IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received January 15, 2021, accepted February 3, 2021, date of publication February 10, 2021, date of current version February 26, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3058582

A Generic Approach for Wheat Disease Classification and Verification Using Expert Opinion for Knowledge-Based Decisions

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This work was supported in part by the Cluster of Innovations in Computers Science (CICS), SSUET, and in part by the Smart VideoSurveillance Laboratory, an affiliated laboratory of the HEC- National Center in Big Data and Cloud Computing (NCBC), FAST-NUCES, Karachi.

ABSTRACT Crop diseases have mainly affected crop production due to the lack of modern approaches for disease identification. For many years, farmers have identified various crop diseases and have local knowledge about disease management. However, the local knowledge of one agricultural region is not utilized in other regions due to the unavailability of knowledge sharing platforms. Agricultural research also suggests that crop production has mainly decreased due to diseases, methods of cultivation, irrigation, and lack of local agricultural knowledge. In this research, the experience of agricultural experts, farmers, and cultivators is gathered through a crowd-sourced platform. The data is then processed for various disease identification. Hence, timely identification of various crop diseases can benefit farmers to apply relevant management methods. In literature, researchers have proposed various methods for disease management, mostly based on the classification of crop diseases using Machine Learning (ML) algorithms. However, these algorithms are unable to give trustful results due to static data provisioning and the dynamic nature of various diseases in different agricultural regions. Further, the agricultural expert's experience is also not considered in verifying the classification results. To identify the dynamic nature of wheat diseases, we acquired high-quality images and symptoms-based text data from farmers, domain experts, and users using a crowd-sourced platform. Different augmentation techniques were also used to enhance the size of training data. In this paper, a modern generic approach has been proposed for the identification and classification of wheat diseases using Decision Trees (DT) and different deep learning models. Also, results of both algorithms were then verified by domain experts that improved the decision trees accuracy by 28.5 %, CNN accuracy by 4.3 % (leading to 97.2 %), and resulted in decision rules for wheat diseases in a knowledge-based system.

INDEX TERMS Agricultural DSS, artificial intelligence, agricultural knowledge management, classification of crop diseases, machine learning, wheat crop diseases.

I. INTRODUCTION

The agriculture domain of Pakistan supports the economy and provides one-fifth of the country's whole Gross Domestic Product (GDP). The country is number 4 in producing cotton and at number 9 in wheat production in the world ranking. The potential of the agriculture industry to contribute to the economy is being exploited the need for investment in this sector [8]. To boost up the agriculture industry, experts have proposed copious measures, including appropriate use of technology to attain an eventual boost for the betterment of people. The cost of production is one of the immense challenges for farmers in Pakistan. There is a need to find ways to cope up with these problems using technology. The crop

The associate editor coordinating the review of this manuscript and approving it for publication was Wajahat Ali Khan.

disease analysis is of great meaning to avoid the blowout of diseases and preserve maintainable development of the agricultural sector. Generally, the diagnosis of the crop disease is performed manually by visiting the land to observe infected plants, by using microscope techniques, or by labor-intensive methods, which are time- consuming and the frequency of error risks is very high due to subjective sensitivities [41]. In this perspective, various spectroscopic and image-based techniques have been studied for the diagnosis and detection of crop diseases symptoms for the last couple of decades. By the involvement of computers and electronics in agriculture, some of the researchers have proposed methods for the automatic detection of diseases and their further classification. Image processing has been used in disease detection and monitoring (Kaur, Pandey, and Goel [17]). It became a common trend to use hyperspectral images as a dataset for the classification of diseases [23], [47]. Mobile applications have been developed to facilitate the farmers for disease monitoring in real fields, farms, and glasshouses [34], [39]. These kinds of applications work on different features and attributes of images with less complexity. Machine Learning algorithms have been used to strengthen these applications. A variety of algorithms and models such as fuzzy clustering [28], Artificial Neural Networks (ANNs), Decision Trees ([35]; ''Wheat Disease Identification Using Classification'' 2011; [46]), k-means, k nearest neighbors, and Support Vector Machines (SVMs) [5] have been used for crop diseases [21], [36]. Collection of data, variables identification, and proper model selection (classification or clustering) can play a vital role in agricultural knowledge management, thereby decreasing the complexities and processing burden of frameworks. Sumane *et al.* suggested that along with quantitative data, qualitative data also needed to be gathered (Kunda *et al.* [19]), so that a hybrid model could be used for data processing in the agricultural knowledge creation. This will help in enhancing the farmer's local knowledge toward precision agriculture.

These methods contribute well in some situations, but due to the dynamic nature of the agricultural domain, they failed to show good results in decision making. Further, agricultural Decision Support Systems (DSSs) are generally static in nature. For example, technology development is not based on the recommendations of researchers. The usability, credibility, and effectiveness of the agricultural DSSs are not adopted according to the agronomists' actual requirements and practices [25]. In this regard, combining farmers' experience with the exiting DSS is important.

Due to limited diseases datasets, used by various researchers, their systems are unable to identify a wide range of wheat diseases. We claim that crowd-based data (diseases' symptoms + images) collection is important to deal with the limited dataset problem faced by many researchers. In addition to this, knowledge-based solutions are also considered helpful while using the expertise of domain experts in improving the accuracy and quality of agricultural decisions [18]. An accurately designed Knowledge Management Systems (KMS) is an integrated software-based system developed to assist decision making by obtaining useful information from a set of raw data, processing methods integrating relevant algorithms along with utilizing experts' experience. The novelty and core contributions of this paper are highlighted as:

1. In this work, we have designed a multimodal dataset consisting of text, images, and voice samples. The dataset on the common bunt and sooty head mold is not publicly available. We have specifically focused samples of these diseases in our dataset.
2. We have proposed a generic approach for the identification of wheat crop diseases. The system works on multimodal data (text+images) and effectively classifies wheat diseases using different ML models.
3. The identification and classification of different wheat diseases were further verified by the domain experts using our designed crowd-sourced platform. This helped us two-fold, (i) it increased the accuracy of the models, and (ii) created agricultural knowledge in the form of rules and disease classes, that efficiently contributed to our existing DSS.
4. In the end, a comparative analysis of our proposed model with the existing state of the art methodologies in the literature based on performance measures is also presented.

The remaining paper is organized as follows: The existing systems for wheat diseases identification and classification have been discussed in Section II. Section III contains the disease classification using symptoms based text data. Classification of image-based data and its results are presented in Section IV. Comparative analysis of our proposed system has been discussed in Section IV F. The paper has been concluded in Section V.

II. EXISTING SYSTEMS FOR WHEAT DISEASES IDENTIFICATION AND CLASSIFICATION

To design and implement the proposed model for wheat diseases classification, a comprehensive study of wheat diseases and existing approaches presented in the literature to detect and classify the diseases have been conducted. Including an analysis of common wheat diseases, this part has been divided into four sub-sections, namely: A) a background study on disease identification based on symptoms, B) existing diseases identification systems, C) decision support systems for crop disease, [2]; [26] and D) Knowledge-based systems [32].

A. BACKGROUND STUDY ON DISEASES IDENTIFICATION BASED ON SYMPTOMS

Any attack on major crops by diseases or insects put a substantial impact on agricultural business. Especially, crops that provide food to people and fulfill the need of societies e.g. Wheat, corn, rice, etc. require effective care and management against diseases. Crop production is being declined due to diseases in the world for the last couple of decades and the agricultural industry bear economic losses as a result. Traditionally used disease diagnosis approaches are not accurately identifying the disease severity level [29]. As a result, the cost of disease management solutions increases. Some proactive approaches are required to be implanted to effectively monitor the health conditions of crops to control the spread of disease in the farms.

Traditionally, the identifications of crop diseases are performed by labor-intensive methods like visual observation by agronomists or using a microscopic-based system. These methods have proven to be slow in processing and the frequency of error risk is high due to a lack of domain knowledge. In this connection, modern techniques are needed to be applied for the identification of disease symptoms [24]. This section covers the classification of crop diseases and their types based on different approaches. In this study, we have selected wheat crop to classify various diseases. Wheat diseases can be identified in three ways, given as:

1. Based on the disease symptoms,
2. Physical parts of a wheat node (“Wheat Disease Identification,” [10], and
3. The agricultural expert’s opinion, integrating with ML algorithms (proposed).

The dataset containing symptoms based text data is shown in Table 2 and the mapping of aggregated data and wheat diseases is depicted in Table 3. Multiple diseases are interrelated hence, the identification and classification of diseases based on symptoms are more effective. Also, the process of diagnosis and method for managing these diseases are generally based on these symptoms. In this regard, diseases can be classified as Fungal Diseases, Bacterial Diseases, Viral Diseases, Nematodes, Insect Pests, Physiologic and Genetic Disorders, Mineral and Environmental Stresses (J. M. Prescott and P. A. Burnett [50]). Some important diseases are described below:

1) FUNGI

Fungi are deficient in photosynthetic ability due to the absence of chlorophyll thus it diverges from other plants. Fungi engross nutrients from healthy or damaged tissues of a plant instead of creating their food. It grows in different ways as may be born from a seed, soil or may be dispersed through the wind, water (either irrigated or rain) and different type of insects and animals. Fungal infection depends on the overwatering of the host plant area, weakness in the density of the host, and environmental temperature. Fungi did not necessarily attack the whole crop but affect its development. The spread of the disease depends on the interaction of infected and healthy plants [7].

2) BACTERIAL PATHOGENS

Bacterial pathogens of a wheat plant are one to three centimeters of slight unicellular bars that spread through insects, air fluxes, flapping rain, and by machine-driven means. Bacterial infections are usually born and penetrated to host tissues through extra moisture, damaged parts of plants, and holes in the leaf and stems. Viruses grew in the host plant and are distributed among crops by insects, nematodes, pollen, grown seed, fungi, and through soil (Whitaker *et al.* [51]). Researchers have mainly provided solutions to leaf blight and leaf spot. Other bacterial diseases need more attention from researchers.

3) VIRAL

Viral diseases are very hard to distinguish as their symptoms are not easily observable and the infected area of the host plant seems like physically disordered or genetically abnormal plants. In the past, these viruses were identified using serological methods and an electronic microscope but deep learning is more effectively being used to detect yellow dwarf and strip.

Some plant disorders are due to insects (Michel, Brun, and Makowski [52]). Many of these are seasonal or infrequent and the other exists for a long time in the fields. Some of them are location or zone-specific and depends on climate conditions and crop type. These insects also exist in special circumstances like a deficiency or over the sufficiency of a parametric value and mixed cropping (Farook *et al.* [53]). For example, aphids are transparent insects with soft bodies and sucking ability. Using this ability, these insects damage and can cause yellowing leading to the death of plant leaves by removing wheat plant juices. These types of insects become the source of the diseases like sooty molds, rolling of infested leaves, sterile heads, and yellow barley dwarf. The most damaging types of species are bird cherry-oat aphid and green bug. Stink Bugs, Armyworms, Cutworms, Cereal Leaf Beetle, are other important insects on wheat crops. Nematodes, known as worms are round-shaped worms that live in soil as well as in water in large numbers.

4) NEMATODE

Nematode feeding decreases plant robustness/ life and induces scratches, plant damaged, rots, deformation, sore, and root knots (Target 2019). Infested fields seem as rough, irregular, usually with dissimilar patches of underdeveloped plants. Physiology or genetic disorders are deficiencies of nutrients and some of the environmental stresses may cause the development of abnormal plants. Different reasons like inherited plant diseases, chromosomal uncertainty, unfeasible genetic combinations, are physiologic or genetic sicknesses that result in leaf spots, chlorosis of leaves, and various blotches [35].

On the other hand, accrual and addition of salts, the inadequate water level in the soil, life-threatening temperatures, and wrong practice of pesticides can also disturb the progress and yield of a crop.

B. EXISTING DISEASES IDENTIFICATION SYSTEMS

After a diagnosis of crop diseases, an important task is to choose relevant and effective management methods to secure the crop and ultimately result in more crop production. The relevant management methods can only be selected when the diseases are classified based on standard approaches discussed in the literature. The taxonomy of some commonly identified diseases and their classification is depicted in Figure 1. In this figure, the classification of diseases could be formed in two ways: (i) based on disease symptoms or (ii) physical parts. The disease's name could be common with these two disease management methods.

In literature, various approaches have been presented to automate and speed up conventional methods for crop disease detection and classification (Sibona, Brickey, and Sibona [54]; Wainer [55]). However, a technology initially transformed all these systems into an embedded and expert system. Many researchers addressed new trends and upcoming challenges associated with the heterogeneous nature of volumetric data, its analysis, algorithm selection for its stream processing, and further utilization of results. In addition, problems related to farmers' hesitation in adopting technology in the form of computerized-based solutions in the agricultural domain also need to be considered.

A method for early detection of crop disease has been proposed by [36] for sugar beet. They used a support vector machine (SVM) for automatic classification in differentiating healthy and infected crop images. Three diseases, namely cercospora leaf spot, powdery mildew, and leaf rust have been focused to examine 15 plants with four fully developed leaves for a period of 21 days. However, in real field farming, 15 plants could not represent the whole land covering acres. Also, 21 days is insufficient time to observe leaf spot and leaf rust as these diseases could affect the plant at any growth stage. Reference [24] have proposed a diagnosis system for diseases of wheat crop using deep learning and Multiple Instance Learning (MIL) for decreasing the burden of labeling effort of the system by assigning annotations to bags. This system may be implemented as a mobile app for real-time disease detection, however, the system is limited to a few diseases.

Effective discrimination of disease categories using algorithms is a challenging task. A matrix-based CNN has been presented in [22] that connects the presented convolutional kernel matrix (CKM) and other relevant tricks. This integrated architecture enhances the representational capability of the model. Their system successfully learned various wheat disease categories and achieved 90.1 % accuracy in testing different instances. It was a good approach towards improvement in the capability of a model, however, it is unable to provide any agricultural knowledge to the farmers to enhance their crop production. Johannes worked on the classification of mobile images using image processing algorithms [16]. They tested their system on a variety of wheat crops in the real fields using their mobile application. Zhang *et al.* worked on head-related diseases. They used Hyperspectral microscopic data for calculating the value of Fusarium head blight index of wheat [47]. They also divided wheat spikelets into healthy and sickly parts with 89.80 % accuracy. Commonly, mobile application based systems are suitable for the detection of diseases from individual images. These could be an alternative solution to a manual disease diagnosis system but while classifying the disease from a huge dataset, these systems could not provide services to the researcher.

The apple leaf diseases have been detected using improved convolutional neural networks [14]. Data of complex images from the real field environment and a dataset of 26377 images has been generated using augmentation and image annotation. The images containing more than one diseases were marked by agricultural experts for labeling. They have used GoogLeNet Inception structure and Rainbow concatenation for disease classification. The proposed model has achieved 78.80 % accuracy. In this system, agricultural experts were involved in the data annotation. More accuracy of the results could be achieved if the services of agricultural experts are utilized in results verification or the generation of decisions.

C. DECISION SUPPORT SYSTEMS FOR CROP DISEASES

Researchers have proposed decision support systems to provide automatic decisions after diagnosing the disease(s). Most of these are computerized-based solutions. An approach for the identification of fungal infection of the plant has been presented by [11] using remote sensing images. They have focused on powdery mildew and leaf rust in a 6-hectare land area of wheat crop. Three high-resolution images have been examined for spatio-temporal analysis of the infected area of the plant. A decision tree has been implemented with MTMF and NDVI to classify the obtained data based on the level of disease sternness. Initially, 56.8% accuracy was achieved, but it has been improved to 96.2 % at the end of the season. However, the accuracy of this system even varies from 21 % to 96.2 % at each growth stage of the crop.

An automated disease detection method has been presented by [31] in which they have used Local Binary Patterns (LBPs) to extract several features of various leaves of different species of the crop. One class classifier focused on the health condition of different crop plants. The algorithm has been trained on the vine crop and tested 46 different crop conditions to observe the behavior of the classifier. The approach was effective for vine crop disease classification due to its wide scope, however, the model was not generalized to crops like wheat and rice.

Du *et al.* proposed a remote sensing-based system to detect and classify two wheat diseases [9]. In this work, the researchers focused on rapid eye satellite images. They used supervised algorithms for classifying wheat diseases with 78 % accuracy. Chen *et al.* used the same dataset of satellite images for the identification of rust disease using random forest and SVM [6]. The authors have also proposed a mapping protocol for wheat rust diseases. They achieved 93.60 % accuracy, using wrapper feature selection while classifying wheat diseases. The results presented in this work conclude that SVM has shown better performance (in terms of accuracy) than the random forest classifier. However, due to rusty and healthy wheat samples, the work inclines more towards a binary classification problem.

Early detection of Fusarium head blight of wheat crop was investigated by Jin *et al.* using CNN [15]. They have

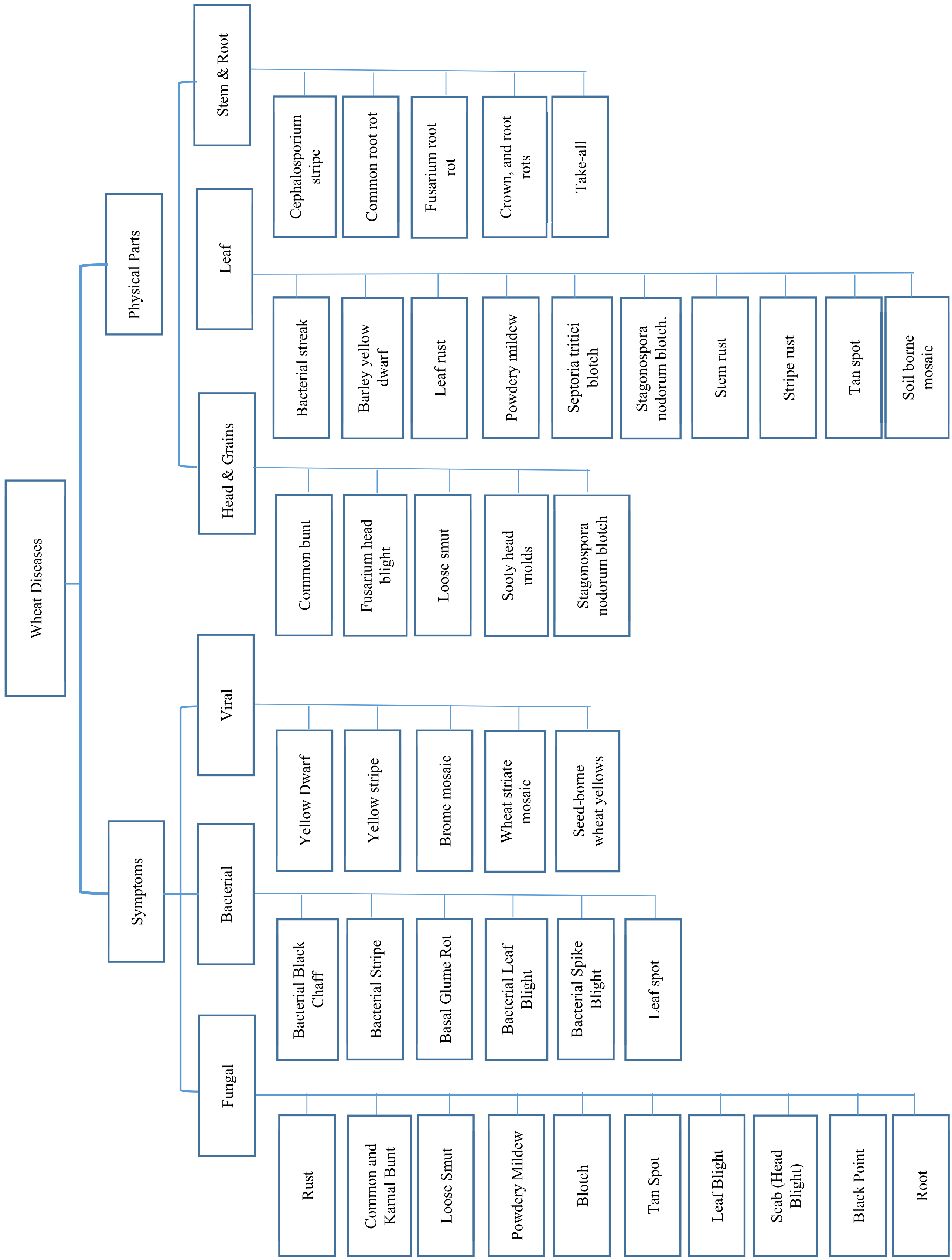


FIGURE 1. Taxonomy of wheat diseases.

preprocessed the hyperspectral image data using the mean removal method and a one and two-dimensional CNN for disease detection. To improve the performance of the model, they have reconstructed a bidirectional recurrent layer with a convolutional layer. In this work, the data was obtained from a self-grown wheat crop in a pesticides free region. After observing the crop for 16 days on a fully ripe stage, 90 samples have been collected for experimentation. The model has achieved 74.3 % accuracy with a 75% F1 score. Since the data was small and limited to artificially controlled pesticides free region, the model can't be used as a source for detecting diseases in real free regions.

Argüeso *et al.* used Few-Shot Learning (FSL) with deep learning for different leaf diseases classification [3]. They have worked on a dataset of 54303 labeled images containing 38 leaf diseases. They used Triplet loss and FSL with Siamese networks for their experimentation. As a result, the network has achieved an accuracy of 91.4 % on the training data and 94 % accuracy on testing and validation. The approach successfully proved that the network can work on small datasets with more than 90% accuracy. Although the approach has significance in the said problem however a dataset containing a large number of classes belong to different crops is not fruitful for farmers. If the dataset has crops of the same season that can be cultivated at a particular soil type or in an agricultural zone, then these kinds of classification could be beneficial for farmers in the real field practices.

D. KNOWLEDGE-BASED SYSTEMS

In literature, the knowledge of domain experts has been used in systems for identification of crop diseases [18], estimation of fertilizers [25] and agricultural decisions [2] as presented in Table 1. Kolhe *et al.* described a system, in which diseases attributes were entered by a user. Based on those attributed, the system then provided relevant decisions. In another system, proposed by Almadhoun *et al.* diagnosed banana diseases using an expert system. The application uses the experience of an expert in disease diagnosis and further application management. Only a few researchers have addressed knowledge-based systems, specifically wheat disease identification and classification. However, we believe that the performance of existing systems has been enhanced using knowledge-based systems. These kinds of systems are fundamentally required for agricultural research. By involving field experts and farmers in the process of these systems and using their experiences in data preparation, cleaning, and rectification, the decisions of these systems could be improved.

Researchers have used an improved version of GoogLeNet and Cifar10 for the identification of maize leaf diseases [48]. A dataset of 500 images comprised of 8 leaf diseases has been obtained from online sources. The data has been assessed by human experts during pre-processing and a dataset of 3060 images has been generated by augmentation. The model has achieved 98.9 % accuracy. The system was good in the identification of maize diseases using CNN but the results are needed to be verified by agricultural experts.

A deep convolutional neural network-based system for efficient detection of wheat diseases has been presented by Picon *et al.* (Picon *et al.* [33]). They have acquired the dataset of 8178 images from two pilot sites in Spain and Germany. Three diseases i.e. septoria, tan spot, and rust were focused. They have acquired the services of an expert technician for the data labeling before training the model. The data has been analyzed using mobile devices and 87 % accuracy has been achieved. The approach is significantly good but the experience of an agricultural expert technician can be used for the verification of results, it could enhance the robustness of the approach.

Convolutional Neural Network with Unmanned Arial Vehicle has been used for the detection of wheat lodging [49]. The data of three-grain filling stages have been used to train three CNN models. The field was divided into sections as lodged and non-lodged areas and images were labeled by an expert using ArcMap 10.3 software during pre-processing. The system has achieved an overall accuracy of 89.23% for all crop stages.

[43] have presented an Android-based system to accurately diagnose multiple diseases of wheat and cotton. They have collected data from various sources containing 160 samples and applied a fuzzy inference system for disease detection. Consequently, 73 rules have been generated using domain expert advice for better decision making. The system can communicate with farmers in the local language Urdu.

To highlight the research gaps, we have found the following limitations in the literature:

1. Most of the work has focused on leaf diseases. However, they have not focused on head diseases, which are comparatively harmful.
2. Data samples have not been annotated and labeled by experts.
3. As real field data can be obtained from the farmer in different formats, there is no standard approach in the literature to deal with multimodal data.
4. The Systems have developed without concerning domain experts. The results of the systems have not been verified by domain experts to get the attention of farmers toward the systems.
5. These approaches have not much contributed to the real field practices of the farmers nor these approaches have got the attention of farmers and experts due to their fixed nature.

III. WHEAT DISEASES IDENTIFICATION AND CLASSIFICATION FOR SYMPTOM-BASED TEXTUAL DATA

In this work, the wheat crop has been selected for the implementation of the proposed generic approach. The implementation of this approach has enabled us to the identification and classification of wheat disease using domain experts' verification. The workflow of the proposed approach has been

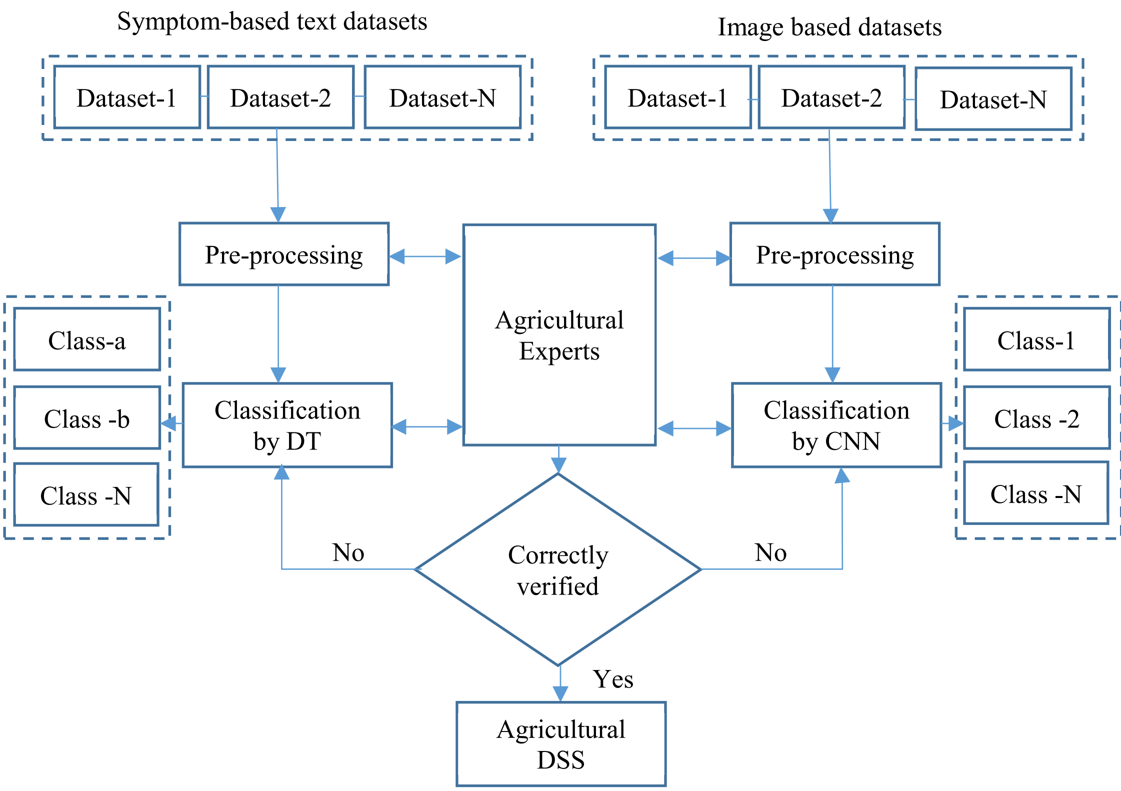


FIGURE 2. Proposed model for diseases identification and classification.

shown in Figure 2. Domain experts have provided data in textual form through our crowd-sourced application.

The model also works on labeled images containing wheat diseases collected through the same application. The proposed generic model is elaborated as follows: The left side shows 1) the classification of diseases based on symptoms, while the right side shows 2) the image-based disease classification.

The model is further discussed as under. First, we have discussed the process of disease classification based on symptoms:

A. DATA ACQUISITION

In this work, a two-fold wheat disease identification model was presented in Section III. In the data acquisition process, field surveys, interviews, online wheat diseases' symptoms form, and field experts' responses to the queries being asked through our system. In the case of field surveys and interviews, symptoms were manually mapped against the target diseases. The data acquired at this stage was free of error. However, the number of instances were few to be used for wheat diseases classification. In this regard, we further worked on the online wheat diseases' symptoms forms and queries from the farmers and field experts using our crowd-sourced application specifically developed for this purpose. In this case, we're able to collect a large number of responses through our forms and queries. At this stage, the data was noisy as shown in Table 2. We worked on the data to spot errors at this stage. Here, we also assured that the data is of the right type and in the right format.

B. DATA PREPROCESSING

Initially, data acquired through different sources such as interviews, surveys, online forms, and queries were aggregated. We used NLTK (''https://www.nltk.org/,'' n.d.) word tokenizer to break users' query responses into words and created a list of stopwords, and filtered out the noise in the data. We also detected named entities such as diseases and symptoms using nltk's pos_tag(token).

Later on, we observed that data acquired through online forms and queries contain noise and need to be prepared before any model can be built. In this regard, data entry errors, missing values (symptoms or diseases), and errors against the codebook were manually overruled. More specifically, data having symptoms not listed in the literature were also not considered due to standardization.

Certain combinations of symptoms that do not occur or against a codebook were also eliminated using our expert-defined rules. Finally, we used word embeddings to convert resultant text into numbers to be used in our model.

We used a CSV file format to store the data and further used it for processing the data using our model. The symptom data comprises 14 attributes as shown in Table 3. In this data, a dependent variable 'Disease' was used as the class, and

TABLE 1. Summary of domain wise implementation of ml algorithms in agriculture.

Domain	Algorithm/ Model	Problem Definition	Solution Description	Results	Crop	Reference
			Disease Identification and Classification			
Disease Prediction & Classification	SVM	Early detection and classification of crop disease.	15 plants with four fully developed leaves examined for a period of 21 days to detect 3 diseases	(I) To distinguish diseased from healthy leaves, (II) To differentiate between the three diseases (III) to recognize diseases before arising clear symptoms	Sugar beet	(Rumpf et al. 2010)
Disease Prediction	CNN	Automatic disease detection	The system works in the supervised deep learning framework to classify image-based data.	97.95% and 95.12% accuracies using two architectures	Wheat	(Lu et al. 2017)
Disease Prediction	Decision Trees	Identification of fungal infection	Spatio-temporal analysis of the infected area of the plant to classify the severity of powdery mildew and leaf rust	56.8% accuracy was then improved to 88.6 %	Wheat	(Franke and Menz 2007b)
Disease Prediction	GrabCut algorithm, One class classifier	Automated crop disease identification	LBP is used to extract features of various samples from different crop species. One class classifier was used.	An algorithm trained on the leaves of vine and tested on different crops. 95% success rate achieved	Wheat,	(Pantazi, Moshou, and Tamouridou 2019)
Disease Prediction		Identification of purple spot	Mean data, spectral derivatives and spectral transformations are used. Multivariate regression is used to find the best model	Field spectroscopy can be used with wide-area remote sensing to calculate disease severity	Asparagus	(Navrozidis et al. 2018)
Disease identification	ANN/MLP	Selection of the features about Spectral reflectance features	Yellow rust has been detected. A method of differentiating infected and healthy wheat plants	97 % accuracy	Wheat	(Moshou, D 2005)
Disease Prediction & Classification	CNN	Discrimination of diseases	Matrix-based algorithm used	90.1% accuracy	Wheat	(Lin et al. 2019)
Disease identification	Image processing	Systems not performed well on mobile images	Candidate hot-spot detection has been used with statistical inference methods	80% accuracy	Wheat	(Johannes et al. 2017)
Disease Detection	Combined Algorithm	Detection of Fusarium	The classification index value of Fusarium head blight has been calculated	89.80 % accuracy	Wheat	(N. Zhang et al. 2019)
			Decision Support Systems for Disease Prediction and Classification			
DSS	Developed by authors	A generic system to accurately identify the diseases	The dataset in the form of symptoms is obtained. A list of symptoms based on keyword search is extracted and managed.	Generic System for crop disease prediction for DSS	All	(Thandapani and Senthilkumar, n.d.)
Knowledge and DSS	Fuzzy Clustering	Agricultural Knowledge Discovery and decision making	Clustering models K-Means, Gustafson-Kessel, Gath-Geva, and Fuzzy C-Means are concisely studied tested on data of 42 farms. 4 classifiers have used	Patterns are recognized from the dataset. The performance of classifiers is examined	All	(Mota, Damasceno, and Leite 2018)
DSS	maximum-likelihood classifier, support vector machine, random forest	Winter wheat affected by diseases	DSS provides the farmers a disease detection using three algorithms	78% accuracy	Wheat	(Du et al. 2019)
DSS	support vector machine, random forest	Feature selection is not effective	Wrapper feature selection is used in place of old feature selection	93.60 % accuracy	Wheat	(Chen et al. 2018)
			Knowledge-based Systems for Agriculture			
Knowledge	Fuzzy and Statistical	Disease identification and management	Attributes of the disease are entered by the user and the system provides relevant decisions.	Developed rules based on the Fuzzy and statistical models	Soybean, groundnut and rapeseed mustard	(Kolhe 2009)
Knowledge	Self-designed	Estimate nitrogen fertilizers	CropSAT developed for estimation of nitrogen fertilizations from satellite photographs	Expert's experience-based knowledge, enhance the accuracy of DSS	All	(Lundström and Lindblom 2018)
Knowledge	Self-designed	Diagnosis of diseases	An expert system to diagnose the banana disease and management using expert experience	Accuracy of the system's decisions, enhanced	Banana	(Almadhoun and Abu-naser 2018)

TABLE 2. Symptoms based text dataset.

User ID	Symptoms	Disease
51	Lesions, Shape change, Stunted growth, Chlorosis/ necrosis	Common Root Rot
253	Black spores, Yellow spores, Blotches resembling holes, Flecks	Stem rust
337	Superficial dark fungal tissue, Lesions, Dark fungal fruiting bodies	Septoria leaf blotch
681	Lesions, Shape change, Stunted growth, Scab infection	Common Root Rot
703	Superficial dark fungal tissue, Pinkish greyish fungal, Flecks	Spot Blotch or Black point
825	Black spores, Shape change, Scab infection	Khuli kangyari
1160	Yellow spores, Blotches resembling holes, Dark fungal fruiting bodies	Kungi
1237	Pinkish greyish fungal, Scab infection, Dark fungal fruiting bodies	Fusarium head blight
1336	Black spores, Scab infection, Shape change	Loose Smut
1456	Yellow spores, Blotches resembling holes	Stripe rust
1548	Black spores, Scab infection, Flecks	Sooty head molds
1602	Black spores, Pinkish greyish fungal, Fungi, Stunted growth	Bargi Kanyari
1689	Shape change, Fungi, Scab infection, Dark fungal fruiting bodies	Karnal bunt
1728	Black spores, Pinkish greyish fungal, Fungi, Stunted growth	Leaf smut
1974	Superficial dark fungal tissue, Shape change, Fungi, Scab infection	Karnal bunt

all other symptoms were used as the predictor variables for predicting the wheat disease based on the listed symptoms.

C. FEATURE SELECTION

In this process, attributes that effectively contribute towards decision making were selected [45]. We have used our crowd-sourced application to acquire data from users. The data contain symptoms and diseases.

We used those symptoms as our predictor variable(s) and wheat disease as their label. In the data verification process, the domain experts also considered these variables/symptoms important to identify diseases. We also found some of these symptoms in the wheat crop diseases literature. In this regard, all symptoms of different diseases which were most common and known in the literature to be used for the classification were selected. These attributes contain the presence of a symptom in any part of the plant.

D. CLASSIFICATION

This section covers the classification of wheat crop diseases of Pakistani regions. For diseases classification based on the symptoms depicted in Table 3, we used the Decision tree. In general, Decision tree learning is used for approximating discrete-valued target functions. In our dataset, the target variable was a discrete-valued function. Further, the dependent variables were fixed and have a small number of possible values (yes/no) in our case. Moreover, some instances that have missing values (for example, if the disease symptom is missing, or does not exist for a disease) were labeled a value 'no' in our case. In this regard, we preferred the decision tree for our diseases classification.

Here, the non-terminal nodes look at one or more properties, that is a test of some attribute instance value while the terminal nodes represent the classification as shown in Figure 4. In our model, we worked on the reduced Error Pruning Tree (RepTree). The method uses information gain as the splitting criteria to construct a decision tree. It then prunes the tree using a reduced error pruning algorithm [13], [27].

We imported our dataset and used C-4.5 classifier for processing our data (Ahmed *et al.* [56]). The steps used for generating the classification results are described as follows.

STEP 1: The algorithm first calculates the information-gain and then obtains the gain-ratio as the standard for splitting the data.

$$info\ (T) = -\sum_{i=1}^{k} ((freq(C_i, T)/\,|T|) \times \log_2 (freq(C_i, T)/\,|T|)) \tag{1}$$

where T is representing our sample, and C_i is termed as attributes or symptoms (Superficial Dark Fungal Tissue, Spot Blotch, Black point, etc.) in our case.

STEP 2: Conferring to the specific assessment of property, the sample ***T*** is divided, afterward the information entropy of property ***T*** is calculated and described as below:

$$infox\ (T) = -\sum_{i=1}^{n} ((|T_i|\,/\,|T|) * info(T_i)) \tag{2}$$

STEP 3: The difference between the original requirement of the information and the newly obtained value is declared as the information-gain [35].

In continuation with Equation. (1) and Equation. (2), we have discovered the gain standard, which is represented as:

$$Gain\ (X) = info\ (T) - infox\ (T) \tag{3}$$

STEP 4: A weakness related to the gain-standard is that in a specific situation, it provides many versions of the output, but on the other hand, the gain-standard is beneficial to provide the compacted decision-tree. So, it needs to be specified through standardization as described under:

$$Split - info\ (X) = -\sum_{i=1}^{n} ((|T_i|\,/\,|T|) \log_2 (|T_i|\,/\,|T|)) \tag{4}$$

We can find the gain-standard using the following equation:

$$Gain - ratio\ (X) = \frac{gain\ (X)}{split} - info\ (x) \tag{5}$$

TABLE 3. Aggregated data shows the relation between symptoms and wheat crop diseases obtained from crowd dataset.

Superficial dark fungal tissue	Lesions	Black spores	Yellow spores	Blotches resembling holes	Superficial white	Pinkish grayish fungal	Shape change	Fungi	Scab infection	Dark fungal fruiting bodies	Flecks	Stunted growth	Chlorosis/ necrosis	Diseases
No	No	No	No	No	No	Yes	No	Yes	Yes	No	No	No	No	Common bunt
No	Yes	No	Yes	No	No	No	No	No	No	No	Yes	No	No	Soilborne mosaic
No	Yes	No	No	No	No	No	Yes	No	No	No	No	Yes	Yes	Common Root Rot
No	No	Yes	Yes	Yes	No	No	No	No	No	No	Yes	No	No	Stem rust
Yes	No	No	No	No	No	Yes	No	No	No	No	Yes	No	No	Spot Blotch or Black point
No	No	Yes	Yes	Yes	No	No	No	No	No	No	Yes	No	No	Leaf rust
No	No	No	Yes	Yes	No	No	No	No	No	No	No	No	No	Kungi/Stripe rust
Yes	Yes	No	No	No	No	No	No	No	No	Yes	No	No	No	Septoria leaf blotch
Yes	No	No	No	No	Yes	Yes	Yes	No	No	No	Yes	No	No	Powdery mildew
No	No	No	No	No	No	No	Yes	No	No	No	Yes	No	Yes	Yellow Dwarf
Yes	Yes	No	No	Yes	No	No	No	Yes	No	No	Yes	No	No	Blotches
No	Yes	No	No	No	No	No	No	No	No	No	No	Yes	Yes	Nitrogen Phosphorus & Potassium Deficiency
No	Yes	No	Yes	No	No	No	No	No	No	No	Yes	No	No	Yellow (leaf) spot
No	No	Yes	No	No	No	No	Yes	No	Yes	No	No	No	No	Khuli kangyari /Loose Smut
Yes	Yes	Yes	No	No	No	Yes	No	No	No	No	No	No	No	Take-All
No	No	No	No	No	Yes	Yes	No	No	Yes	Yes	No	No	No	Fusarium head blight
No	No	Yes	No	No	No	No	No	No	Yes	No	Yes	No	No	Sooty head molds
No	No	Yes	No	No	No	Yes	No	Yes	No	No	No	Yes	No	Bargi Kanyari /Leaf smut
Yes	No	No	No	No	No	No	Yes	Yes	Yes	Yes	No	No	No	Karnal bunt
No	No	No	Yes	No	No	No	No	No	No	No	Yes	Yes	Yes	Akhaira

E. DISCUSSION OF RESULTS

In this section, we are discussing the classification results of our wheat diseases based text data performed through decision trees. In the first subsection, we'll present the results of this classification using a confusion matrix. Further, the accuracy of the model will be discussed followed by some more performance criteria i.e. tree stability and simplicity. In the second section, the corresponding knowledge-based rules resulted from the model have been described. In the end, the accuracy improvement using verification of class assignment has been illustrated.

Here, we illustrate the performance of our decision trees model used for classification. We used 2324 symptoms samples from our symptom-based text dataset as the testing data. Then we evaluate our model in terms of the class individual as well as the overall accuracy, precision, recall, and F1-measure of the initial classification directly obtained from the crowd-sourced dataset. The results were communicated with the domain experts through our crowd-sourced application. Here, the data related to the incorrect classified results were reviewed by the domain experts, and the symptom(s) related to the disease was revised. This helped us revising the incorrect classified instances in our dataset. We again used the revised dataset for the same model, and in this case, the accuracy of the miss-classified instances was drastically improved by 14.45 %.

As shown in the confusion matrix of Table 4, the model was miss-classifying 'Spot Blotch/ Black point' disease 82.05% because it has many symptoms such as Superficial dark fungal tissue, Pinkish grayish fungal, and Flecks. In the original dataset, only a few users were able to label this disease with all these three symptoms. That's why the classifier was

TABLE 4. Confusion matrix of dt presents accuracies of model before verification of result by the experts.

	Sectorial Leaf Blotch	Spot Blotch/ Black point	Stem Rust	Khuli kangyari/ Loose Smut	Flusarium-Head-Blinght	Kungi/ Stripe rust	Sooty-Head-Mold	Common Root Rot	Common Bunt
Sectorial Leaf Blotch	0.86	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.01
Spot Blotch/ Black point	0.02	0.82	0.02	0.02	0.01	0.03	0.03	0.03	0.03
Stem Rust	0.02	0.02	0.83	0.02	0.02	0.02	0.01	0.02	0.02
Khuli kangyari/ Loose Smut	0.02	0.02	0.03	0.78	0.03	0.03	0.03	0.03	0.03
Eusarium-Head-Blinght	0.02	0.02	0.03	0.03	0.79	0.03	0.03	0.03	0.03
Kungi/ Stripe rust	0.04	0.03	0.03	0.04	0.03	0.72	0.04	0.04	0.03
Sooty-Head-Mold	0.01	0.01	0.01	0.02	0.01	0.02	0.88	0.02	0.02
Common Root Rot	0.02	0.02	0.02	0.02	0.01	0.02	0.01	0.85	0.02
Common Bunt	0.03	0.02	0.03	0.03	0.03	0.05	0.04	0.03	0.75

TABLE 5. Confusion matrix of DT shows class wise accuracies after verification of result by the experts.

	Sectorial Leaf Blotch	Spot Blotch/ Black point	Stem Rust	Khuli kangyari/ Loose Smut	Flusarium-Head-Blinght	Kungi/ Stripe rust	Sooty-Head-Mold	Common Root Rot	Common Bunt
Sectorial Leaf Blotch	0.96	0.005	0.01	0.01	0.005	0.00	0.00	0.01	0.01
Spot Blotch/ Black point	0.01	0.94	0.01	0.00	0.00	0.01	0.00	0.00	0.00
Stem Rust	0.00	0.01	0.94	0.01	0.00	0.00	0.00	0.00	0.00
Khuli kangyari/ Loose Smut	0.01	0.01	0.00	0.94	0.01	0.00	0.00	0.00	0.00
Eusarium-Head-Blinght	0.00	0.01	0.01	0.01	0.96	0.02	0.01	0.01	0.01
Kungi/ Stripe rust	0.00	0.00	0.00	0.01	0.00	0.94	0.00	0.01	0.00
Sooty-Head-Mold	0.00	0.00	0.00	0.00	0.01	0.00	0.96	0.01	0.01
Common Root Rot	0.00	0.01	0.00	0.01	0.01	0.01	0.02	0.94	0.02
Common Bunt	0.01	0.01	0.00	0.01	0.005	0.005	0.01	0.01	0.94

miss-classifying this class with other classes such as Septoria leaf blotch, Powdery mildew, Blotches similar symptoms with nearly similar symptoms like Superficial dark fungal tissue, Pinkish grayish fungal, and Flecks. In the case of 'Khuli kangyari/ Loose Smut' the accuracy was 77.95%. The main reason behind this less accuracy was different diseases' names were labeled against the same list of symptoms. After the domain expert verification, the problem of the two names of the same disease was solved. The same problem for the 'Kungi/ Stripe rust' was also resolved for this wheat disease. Most importantly, two wheat diseases Common Bunt and Eusarium-Head-Blinght symptoms characteristics are almost similar in nature. In our original dataset, they were incorrectly labeled due to their physical appearance. Due to this, the miss-classification accuracy was 78.90 % and 74.58 % respectively. The classification accuracy, precision, recall, and F1 measure of this experiment have been shown in Table 5.

After getting 82.05% accuracy for 'Spot Blotch/ Black point' disease, we forwarded its data (i.e. symptoms) to experts to identify the main cause of this increased misclassification. We found the disease assignment problems for this disease. In our revised dataset, more than 41 instances of this disease were modified. In two other cases, two diseases, 'Khuli kangyari/ Loose Smut' and 'Kungi/ Stripe rust', the experts found separate class labels to the same symptoms. For example, Yellow spores and Blotches resembling holes' symptoms were separately assigned to Khuli kangyari and Loose Smut. The same problem was identified for the symptoms Black spores, Yellow spores, and Blotches resembling holes to 'Kungi and in some cases for 'Stripe rust' disease. In this regard, the domain experts found 65 and 78 instances

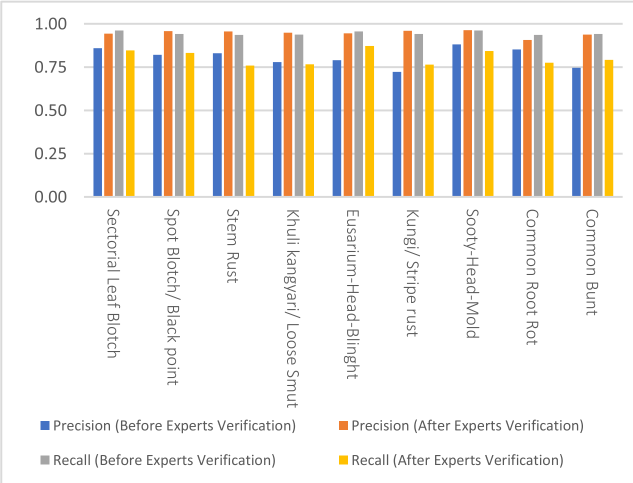


FIGURE 3. Performance of proposed model on symptom based text data.

respectively for the above two classes. Due to the use of expert knowledge for the miss-classification instances, the classification accuracy for all the cases was improved. As we can see from the confusion matrix of Table 5, the class accuracy of 'Spot Blotch/ Black point' diseases were improved by 12 %, i.e. in this case we got 94 % accuracy. Further, the accuracy of our two other classes 'Khuli kangyari/ Loose Smut' and 'Kungi/Strip rust'' was also improved by 16% and 22 % respectively. Similarly, the classification accuracies of other classes were also improved due to different aggregation of the symptoms to diseases assignments.

In the initial and later on in the revised model evaluation, the following set of formulas was used to calculate precision, recall, and the F1 measure of individual classes. These values are depicted in Figure 3.

The overall accuracy of the model was calculated using the formula:

$$\text{Precision} = \frac{\text{true Positive}}{\text{true positive} + \text{false positive}} = \frac{\text{diseases correctly identified}}{\text{diseases correctly identified} + \text{instaces Incorrectly labeld diseases}} \tag{6}$$

$$\text{Recall} = \frac{\text{diseases correctly identified}}{\text{diseases correctly identified} + \text{deseases incorrectly labeled asnot diseases}} \tag{7}$$

$$\text{F1 Score} = 2 * \frac{\text{precision} * \text{recall}}{\text{precision} + \text{recall}} \tag{8}$$

In our resultant model for the Wheat symptoms text-based dataset, we got 94.7 % overall accuracy. Moreover, the model also achieved 94.6 % overall precision and F1 score and 94.5 % average recall as depicted in Figure 3.

TABLE 6. What diseases stability values: A performance criterion of DT.

CLASSES / LEAVES	CLASS-WISE STABILITY VALUES BEFORE EXPERT VERIFICATION	CLASS-WISE STABILITY VALUES AFTER EXPERT VERIFICATION
Sectorial Leaf Blotch	0.97	0.98
Spot Blotch/ Black point	0.98	0.98
Stem Rust	0.99	0.97
Khuli kangyari/ Loose Smut	0.99	0.99
Eusarium-Head-Blinght	0.96	0.99
Kungi/ Stripe rust	0.96	0.98
Sooty-Head-Mold	0.98	0.98
Common Root Rot	0.98	0.96
Common Bunt	0.97	0.99
Overall Stability Values	**0.97**	**0.98**

F. OTHER PERFORMANCE CRITERION

Besides the predictive accuracy rate, there are some other performance measure criteria for Decision Trees. Kweku and Osei [30] in their work on the evaluation of decision trees have suggested stability as a coarse measure. This performance criterion recommends that the variation in the classification accuracy should be low when the decision tree is applied to different datasets. Mathematically,

$$\text{Stability} = \min\{\text{Train}_{\text{Acc}}/\text{Validation}_{\text{Acc}}, \text{Validation}_{\text{Acc}}/\text{Train}_{\text{Acc}}\} \tag{9}$$

where $\text{Train}_{\text{Acc}}$ and $\text{Validation}_{\text{Acc}}$ are the training and validation accuracy rates. In our case, the overall Stability $\in$ (0,1) and class-wise Stability values (a very fine measure of the class frequencies of each leaf based on the training and validation datasets) were improved after expert verification of the textual-based symptoms. Higher values indicate more Stability and low variation in the classification accuracies. The Stability values are given in Table 6:

Many researchers have also considered Tree Simplicity which is a function of the number of leaves and its associated Rule-length in the decision trees, a performance measure. Simplicity based on the number of leaves S_{Leaf} is a function of N, where N is the index set of the leaves in the decision trees, i.e. $S_{\text{Leaf}} = \text{Fuction}_{\text{Leaf}}(|N|)$. In our case, the value of N was 7, suggesting high simplicity. On the other hand, simplicity based on the size of a rule was also good for our text-based symptom data used for testing. The simplicity based on the size of a rule is the weighted sum of the number of conjuncts x_N in each rule.

Mathematically, the mean length $X_{\text{Mean}} = \sum_{N=0} w_N x_N$ of each rule is the weighted sum of each rule length. In the above formula, for a given leaf N, w_N is the proportion of

TABLE 7. Comparison of machine learning (ML) algorithms and proposed model.

	Decision Trees	Ada-Boost	SVM	Naive Bayes Classifier
Accuracy	94.70	78.45	83.37	83.70
Precision	94.60	78.5	82.80	84.10
Recall	94.50	77.4	82.70	83.90
F1 score	94.60	77.5	82.70	84.00

validation dataset cases associated with leaf N. In our case, the average number of conjuncts (symptoms in our dataset) were $3 \leq x_N < 4$, which indicates, that the simplicity based on the length of a rule was higher as discussed in the sub-section G.

Despite decision trees, we have also worked on different machine learning algorithms such as Ada_Boost, SVM, and Artificial Neural Network for symptom-based disease classification. The testing accuracies of these models are shown in Table 7. For our symptom-based text dataset, we found that:

1) ADA-BOOST

It works well against overfitting when less noisy data is provided to the classifier (Banerjee *et al.* [4]). However, due to its binary nature, Ada-Boost provided relatively less accuracy on our data. The model has achieved 78.4 % accuracy with 78.5% precision and 77.4 % recall.

2) SUPPORT VECTOR MACHINE (SVM)

It doesn't perform well when the dataset has noise. In our case, the target classes are overlapping due to the same symptoms present in different diseases. In this regard, it classified some instances well, where the target classes are not overlapping. However, the classifier has not performed well, when noisy data of the same symptom leading to different diseases. In our case, we got 83.37 % accuracy, with 82.8 % precision, and 82.7 % recall and F1 score.

3) THE NAIVE BAYES CLASSIFIER

It was also used for the symptom-based disease classification [1]. The Naïve Bayes classifier assumes that the features, in this case, the symptoms are independent of each other. However, the symptoms in our dataset are dependent on each other and are related to each other in a class. The classifier, in this case, resulted in an accuracy of 83.7 % due to the probability of a hypothesis that it is class Fusarium Head Blight when these n symptoms are present. The classifier has also resulted in a precision of 84.1 %, recall of 83.9 %, and an F1 score of 84.0 %.

4) DECISION TREES

The main rationale behind the Decision Trees (DT) was to come up with 'Symptoms to diseases mapping', leading to the generation of knowledge-based decisions from the symptoms. We believe that these decision rules are helpful for the agricultural community. Also, in the case of decision trees, we got a good accuracy of 94.7 %. In this regard, we considered decision trees in our work.

G. DEDUCING KNOWLEDGE-BASED RULES FROM SYMPTOMS-BASED TEXTUAL DATA

After evaluating the model, we identified 14 different symptoms used to classify 20 different diseases. From our decision tree model, we have summarized the following rules which are helpful for farmers and field experts to use the symptoms to identify most wheat diseases in the agricultural domain.

According to the rightmost leaf first:

R1: *IF (Superficial Dark Fungal Tissue = Yes) AND (Lesions = Yes) THEN Disease = Sectorial Leaf Blotch.*

R2: *IF (Superficial Dark Fungal Tissue = Yes) AND (Lesions = No) THEN Disease = Spot Blotch or Black point.*

R3: *IF (Superficial Dark Fungal Tissue = No) AND (Black Spores = Yes) AND (Yellow Spores = Yes) THEN Disease = Stem Rust.*

R4: *IF (Superficial Dark Fungal Tissue = No) AND (Black Spores = Yes) AND (Yellow Spores = No) THEN Disease = Khuli kangyari/Loose Smut.*

R5: *IF (Superficial Dark Fungal Tissue = No) AND (Black Spores = No) AND (Yellow Spores = Yes) THEN Disease = Kungi/Stripe rust.*

R6: *IF (Superficial Dark Fungal Tissue = No) AND (Black Spores = No) AND (Yellow Spores = No) AND (Shape Change = Yes) THEN Disease = Common Root Rot.*

R7: *IF (Superficial Dark Fungal Tissue = No) AND (Black Spores = No) AND (Yellow Spores = No) AND (Shape Change = No) THEN Disease = Common Bunt.*

Seven rules have resulted from the decision tree depicted in Figure 4 i.e. Septorial Leaf Blotch, Spot Blotch or Black Spot, Stem Rust, Khuli kangyari/Loose Smut, Kungi/Stripe rust, Common Root Rot, and Common Bunt.

To provide more clarity of the results, the first three decision rules of the wheat crop disease classes have been elaborated as below:

1) "SEPTORIAL LEAF BLOTCH" CLASS RULE

R1: *IF (Superficial Dark Fungal Tissue = Yes) AND (Lesions = Yes) THEN Disease = Septoria Leaf Blotch.*

It enumerates that when Superficial Dark Fungal Tissue is equal to yes and Lesions is equal to yes, then predicted Wheat Crop Disease class is Septoria Leaf Blotch.

2) "SPOT BLOTCH OR BLACK SPOT" CLASS RULE

R2: *IF (Superficial Dark Fungal Tissue = Yes) AND (Lesions = No) THEN Disease = Spot Blotch or Black point.*

It enumerates that when Superficial Dark Fungal Tissue is equal to yes and Lesions is equal to no then predicted Wheat Crop Disease class is Spot Blotch or Black point.

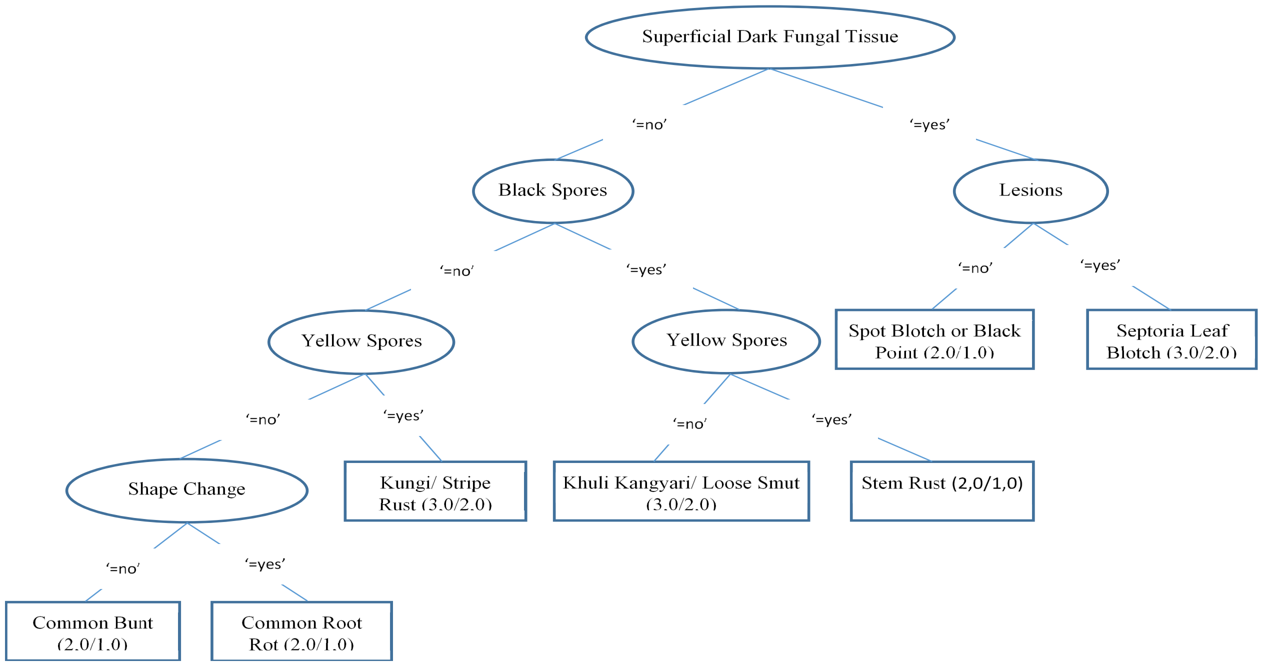


FIGURE 4. Decision tree showing decisions on the bais of based on different symptoms from our symtoms-based text dataset.

3) "STEM RUST" CLASS RULE

R3: *IF (Superficial Dark Fungal Tissue = No) AND (Black Spores = Yes) AND (Yellow Spores = Yes) THEN Disease = Stem Rust.*

It enumerates that when Superficial Dark Fungal Tissue is equal to no and Black Spores is equal to yes and Yellow Spores is equal to yes then predicted Wheat Crop Disease class is Stem Rust.

These rules will support agricultural decision Support Systems in taking better decisions.

H. KNOWLEDGE-BASED RULES VERIFICATION

In our symptoms based diseases classification, we used the expertise of domain experts to verify the results. In this case, we selected some of the results generated by our model from our classification and were manually verified by them. We did this because the accuracy of the initial result was less than our pre-defined threshold (say 80%). These domain experts belong to various agricultural zones in Pakistan. They shared their experience in the form of decisions about the precise identification of diseases based on the symptoms provided by users and learned by our model. If the class is correctly assigned by the algorithm, the relevant rule is saved as a decision in the DSS for further use. Otherwise, the updated disease labels and/or symptom(s) are used in re-training our decision tree to improve our classification accuracy. In our case, rules no. 2 and 7 have been revised by the experts e.g. Rule 7 has been revised as R7: IF (Superficial Dark Fungal Tissue = No) AND (Pinkish grayish fungal = Yes) AND (Scab infection = Yes) THEN Disease = Common Bunt.

IV. WHEAT DISEASES IDENTIFICATION AND CLASSIFICATION BASED ON WHEAT DISEASES IMAGES

In this section, we discuss the second contribution of our work, which is the classification of wheat diseases based on the symptoms present in the images acquired using our crowd-sourced application. Different diseases in those images were also labeled using one or more symptoms.

In this regard, we worked on different algorithms to classify diseases based on the symptoms depicted in images. The detail of algorithms is given in section IV, C-I-IV and their results are discussed in section F-1. However, we observed that the Convolutional Neural Network (CNN) performs better with our image data. The workflow of the proposed approach has been presented in Figure 5. This part of the classification has been discussed as under:

A. DATA ACQUISITION

To the best of our knowledge, no dataset is available regarding the wheat crop. In this regard, we worked on the collection of images from different sources. Finally, we were able to collect 9340 images. In this data retrieval process, 200 farmers also shared wheat crop disease images of their respective regions. Later on, using our mobile application, we labeled the symptoms of wheat crop diseases. In this case, field experts and farmers belonging to five agricultural regions of Pakistan participated in labeling our dataset images. In this way, the dataset has been prepared for our experiments.

Table 8 presents the randomly selected images related to three wheat diseases used for classification. We can see that images of different head diseases have similarities and the classification of such a dataset is not an easy task.

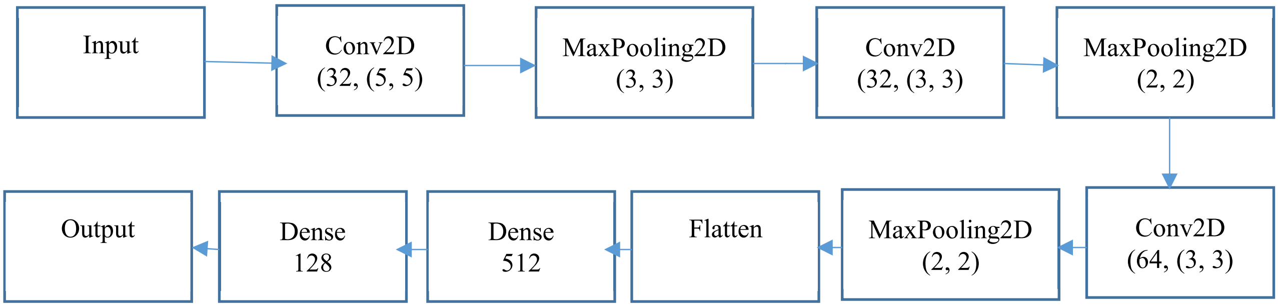


FIGURE 5. CNN Architecture used in the proposed model.

TABLE 8. Samples of wheat disease images.

Samples	Images		
Common Bunt			
Fusarium Head Blight			
Sooty Head Mold			

B. DATA PREPROCESSING

As discussed earlier, the images dataset has been formed from different sources. The dataset needs to be standardized and cleaned up before feeding it to some machine learning algorithms, such as CNN. In this regard, we worked on resizing our images to a unified dimension and ensured that the physical geometry of all images across the dataset is consistent. Next, we worked on the resolution of the images, as simply resizing images to a uniform dimension will consent to distortion in the data being used for building a model. Therefore, all images were scaled to the desired pixel layout. In addition, we also removed image noise which is a random variation in color information or brightness of an image using a Gaussian Blur function. Finally, data augmentation methods such as rotation, random cropping, resizing, horizontal flipping, random erasing (Picon *et al.* 2018; [22], and Mixup were used to generate significant data from the existing samples to improve the model learning. This helped in enlarging our dataset. It also helped in exposing our dataset to the neural network (CNN in our case) with a varied set of images in any form and shape. The details of data augmentation are given in sub-section E under the data description.

C. DEEP NEURAL NETWORK FOR DISEASE DETECTION AND CLASSIFICATION

In literature, deep learning-based architectures have majorly used for crop diseases classification using images. From the existing algorithms, we have used the Convolutional Neural Network (CNN) for wheat disease detection and its classification. Due to its flexible nature, CNN has significant importance in image classification. The CNN learns with fewer parameters in a very short time and required a small amount of data to train the model. It reduces the time required for tuning of different features. Instead of feature extraction from all pixels, it uses weight values to examine a patch of image for learning. The system extracts the features by self-learning using the convolution of the image and passes these to the next layer. Some approaches have used CNN for the classification of wheat diseases. Jiang Lu presented an approach using VGG-FCN-VD16 and VGG-FCN-S to identify the leaf disease and its classification. They obtained 95.12 % accuracy with their proposed model. Xiu Jin *et al.* have achieved 84.75% accuracy for the classification of wheat head diseases using a two-dimensional convolutional bidirectional gated recurrent unit neural network (2D-CNN-BidGRU) on 90 real field images of Fusarium head blight.

It is investigated from the existing approaches that previously used datasets have been used in most of the neural networks and did not explain the utilization and effectiveness of classification results for farmers working in real fields. Farmers and agricultural experts are not being involved at any stage of their work in the fields to improve diseases identification and classification using verification. Using the experience of the agricultural experts, the data can be cleaned and the results of the classification algorithms could be improved. In light of the mentioned requirements, we have used experts' experience on the data and results obtained from the DT and CNN to provide knowledge-based decisions.

1) KERAS SEQUENTIAL CNN

In this paper, we have investigated CNN architecture with 3 convolution and 3 pooling layers on our wheat diseases images dataset acquired through our crowd-sourced application. The architecture was mainly used for the identification and classification of diseases in the dataset.

The working of the architecture has been described as under Deep Convolutional Neural Network (CNN) entails four parts [24]:

a: CONVOLUTIONAL LAYERS

are used to learn the fundamental patterns like edges, shapes, and colors of the input images. This feature detection is mainly done through a matrix containing kernels also called filters. As a result, features or activation map is produced. This aims to reduce the size of images and results in fast data processing [22]. Using the activation map, the network averts the information loss from the images, as every feature map identifies the location of lost information in the image.

b: POOLING LAYERS

distinguish the features from the images regardless of the color attributes and angles. The Max. Pooling layer inserts a matrix with a size 2×2 (or 3×3) to move on the feature map and stores the largest value in the matrix to create a pooled map. This layer is also used to reduce the image size and to avoid overfitting arising due to the irrelevant information provision in the network.

c: FULLY CONNECTED LAYER

is used to calculate parameters or weights using neurons of current and previous layers.

d: OUTPUT LAYERS

hold the predicted classes after calculating errors and backpropagate these errors in the system for improving predictions.

For our wheat diseases images dataset, we used a sequential model consisting of three conventional (Conv2D) and three Max-pooling (MaxPooling2D) layers. The three convolutional 2D layers were initiated with (32, (5, 5)), (64, (3,3)), and (64, (3,3)) filters followed by an activation of Rectified Linear Unit (ReLU) function. The function rectified dissimilar images that were not linear. Its default range is from zero to infinity. The CNN architecture used in our case has been depicted in Figure 5.

As discussed earlier, three Max-pooling layers have been used in the architecture. The first Max-pooling layer has a size (3, 3). The size of the remaining two layers was set as (2, 2), and (2,2) respectively. On these layers, a matrix of the above-defined size was moved continuously through a complete feature map (left to right). The matrix chooses a maximum value in every pass. These chosen values are stored in another matrix called the pooled matrix. In addition, the Max-pooling layers are also focusing on reducing the size of images and control overfitting during the processing. Here a dropout layer was added to overcome the overfitting problem. This layer also played a vital role in reducing the validation loss that occurred due to overfitting during testing.

The model also includes a flatten layer that was used to transform all the features obtained by pooling layers into a single column called a vector. The vector was then forwarded for processing the data using a fully connected layer over the designed neural network. For setting the fully connected layer in the neural network, the dense layers' sizes were set to 512 and then 128 units, accompanied by the ReLU activation function. The last dense layer was connected with the Softmax activation function that handled the multiclass classification problem in the network.

2) AlexNet

AlexNet was created by the SuperVision group of the University of Toronto. The model won the image classification competition called ImageNet-2012. The model proved that deep learning can be used to achieve the least error-rates. The major feature of the model is to reduce the size of the network by overlapping the pooling layer operation [37]. The model used five convolutional layers (CONV), three fully connected layers (FC), and a ReLU function as its activation function. The function is applied after every CONV and FC. The ReLu function spreads the training rate to increase the classification accuracy. AlexNet also uses a regularization technique known as a dropout for reducing overfitting on the training dataset.

3) VGG

This architecture was created by the Visual Geometry Group (VGG) researcher at the Oxford University. The researchers used smaller filters in this case, however, the depth of the network was built deeper than the CNNs. VGG-16 consists of 13 CONV, 3 FC layers, and 5 Max-pooling layers. In VGG-16, instead of a large number of hyperparameters, the model uses a simpler network consisting CONV layers, which are 3×3 filters with a stride of 1, and with the same padding. A 2×2 filter with a stride of 2 is used in all Max-pooling layers. At the output, the model has a softmax layer having 1000 outputs/image category in the ImagNet dataset. The model has also outperformed well on many complex image classification tasks in the ImagNet-2014.

4) ResNet

As we build the CNN deeper by adding more layers to the existing neural network, the derivative upon back-propagation to the initial layers becomes insignificant in value. This problem is called the vanishing gradient problem. The architecture introduces the shortcut connection and features heavy batch renormalization to address the vanishing gradient problem. The shortcut connection fits the input from the previous layer to the next layer without any modification of the input. This enables the network to go much deeper. The model won the ILSVRC ImagNet-2015 and MS COCO 2015 for image detection, classification, segmentation, and localization-related complex tasks. The most common Resnet architectures are ResNet 50, ResNet 101, and ResNet 152.

D. THE USE OF KNOWLEDGE CREATION

Once the whole wheat diseases images dataset was processed, the classification result was sent to the agricultural experts using our crow-sourced application. Both, correctly and incorrectly classified instances were duly checked by them. At this phase, the image classification using our deep learning model was verified. After their assessment, the image labels were corrected. This integration of experts' experience with decisions created new knowledge in the wheat classification domain. The iterative process of this result verification enhances the quality of knowledge. Using the proposed approach, the results of ML algorithms such as losses, errors, and accuracy were improved to support the existing DSSs.

E. EXPERIMENTAL SETUP

In this paper, we've worked on two different datasets for the classification of wheat diseases. At first, we worked on the symptoms based text dataset. In that use case, we classified the available data using decision trees. Then, in the previous section, we explored another dataset, named the wheat diseases images dataset using a deep neural network architecture called CNN. In this section, findings of our deep learning model have been described below:

As discussed earlier, we collected 10857 wheat crop diseases images from farmers and domain experts, through our crowd-sourced application. In this dataset, we found 18 groups of labeled diseases. However, we selected a set of 9340 images comprising wheat diseases of three species i) common bunt, ii) Fusarium head blight and iii) sooty head molds. These three diseases are related to the head and grains. By themselves, these diseases are more harmful for wheat production, as the recovery of a diseased plant is very hard if they are not identified and diagnosed on-time. The details of the data being used in the model are discussed in the next subsection.

1) DATA DESCRIPTION

In the literature, most of the researchers have proposed the classification methods for wheat leaf diseases. These diseases are easy to be recognized, and their proposed algorithms outperform well on such diseases. These classifications are substantial for more production. The diseases related to the **head and grains** are more harmful for wheat production, due to the fact, the recovery of the diseased plant is very hard if they are not identified and diagnosed in the initial stages. Due to the importance of head and grain diseases, in this work, we focused on three main wheat diseases.

Initially, we processed 500 images using a CNN architecture. The performance of the network as low as 66.6% accuracy with a 65.7% loss on the training data. The model also showed 70.9 % accuracy with a 59.7% loss on the testing data. Further, we worked on removing noise from the dataset and increased the number of images. In this regard, we used the expertise of 10 agricultural experts for looking at the wheat image labels and image augmentation for removing noise in the images and only focused on the target area of the head and grain. Further, the images' labels were also verified by the domain experts. It is important to mention here that 3 out 10 experts are officials, nominated to monitor whole cultivation in the village called "Number Dar" in the local language.

FIGURE 6. Data augmentation techniques used on image data.

Now we enhanced our dataset to 1100 images. In this case, we excluded 91 low quality and irrelevant images. Finally, the dataset consists of 1009 images were processed on the same network. This time, the results were better with an accuracy of 82 %, but we worked for improving our model, and in this case, we worked for higher performance of the network. We acquired a dataset of 2800 images, in which 197 irrelevant images were removed by the domain experts. They also helped us in collecting new samples of Fusarium head blight, sooty head mold, and common bunt through our crowd-sourced platform. In this regard, we have managed to increase the number of samples from 2603 to 9340.

We have also used different data augmentation methods on the training data to increase the number of samples. Data augmentation methods such as rotation, random cropping, resizing, horizontal flipping, random erasing (Picon *et al.* 2018; [22]), and Mixup were used to generate significant data from the existing samples to improve the model learning. In random erasing, we randomly choose a rectangle area in the image and erase its pixels with random values. In this regard, images with random occlusion are generated as shown in Figure 6.

This reduces the risk of overfitting, the potential weaknesses of limited data samples and helps in making the model robust.

Another data augmentation technique Mixup has also been used. In this technique, each time, a new sample is generated by a weighted linear interpolation of randomly picked training samples (x_i,y_i) and (x_j, y_j).

$$x' = \lambda x_i + (1-\lambda)x_j \tag{10}$$
$$y' = \lambda y_i + (1-\lambda)y_j \tag{11}$$

This technique has already shown good results on the ImagNet-2012, CIFAR-100, and CIPAR-10 image classification datasets (Wang [44]).

The details of the used datasets are presented in Table 9.

TABLE 9. Details of the used datasets.

Diseases	Training	Testing	Removed by experts in pre-processing	Total used
Sooty Head Mold	1990	716	82	2624
Common Bunt	1876	998	74	2800
Fusarium Head Blight	2988	1055	127	3916
Grand Total	6854	2769	283	9340

TABLE 10. Configuration of workstation.

Configuration Parameter	Parameter Value
Chip model	NVIDIA Quadro 2000M / Intel HD Graphics 3000
RAM capacity	32 GB
Processor	Intel Core i7 2720 QM / 2.20 GHz (8CPUs)
Raster processing unit	64
Current display mode	1920 × 1080

2) EXPERIMENTAL ENVIRONMENT

To perform maximum iterations on the training and testing data while applying CNN, a workstation with the resilient graphic card was primarily required. The basic configuration of the machine is shown in Table 10. We used the Lenovo ThinkPad W520 with a 32 GB memory workstation. We also used Python with Keras library and a TensorFlow framework to process our wheat diseases dataset.

3) IMPLEMENTATION

The implementation of the model is discussed as under:

a: In the pre-processing

step, first, the dimensions of all the training and testing images were set. Here, we resized all the images by setting the ranges for re-scale, shear, zoom, split, and flip of the images. Then the images were converted into a uniform format (.png), and the type was set to float32. Now before loading the data into the network, the class labels were converted into a common encoding called hot encoding vector that generates a Boolean column for each class. This is due to the fact machine learning algorithm are unable to work on categorical data. After assigning the labels, a network structure was established to train and test the data. Here a sequential model was used in the architecture with three convolutional layers and three Max-pooling layers, as discussed earlier in Section IV C. Layers, their output shapes, and training parameters of the designed CNN models for training and testing are summarized in Table 11. Pooling layers have no learning parameters because these are involved in calculating the feature values without backpropagation.

b: The training

workflow was implemented using the Keras optimizers. The labeled images were properly segmented before training.

TABLE 11. Architecture of the designed network.

Layer type	Layers	Output Shape	Parameters
Convolutional	conv2d_1	252, 252, 32	2432
	conv2d_1	82, 82, 32	9248
	conv2d_1	39, 39, 64	18496
Pooling	max_pooling2d_1	84, 84, 32	0
	max_pooling2d_2	41, 41, 32	0
	max_pooling2d_3	19, 19, 64	0
Flatten	flatten_1	None, 23104	0
Dense	dense_1	None, 512	11829760
	dense_2	None, 128	65664
	dense_3	None, 3	387
Dropout	dropout_1	None, 512	0

We used 70% of the images in the training process and the remaining randomly selected 30% images were fed into the network for validation and testing. The uniform size of images was set as 256, 256, 3, along with a batch size of 16.

This time, the model tuned the network for 30 epochs in training the network. In the last, the dataset was loaded to the network for training.

c: To validate

the trained network, randomly selected 30% of images were also loaded to the network. The network positively responded to the cleaned dataset and reached its maximum accuracy after 20 epochs with a minimum loss.

d: CNN Training

configuration for other deep learning models: In this work, several CNN models such as AlexNet, VGG-16, and ResNet50 were also investigated. The models were trained on the training dataset selected randomly by splitting the wheat diseases image dataset into 70% training set, 15% validation set, and 15% testing set. The distribution of the samples per class in each set was kept similar. The CNN models were initialized with the parameters learned for the ImageNet image classification by the respective models. The balanced/weighted Softmax loss was applied to cater to the class imbalance distribution. These weights were related to the inverse of the class volume. Further, L2 regularization was applied on these CNN weights, and a 0.001 learning rate was set with a mini-batch size of 16. Different data augmentation methods such as horizontal flip, rotation, random resize, and mix-ups were applied on the Wheat-Image Dataset.

4) PERFORMANCE EVALUATION SETUP

To evaluate the performance of our model, the following measures were considered. Here, the accuracy was measured for each epoch of the data processing. Since performance is not the only method for looking at how better the model will work on the test data [15], we also used precision, recall (sensitivity), and F1 score, specificity, and balanced accuracy to evaluate the prediction and classification performance of the model. A confusion matrix was used to show the classification accuracy for each class.

F. DISCUSSION OF RESULTS

As discussed earlier in the data description, initially 500 images were used for building the model. The performance of the network as low as 66.6% accuracy with a 65.7% loss on the training data. The model also showed 70.9 % accuracy, 63% validation accuracy with a 59.7% loss on the testing data. The main reason behind this low accuracy was the noise in the images dataset, and badly labeled images, so that the network was unable to learn. The small dataset was also highly imbalanced in that case. Moreover, the expressive power of the network was unable to capture the target function.

As mentioned in the data description, we worked on the above problem and used the expertise of 10 agricultural experts for looking at the wheat image labels and image augmentation for removing noise in the images and only focused on the target area of the head and grain. Further, the images' labels were also verified by the domain experts.

Now we enhanced our dataset to 1100 images. In this case, we excluded 91 low-quality and irrelevant images. Finally, the dataset consists of 1009 images were processed on the same network. In this iteration of the model, we got relatively good results. The model showed 82.9% accuracy on the training set and 84.6% validation accuracy with a 44.5 % loss. The model also showed better results with 89.9 % accuracy on the testing data. As depicted in Figure 8.

At the initial epochs, a high value of the loss was observed during the training. This was mainly due to bad labeling. However, we worked for improving our model and acquired a dataset of 9623 images, in which 283 irrelevant images were removed by the domain experts. They also helped in the wheat crop image augmentation, removed noise in the images, and corrected the class labels. In addition to the increased number of images, we also added more layers (or more hidden units) in the fully connected layers of our architecture and increased the number of epochs.

On this new dataset, the model was trained, with parameters shown in Table 10. The trained network performed well and high accuracy values for all classes were achieved. On training, the model obtained 90.4% accuracy, 91.4% validation accuracy with a 10 % loss. The training accuracies, validation accuracies, training loss at each epoch has been shown in Figure 7 a). Similarly, 97.2% accuracy on the testing data was achieved with 2.1 % loss as shown in Figure 7 b). The overall processing results of the three datasets have been presented in Table 11. As we can summarize from the table, the overall classification accuracies have been improved due to the involvement of agricultural experts. The approach provided a significant enhancement in the performance of the network. Hence, the involvement of agricultural experts in the data cleaning and results verification is a new source of agricultural knowledge.

TABLE 12. Summary of performance using CNN architecture.

Status of Dataset	Performance of Network Training		Performance of Network Testing		Loss (%)	
	Training Accuracy (%)	Validation Accuracy (%)	Training Accuracy (%)	Validation Accuracy (%)	Training	Testing
Before data rectification	66.6	44	70.9	63	65.7	59.7
1st data rectification	82.9	84.6	88.6	89.9	44.5	32.7
2nd data rectification	90.4	91.4	96.6	97.2	10	2.1

TABLE 13. Confusion matrix of different wheat diseases.

	Sooty-Head-Mold	Common-Bunt	Fusarium-Head-Blight	Producer Accuracy (Precision)
Sooty-Head-Mold	698	11	16	96.27
Common-Bunt	14	982	12	97.42
Fusarium-Head-Blight	19	23	1027	96.07
User Accuracy (Recall)	95.48	96.65	97.34	96.61

In order to train the model, we fine-tuned the network for 30 epochs on the resultant final dataset. Consequently, the model started learning early with less value of the loss as shown in Figure 7 (a). However, the model responded quickly in learning at epoch 3 and 15, and we further observed a rapid decrease in the loss at epoch 3 and 16, and 25. If we intensely see Figure 7 (b), where the impact of our proposed approach has been highlighted. This time, the model was tuned for 20 epochs. The network has performed well at epoch 15 and showed 97.2% accuracy. This study reveals that the experience of experts has given new ways to image-based classification using ML algorithms. The performance of the model has been tested using other measures i.e. precision, recall, and f1 score [38].

Table 12 summarizes the performance of our designed CNN architecture on the used datasets. It presents the step by step improvement in the performance of the designed architectures in the form of accuracies and loss values.

We have also measured the performance of the model using a confusion matrix. The misclassified elements are shown in Table 13 with class-wise true positive values. Truth overall represents actual instances in the matrix and values under predicted accuracy are representing predicted instances of the confusion matrix.

The model also showed 96.5 % and 96.4 % overall precision and recall/sensitivity respectively on the image classification with kappa value of 94.9. The model has achieved

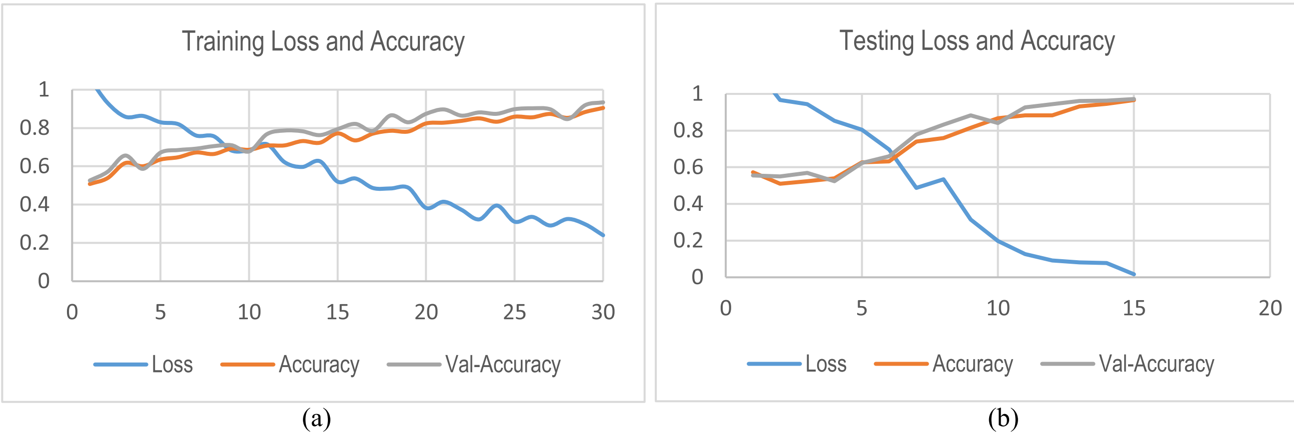


FIGURE 7. (a) and (b). Accuracies and loss at each epoch during training and validation.

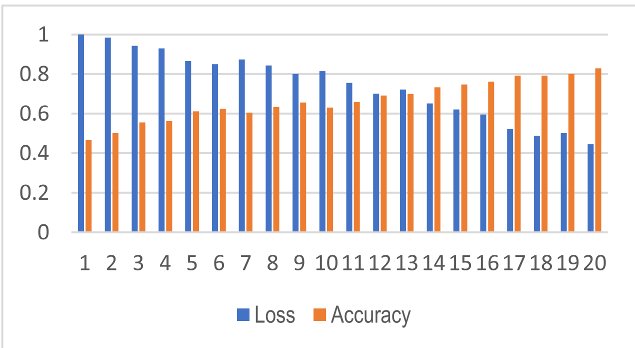


FIGURE 8. Performance of the network on 1009 image dataset.

a 96.5 % overall F1 score as a result. The model shows good performance on this dataset as shown in the confusion matrix. This classification accuracy also affects the F1 score and balanced accuracy as shown in Table 15. In our case classification accuracy of common bunt is slightly lesser than other classes and consequently, the F1 score has been achieved accordingly. However, the overall prediction and classification of the model are good and satisfactorily high.

1) COMPARATIVE ANALYSIS OF DIFFERENT CNN MODELS ON THE WHEAT DISEASES IMAGE DATASET

For the wheat diseases identification, Sequential CNN and ResNet 50 performed well as compared to other state-of-the-art deep learning models. The training, validation, and testing accuracies and respective loss values of these models are reported in Table 14. Comparatively, our proposed Sequential CNN model has outperformed on the image-based dataset and achieved 97.2% validation accuracy with a 2.10 validation loss, which means that over-fitting had not happened in the training process. The other CNN performance is discussed as under:

a: ResNet50

In the case of ResNet, the model has achieved a high accuracy of 97.12 % and 1.92 % loss due to the concept of residual

TABLE 14. Performance comparison of proposed network with other CNN models.

	VGG16	ResNet50	AlexNet	Sequential CNN
Training accuracy	88.62	90.38	88.43	**90.40**
Training loss	10.70	**6.174**	10.40	9.80
Validation accuracy	95.72	**96.77**	95.10	**96.60**
Validation loss	2.60	**1.92**	2.71	2.10
Testing accuracy	96.72	97.12	95.10	**97.20**

learning. The model has also a low validation loss which means that over-fitting had not happened in the training process. Although ResNet has shown good results in our case, however, the model requires hundreds of hours for training the model, thus making the model infeasible for the wheat diseases classification based on different symptoms.

b: VGG16

In the case of VGG16, we can see that the validation loss has an increased value due to the vanishing gradient problem experienced by the model. The network architecture weights in VGG16 are also very large, thus making the model training very much slow.

c: AlexNet

In AlexNet the depth of the model is very less and hence it struggles to learn features from image sets. The model also takes more time to obtain good accuracy as compared to other models.

2) OTHER PERFORMANCE MEASURES

We have also worked on other performance measures such as class-wise specificity and balanced accuracy (BAC) using

TABLE 15. Class-wise performance of proposed model.

Classes	Specificity	Recall/ Sensitivity	Precision	F1 Score	BAC
Sooty-Head-Mold	0.976	0.954	0.96	0.966	0.974
Common-Bunt	0.987	0.966	0.962	0.958	0.970
Fusarium-Head-Blight	0.985	0.973	0.974	0.970	0.976

equations (12) and (13) respectively.

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{12}$$

$$\text{Ballence Accuracy} = \frac{\text{Sensitivity} + \text{Specificity}}{2} \tag{13}$$

Specificity shows the fraction of class-wise actual negative diseases that have been predicted as negative using our model. To easily understand the specificity values in our results, It is the ratio of truly predicted negatives by our model to all negatives in the dataset by equation (12). In our case, the model has outperformed and achieved 97.6 % and 98.7 % specificity for sooty head mold and common bunt respectively. As we have used a different number of images for each disease in the training and testing, we have calculated a balanced accuracy to examine the performance of the model. our model has achieved an average of 97.3 % balanced accuracy which shows good performance of the model on test data. The model also achieved class-wise high balanced accuracy. Fusarium head blight has achieved higher balanced accuracy than other classes as shown in Table 15.

As discussed, a multimodal dataset has been used for wheat disease classification, a comparative analysis of DT and CNN in terms of Predictive Accuracy, Stability, Simplicity, and other evaluating criterion explored in Section III are also depicted in Table 16. A clear improvement in the accuracy values before and after the involvement of agricultural experts has been observed. DT and CNN have achieved stability of 99% and 96.12% respectively which shows less variation in the predictive accuracy rate when both algorithms were applied to the dataset.

3) COMPARISON OF PERFORMANCE OF PROPOSED MODEL WITH EXISTING SOLUTIONS

In the literature, researchers have presented various approaches to the classification of wheat diseases. Most of them have focused on leaf disease. According to agricultural experts, diseases related to head and grain are more destructive to crops in decreasing the yield production. So, we have worked on three diseases of the wheat's head and grain as discussed earlier. Very few approaches have been seen in the literature for the classification of sooty head molds and common bunt.

For instance, paper names listed in Table 17, the authors have traditionally used image-based data, obtained from

TABLE 16. Evaluating criterion for DT and CNN used in the proposed model.

Criterion	Text-based Symptoms Dataset	Image-Based Diseases Dataset
Model	Decision Trees (DT)	CNN
Number of Classes	9 (all classes)	3 (investigated)
Training Accuracy before Expert Verification	82.33 %	70.90 %
Testing Accuracy before Expert Verification	80.88 %	63.00 %
Training Accuracy after Expert Verification	95.88 %	93.4 %
Testing Accuracy after Expert Verification	94.66 %	97.2 %
Simplicity(Leaf)	7.00	-
Simplicity(Rule)	$3 \leq x_N < 4$	-
Stability before Expert Verification	0.98	0.89
Stability after Expert Verification	0.99	96.12

online sources. They have worked on the classification of wheat heads and leaves using different deep neural network architectures to improve accuracy and other performance measures.

Siddharth *et al.* used CNN with Bacterial foraging optimization based Radial Basis Function Neural Network (BRBFNN) on 270 images for the classification of what leaf. In this approach, limited statistical criteria are used to measure the performance of the model e.g. they have only focussed on specificity and sensitivity. Zhongqi Lin *et al.* used the matrix-based convolutional neural network (M-bCNN) for the head diseases classification on the real field dataset comprising 16652 images. They claimed 90.1 % accuracy using their proposed matrix-based approach. Similarly, Jiang Lu used VGG-FCN-VD16 and VGG-FCN-S for the leaf disease identification and classification and obtained the results with 95.12 % accuracy. Xiu Jin *et al.* have employed a two-dimensional convolutional bidirectional gated recurrent unit neural network (2D-CNN-BidGRU) on 90 real field images of Fusarium head blight. They have achieved 84.6 % accuracy for the classification of wheat head diseases.

Reference [15] have used one and two-dimensional CNN for the classification of Fusarium head blight of wheat crop. They have reconstructed a bidirectional recurrent layer with a convolutional layer to improve the performance of the model. in a pesticide-free region, they have collected 90 samples of the crop at the fully ripe stage. The model has achieved 74.3 % accuracy and a 75% F1 score. Instead of real fields, the small data has been obtained from pesticides free zone. Therefore

TABLE 17. Comparative analysis of our proposed model with existing approaches in literature.

Reference	Approach	Crops	Diseases	No of Samples	Accuracy (in %)	Decisions Improves using Experts' Knowledge	Other Shortcoming
(Franke and Menz 2007	Decision Trees	Wheat	Powdery mildew and leaf rust	54	96.2	No	Decisions not provided Variation in accuracies
(Lu et al. 2017)	AlexNet, VGG-19	Wheat	Insects	9230	95.97	No	Pests belong to different irrelevant crops
(Jin 2018)	CNN	Wheat	Fusarium head blight	96	74.3	No	Small dataset not obtained from real fields
(Tibola and Pavan 2018)	Transfer learning	Wheat	Head blight	11555	81	No	More Misclassifications observed
(Picon et al. 2018)	Deep Residual Neural Network	Wheat	Septoria, Tan spot, Rust	8178	87	Partially	Results are not verified by expert technician
(X. Zhang et al. 2018)	GoogLeNet and Cifar10	Maize	Leaf	500	98.9	Partially	Dataset is very small, Results not verified by the experts
(Jin 2018)	(2D-CNN-BidGRU)	Wheat	Fusarium head blight	90	84.6	No	Decisions not provided
(Chouhan et al. 2018)	(BRBFNN)	Wheat	Leaf spot, Common rust	270	82	No	Limited performance criteria was used
(Lin et al. 2019	Matrix based CNN	Wheat	Multiple	16,652	90.1	No	Unable to provide agricultural knowledge to the farmers to enhance their crop production
(Du et al. 2019)	SVM, Random Forest	Wheat	Yellow rust and aphid	1900	78	No	Decisions are not provided
(N. Zhang et al. 2019	Mixed	Wheat	Fusarium head blight	86	89.80	No	Not suitable for large datasets
(Li 2019)	AlexNet, GoogleNet	Multiple (26)	Leaf	20000	98.48	No	Mixed dataset was used
(Zhao et al. 2020)	CNN	Wheat	Stem (Lodging)	8000	89.23	Partially	Under-utilization of experts' knowledge
(Argüeso et al. 2020).	CNN, Few-Shot Learning (FSL)	Multiple (26)	Leaf	54,303	91.4	No	Classification of mixed dataset is not practically useful for farmers
Waleej et al.	CNN	Wheat	Head blight, Common bunt, Sooty head mold	9340	97.2	Yes	System has not completely delivered to the farmers

the impact of pesticides could not be observed to recommend a relevant disease management method. In another approach, they have worked on the same disease using and achieved 84.6% accuracy.

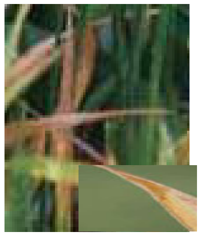
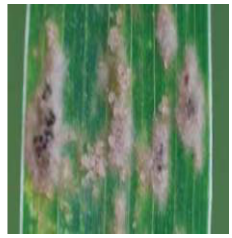
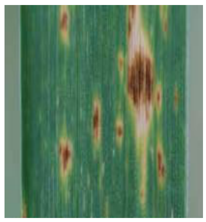
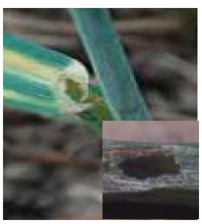
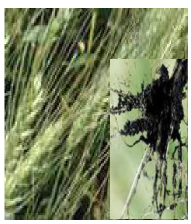
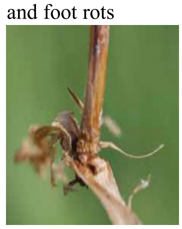
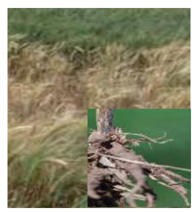
(Tibola and Pavan [42]) *et al.* worked on wheat head blight using transfer learning. A dataset of 11555 samples was used. The system has achieved 81% accuracy. Their data has not been labeled by experts, so more misclassifications have been observed as a result.

Zhang *et al.* worked on 86 samples of fusarium head blight. They used mixed models to calculate Fusarium index and achieved 89.8% accuracy by their system. Generally, mobile application based systems are suitable for the detection of diseases from individual images. While classifying the disease from a huge dataset, these systems could not provide services to the researchers.

As we can see from the existing approaches, most of the work has been done on the previously used datasets and did not explain how the classification results could be helpful for farmers working in real fields. They also do not engage farmers and domain experts at any stage of their work to improve diseases identification and classification using verification.

As shown in Table 17, only a few models have provided decisions for disease identification. We hardly found only three systems (Picon *et al.* 2018), [48], and [49] where expert knowledge was partially used in wheat diseases

TABLE 18. Wheat disease classification based on physical parts of the plant.

Class	Disease			
	Common bunt	Fusarium head blight	Loose smut	Sooty head molds
Diseases affecting heads and grain				
	Bacterial streak	Barley yellow dwarf	Leaf rust	Powdery mildew
				
	Septoria tritici blotch	Stagonospora nodorum blotch	Stem rust	Stripe rust
Diseases affecting leaves				
	Tan spot	Wheat soilborne mosaic	Wheat spindle streak mosaic	Wheat streak mosaic
				
	Cephalosporium stripe	Common root rot	Fusarium root, crown, and foot rots	Take-all
Diseases affecting stem and roots				

identification. Specifically, the knowledge of agricultural experts has been rarely utilized for data rectification. Further, agricultural experts' knowledge has not been used in the wheat diseases classification verification process. Technically, the involvement of agricultural experts in the development of agricultural solutions is very important. However, in our work, we have used the expertise of agricultural experts in (i) verifying diseases identification rules,

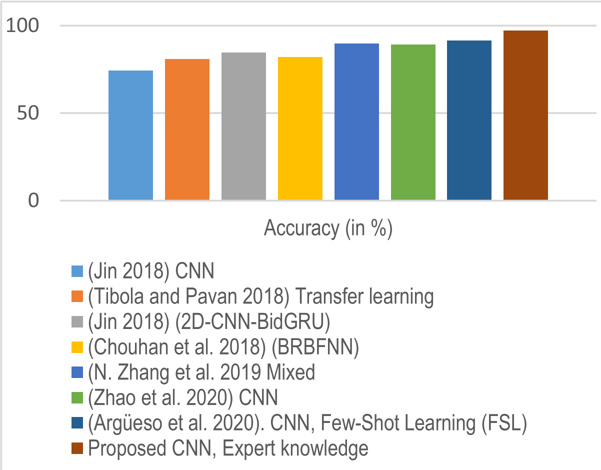


FIGURE 9. Comparison of performance of proposed model and other approaches using convolutional networks.

and (ii) verifying the wheat diseases classification on images performed by our model. This not only helped in verifying our wheat diseases classification results but also helped in increasing the classification accuracy from 93.4 % to 97.2 %. In this way, our model will not only verify the decisions but will also help in identifying wheat diseases in real field practices.

Moreover, in Table 18, our model has been compared with the existing models in terms of the crop, its diseases, number of samples, accuracy, and the use of experts' knowledge. It is clear that in all instances of head diseases, our accuracy of 97.2 % was better than [15] having an accuracy of 74.3%, (Tibola and Pavan 2018) having an accuracy of 81 %, and [47] having an accuracy of 89.80 % present in the research literature. The GoogLeNet and Cifar10 (Li [15]) model achieved 98.90 % accuracy. In this system, leaf diseases were focused, which are relatively easy in identification and classification.

To compare the performance of our proposed approach with existing approaches in the literature for the classification of diseases related to wheat's head and grain, accuracy is considered as a performance measure. Figure 9 shows that a matrix-based convolutional neural network (M-bCNN) presented by Zhongqi Lin *et al.* shows the highest accuracy of 90.1% after the classification of Fusarium head blight disease. Other approaches based on transfer learning and 2D-CNN-BidGRU have obtained resultant accuracy of 81 % and 84.6% respectively. Our proposed model based on the experience of agricultural experts has achieved 97.2 % accuracy which is much better than the others presented approaches.

V. CONCLUSION

This work mainly focuses on the modern and effective generic approach of fast identification and classification of wheat diseases using DT and CNN algorithms. To improve the performance of the algorithms, an iterative process of data rectification and results verification by the agricultural experts has been presented to provide knowledge-based decisions. The results show that the proposed approach delivers substantial improvements over the traditionally used approaches using the same algorithms. Also, the proposed approach can provide a classification of diseases based on symptoms and physical parts of the plants. Accuracy after the verification of the results of both algorithms leads to more effective utilization of the proposed approach for classifying various wheat diseases.

ACKNOWLEDGMENT

The authors would like to thank the reviewers for their valuable comments for improving the quality of this paper. They also thank agricultural experts for their precious time and services, users for data provision, and Mr. Asif Raza, for his expertise in Machine Learning.

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