefact could attract many farmers, and they mentioned that the benefits they gained through the proposed artefact were remarkable. This is evident through the charts presented in J, K, L, and M of Figure 8.

In addition to the above, understanding the limitations of the proposed artefact and incorporating further refinements are important tasks to be performed before rolling out the artefact to a broader community. One of the important limitations identified was the incorrect selection of disorder identifiers by farmers from the selection as depicted in screen 4 of Figure 6. This has resulted in the wrong identification of the crop disorder and the wrong control measures. Upon analysing the attached images of the reported incidents, we found that, even though the suitable choices exist in the populated list of disorder identifiers, farmers have made wrong choices. Utilizing digital technology in the crop disorder management process is a relatively new concept to farmers. Even though the proposed artefact carries significant benefits regarding the overall crop disorder management, some farmers have faced difficulties in interpreting the provided information when comparing with the field observations. Hence, to minimize the chances of farmers making an incorrect selection of the disorder identifiers and minimize human errors, necessary refinements must be introduced to the existing design.

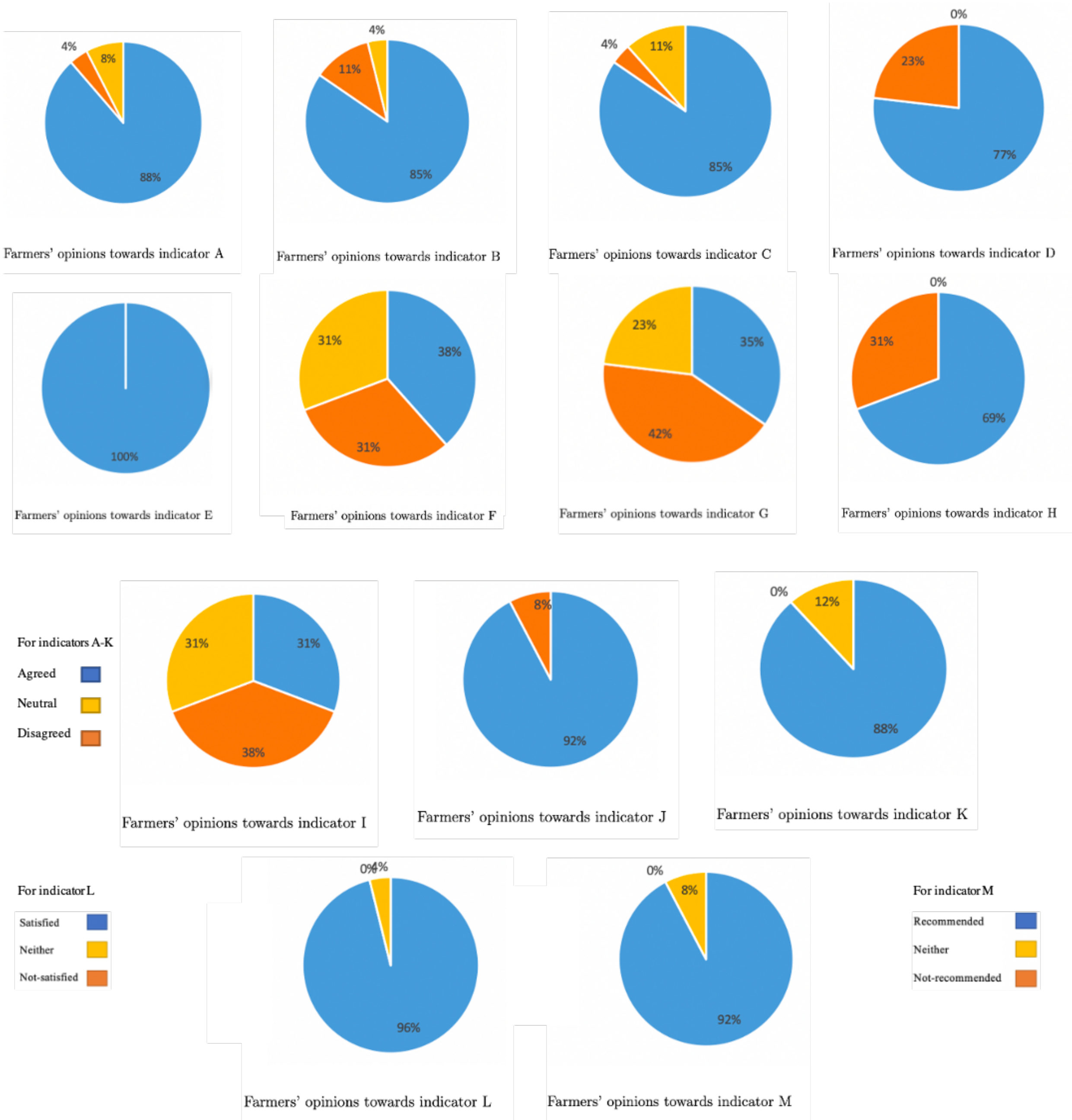



**Figure 8.** Summary of the farmers' opinions according to the identified qualitative indicators.

## 6. Refinements to the Artefact

Presently, the information relevant to the disorder identifiers is presented in textual format in the proposed artefact. Hence, as a possible improvement, a refinement was made to the existing design of the mobile artefact to include both text and images with an exact depiction of the disorder identifiers to assist farmers in selecting the correct choice. In general, providing a piece of information in the form of visual representation has several advantages, such as visuals convey more in-depth and detailed level information than textual representation, and the human brain can interpret visuals much faster compared to text [72]. Notably, this contrasts with the existing approaches reported in the literature where farmers have to provide images, and with the proposed approach, the farmer is shown with the disorder identifier along with the relevant images. Thus, farmers can use the combination of both text and images of the disorder identifier when deciding on a suitable choice. This helps to reduce the chances of farmers selecting incorrect choices. Accordingly, to reflect the proposed changes, the mobile screens were also modified as presented in Figure 9.

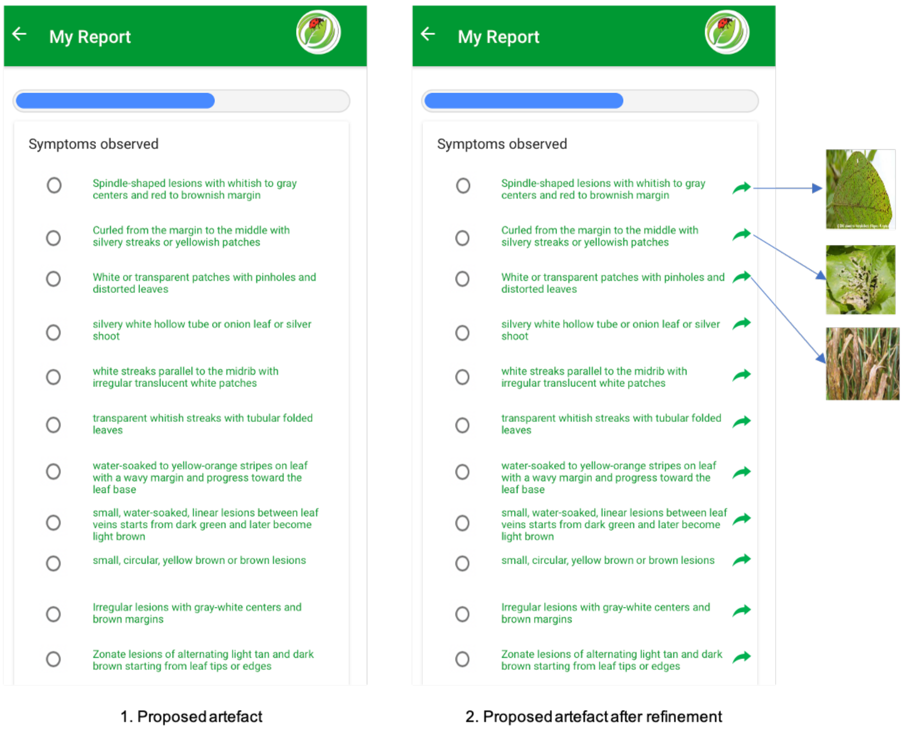



**Figure 9.** The implementation of both proposed artefact and revised version of the artefact.

Similar to the previous experiment, the revised version of the mobile artefact was also intended to be introduced among the selected sample. However, with the COVID-19 travel restrictions, we were compelled to select 20 new paddy farmers who live close to the research station to introduce the revised version of the mobile artefact. Accordingly, the new experiment is designed as follows, and the results of the experiment are presented in Table 9.

- Farmers were given both older and revised versions of the mobile artefacts to carry out the experiment.
- Twenty random images that depict different crop disorders were selected, and the farmers were instructed to use the older version of the mobile artefact as given under Screen 1 of Figure 9 to identify the suitable choices of disorder identifiers for each image. The same experiment was repeated with the revised version of the mobile artefact as given under Screen 2 of Figure 9. Further, the manual identification of crop disorders was disabled in both versions of the mobile artefact because the

used images in the experiment had their corresponding choices in the given list of disorder identifiers.
- The responses were recorded for both older and revised versions of the mobile artefacts and compared to see any positive outcome.

**Table 9.** Comparison of the results between older and revised versions of the mobile artefact.

| **Farmers** | **Older Version (Number of Correctly Identified Crop Disorders)** | **Revised Version (Number of Correctly Identified Crop Disorders)** |
|---|---|---|
| Farmer 1 | 15 | 17 |
| Farmer 2 | 14 | 16 |
| Farmer 3 | 10 | 15 |
| Farmer 4 | 11 | 12 |
| Farmer 5 | 13 | 17 |
| Farmer 6 | 9 | 13 |
| Farmer 7 | 13 | 17 |
| Farmer 8 | 15 | 18 |
| Farmer 9 | 9 | 13 |
| Farmer 10 | 9 | 11 |
| Farmer 11 | 15 | 17 |
| Farmer 12 | 6 | 11 |
| Farmer 13 | 12 | 13 |
| Farmer 14 | 13 | 14 |
| Farmer 15 | 13 | 15 |
| Farmer 16 | 11 | 12 |
| Farmer 17 | 9 | 13 |
| Farmer 18 | 11 | 14 |
| Farmer 19 | 10 | 13 |
| Farmer 20 | 12 | 15 |
| **Average** | **11.5** | **14.3** |
| **Correctness** | **57.5%** | **71.5%** |

As per the results, on average, the correct choices made by the farmers using the older version of the mobile artefact was 11.5 out of 20, and using the revised version of the mobile artefact was 14.3 out of 20. Upon calculating the correctness of both versions of the mobile artefact, the older version registers 52.5%, and the revised version registers 71.5%. Thus, presenting both visual and textual representation of the disorder identifiers has resulted in farmers making better decisions than presenting information in textual format alone. However, before making any conclusions, the relevant statistical test has to be performed on the data to make sure that the difference is not randomly occurred by chance and instead likely to be attributable to a specific reason. In order to perform a relevant statistical test, the data of both samples have to be normally distributed. Furthermore, the tests for normality can be performed through various techniques. Accordingly, the Anderson Darling test for normality was used in this experiment, and the outcome is presented in Figure 10. Further, the hypotheses for this statistical test were defined as follows:

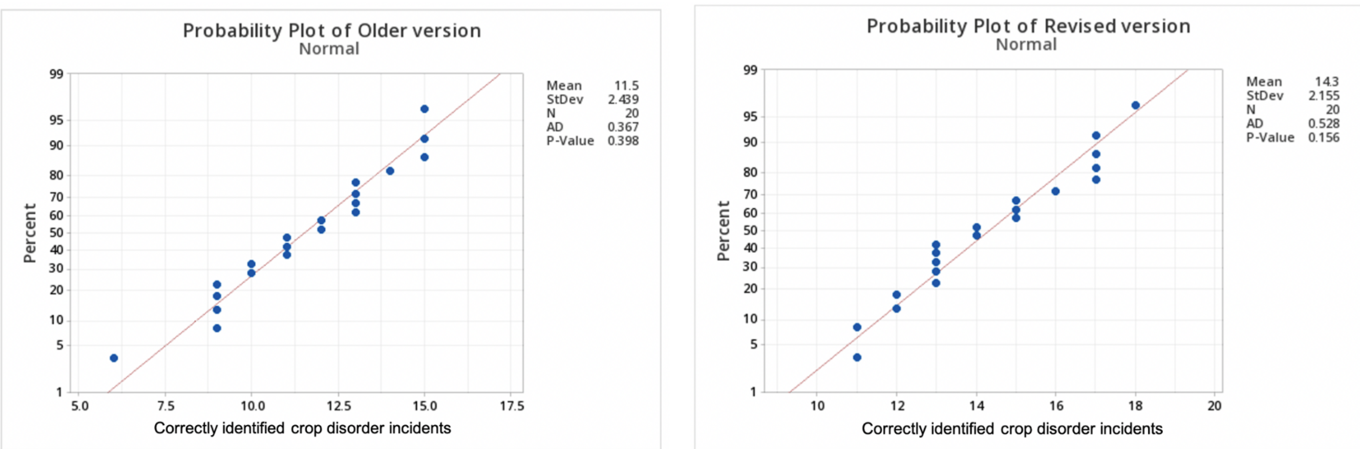
**Hypothesis 1.** *Null hypothesis ($H_0$): Data follow a normal distribution*

**Hypothesis 2.** *Alternative hypothesis ($H_1$): Data do not follow a normal distribution*

In these two outcomes, the p-values of the data in both samples are 0.398 and 0.156, which are greater than the significance level of 0.05. Hence, in both instances, we cannot reject the null hypothesis (Hypothesis 1). Moreover, in the given probability plots, the data in both samples form an approximate straight line. Thus, it can be concluded that the data of both samples appear to be a good fit for normal distribution. After the initial experiment, the next decision has to be made on selecting a suitable statistical test to verify a claim that the revised version of the artefact has improved the correct identification of crop disorder incidents compared to an older version of the artefact. Upon analysing the nature of the experiment, the results were collected from the same group under two different experiments. Considering these factors, paired sample *t*-Test (one-tail) was selected to test the claim made at the significance level of 0.05. Accordingly, the hypotheses were defined as follows, and the outcome of the test is presented in Table 10.

**Hypothesis 3.** *Null hypothesis ($H_0$): $\mu_{revised} \leq \mu_{older}$*

**Hypothesis 4.** *Alternative hypothesis ($H_1$): $\mu_{revised} > \mu_{older}$*




1. Probability plot for older version

2. Probability plot for revised version

**Figure 10.** Outcome of the normality test for data obtained from both older and revised versions of the mobile artefact.

**Table 10.** The results of the paired sample *t*-Test (one-tail).

| | Revised Version | Older Version |
|---|---|---|
| Mean | 14.3 | 11.5 |
| Variance | 4.642105263 | 5.947368421 |
| Observations | 20 | 20 |
| t Stat | 9.472852778 | |
| P(T<=t) one-tail | $6.2502 \times 10^{-9}$ | |
| t Critical one-tail | 1.729132812 | |

Based on the results, the *p*-value is calculated as $6.2502 \times 10^{-9}$, which is largely less than the significance level of 0.05. Thus, the null hypothesis can be rejected (Hypothesis 3), and it is concluded that the revised version of the mobile artefact has significantly reduced the selection error that arose when farmers select relevant disorder identifiers compared to the older version. This was achieved through representing the information in the form of visual and text format.

## 7. Conclusions and Future Work

This paper presents a process enabled by a mobile artefact to effectively identify crop disorder incidents and support farmers to manage them using recommended control measures on time. The study found that correct identification of field observations from farmers is essential to identify relevant crop disorders. In order to serve this purpose, symptoms attached to different crop disorders specific to a crop were identified and grouped according to their characteristics. After that, the relevant symptoms from such groups were mapped to each crop disorder. This has resulted in a model similar to a search space to find crop disorders from field observations. In addition, symptoms that provide unique search space specific to different crop disorders were also identified and such identifiers were presented to farmers in the form of text and images using a mobile artefact. This feature used in the developed artefact provides a unique search space specific to crop disorders and can easily differentiate a crop disorder from others.

The distinguishing feature in the developed approach is that farmers were empowered to engage in the crop disorder identification process instead of the existing attempts in the literature that carry many limitations. In the developed approach, the effort required to identify a specific crop disorder from larger possibilities of crop disorders was drastically minimized. The developed approach can identify a larger number of crop disorders specific to a crop, irrespective of the growth stage of the crop, development stages of the crop disorder, and affected parts. The model can also be extended to identify new crop disorders as the information relevant to new crop disorders can be easily incorporated. Moreover, manual identification of crop disorders is also incorporated in the developed approach to handle situations specific to difficulties in identifying the symptoms that provide unique search space. Upon confirmation of relevant crop disorders, the recommended control measures consisting of different types of control methods were given to farmers concerning the environment and human-health safety aspects. The farmers' perception of various usability aspects of the solution revealed that farmers were highly satisfied with the services rendered through the solution and regarded it as a recommended tool to manage crop disorder incidents on time.

The methodology, tools, and findings of this work also can be used beyond this scope in many ways. Notably, with the recent widespread COVID-19 pandemic, going digital has become a vital component in any parts of the world. Henceforth, such interventions, especially in agriculture, can significantly add values. Different types of extensions and experiments have been left for the future to complement the work presented in this study. Accordingly, the identified future directions are: extending the model to other field crops that with extensive application of agrochemicals, a real-time notification service can be introduced based on the reported crop disorder incidents to inform farmers about the outbreaks in nearby areas and alert them to take precautionary control measures, the usability aspects of the developed artefact can be further enhanced to give the end-users with a better user experience, and also, the data generated through the system can also be better utilized to determine the input requirements of farmers and inform relevant authorities to adjust the incentives accordingly.

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