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RESEARCH ARTICLE

Wheat Disease Classification Using Continual Learning

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ABSTRACT As wheat is one of the major crops worldwide, therefore, accurate disease detection in wheat plants is critical for mitigating effects and halting disease spread. Nowadays, the detection of diseases through images using machine learning and deep learning has achieved state-of-art results. Yet these models suffer from two shortcomings, one is the data-hungry models of deep learning, and the second is the adaption of new classes with previous ones, i.e., if a new disease arrived, one must retrain the entire model with a new dataset which has led to the origination of few-shot learning that solves both problems. A wheat disease classification network is proposed based on a few-shot learning method for the classification of 18 wheat diseases using EfficientNet as a backbone. Also, the attention mechanism is incorporated to facilitate efficient feature selection. Our proposed network has achieved 93.19% accuracy on the 40 images of 18 disease classes manually collected from the internet while that of our backbone network EfficientNet has gained an accuracy of about 98.5% accuracy on CGIAR Dataset. The evaluation demonstrates that despite the presence of only a few images in both the training and query sets, the proposed model has achieved superior performance in terms of accuracy and computation cost. Furthermore, the evaluation also highlights the effectiveness of our model in terms of data and computation cost. The proposed method can be used for disease detection in wheat crops requiring less amount of data.

INDEX TERMS Few-shot learning, Siamese network, wheat diseases classification, support, query set.

I. INTRODUCTION

Wheat plant is one of the major crops grown across the world. Its production is very determining for food requirements and the economic growth of many countries. It is the major export for countries like Russia, Canada, the United States, France, and Ukraine.[1] FIGURE 1 is the graphical representation of how much wheat has been consumed globally from 2017 to 2022.[2] However, wheat plants are vulnerable to diseases that can severely affect their growth. Every year, a significant amount of wheat crop is wasted due to different viral and bacterial diseases. According to a study [1] conducted for analysis of pathogens and pests on the field crops, a 21.5% loss in wheat production had been estimated due to wheat diseases and pest attacks on crops. There are numerous reasons for the spread of these diseases, viral and non-viral [2].

Methods such as spectroscopy strategies etc. can be used to detect these diseases; however, they can be time-consuming and expensive due to the usage of multiple sensors [3]. Furthermore, these procedures require laboratory and domain specialists which may be expensive. Therefore, there is a need for the automatic detection of these diseases.

Machine learning and deep learning methods have achieved success in various computer vision tasks such as image classification, object identification, and recognition [4], [5]. These methods have also been successfully applied in plant disease detection [6], [7]. Convolutional Neural

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[1]https://oec.world/en/profile/hs/wheat/
[2]https://www.statista.com/statistics/

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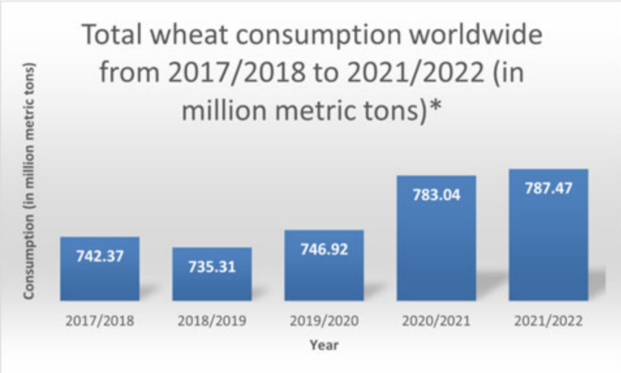


FIGURE 1. Global Wheat Consumption from 2017 till 2022 (in million metric tons).

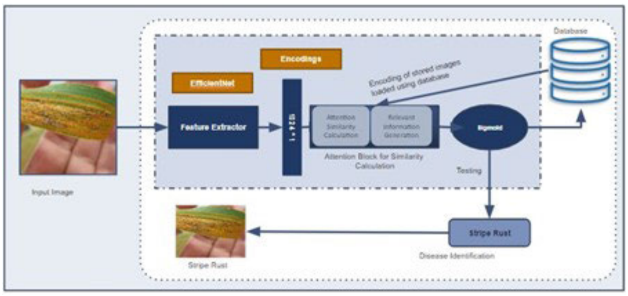


FIGURE 2. Workflow of the entire few-shot network.

Networks (CNN) learn a large number of parameters from input data. However, a trained CNN model cannot accommodate new classes. On the arrival of a new class, the whole network needs to be re-trained. This issue is referred to as catastrophic forgetting [8]. Continual learning can be used to tackle this issue [9], [10]. Continual learning, also called lifelong learning, is achieved through methods such as zero-shot learning (ZSL), one-shot learning (OSL), or few-shot learning (FSL). These methods are also effective when training examples are scarce or the data annotation is costly [11]. In this paper, we propose a wheat disease identification method based on FSL. A simple workflow diagram of the proposed approach can be visualized in FIGURE 2.

The main contributions of our network are as follows:

- The proposed network can accommodate new wheat diseases without retraining the whole network with good accuracy.
- Implementation of an efficient and effective method of disease classification with very few amounts of data using the proposed network.
- The network has applied few-shot learning techniques with state-of-art EfficientNet to make the network computationally efficient.
- Utilization of the attention-based mechanism for the extraction of the relevant feature so that it leverages to reduce the false positive even with a limited number of images from new classes.
- Classification of eighteen classes of wheat diseases that can occur in crops. The evaluation demonstrates that despite the limited number of images in both the training and query sets, our model has performed better in terms of accuracy and computation cost.

The rest of the paper is divided as follows: Section II presents related work. Section III describes the datasets used. Section V presents a detailed methodology while section VI is related to experimentation. Results are mentioned in section VII, and conclusions and future directions are mentioned in section VIII.

II. RELATED WORK

AI has been widely used in several areas including medicine [12], criminology [13], agriculture [14], etc. Similarly, many machine learning and deep learning methods have been applied in the domain of agriculture such as plant disease classification for cereal and vegetable crops, fruit trees, wheat, etc. In this section, the existing methods are presented that utilize machine learning and deep learning techniques in the domain of wheat disease identification.

A. MACHINE LEARNING-BASED METHODS

A. Badage [15] proposed a system for regularly monitoring the cultivated area and detecting diseases using remote sensing images. RGB feature-based techniques were used to process the images and then color image segmentation was applied to spot the disease. Using Sobel and Canny filters, edge features were extracted to identify the disease. Similarly, Ramesh et al. [16] applied a random forest classifier to classify diseased and healthy leaves. A dataset was created, and feature extraction was applied by using the Histogram of an Oriented Gradient (HOG). The authors experimented with different machine learning classifiers, including logistic regression, SVM, etc. but the random forest classifier gave the best results. Tulshan and Raul [17] reported that primary crop production is lost due to plant leaf diseases and presented an ML pipeline for successfully classifying these diseases. After preprocessing, k-means clustering was used to segment the image to separate the noise. Gray-level co-occurrence matrices (GLCM) were used as feature extractors to extract 13 features of leaves. The overall accuracy using the KNN classifier was 98.56 Khan et al. [18] used hyperspectral images to study the powdery mildew disease in wheat. Vegetation indices (VIs) and normalized difference texture indices (NDTIs) were extracted first to calculate the difference between normal and diseased leaves. Then linear discrimination method was used to detect powdery mildew disease with an accuracy of 82.35%, and a regression model was used to identify the disease severity with a coefficient of determination (R2) of over 0.748. Azadbakht [19] presented a method based on machine learning techniques and under different leaf area index (LAI) levels of canopy leaf. The ν-support vector regression (ν-SVR) algorithm achieved the highest results. An ML-based method was presented by

H. Khan et al. [20] for the classification of yellow and brown wheat rust diseases. The dataset of 1050 images of wheat leaves, was gathered from different fields in Pakistan and preprocessed to separate the healthy and diseased plants. Various feature extraction techniques were used, including a Histogram of Oriented Gradient (HOG), Local Binary Pattern (LBP), HueMoment (HM), and Color Histogram (CH), to extract shape, texture, color, and Haralick Texture (HT) features. These extracted features were classified using the random forest classifier with an accuracy of 99.8%. These techniques obtained good results, but the feature extraction process was time-consuming and effort-taking; therefore, the paradigm was shifted to deep learning-based methods where instead of extracting features manually, it is done automatically.

B. DEEP LEARNING-BASED METHODS

Deep learning-based convolutional neural networks(CNN) have been applied successfully in many areas without the need for manual feature extraction. Hussain et al. [21] used a deep learning model AlexNet to classify four wheat diseases into four classes: stem rust, yellow rust, Powdery mildew, and normal. The proposed method obtained an accuracy of 84.54% with different hyper-parameters. Goyal et al. [22] presented an automatic disease classification using deep learning techniques in leaves and spikes of wheat. The proposed model consisted of 21 convolutional layers and three fully connected layers. LWDCD2020 dataset with ten classes was used for evaluating the model. The proposed method gained a high testing accuracy of 97.88%. A comparison with ResNet50 and VGG16 was given in the paper showing the proposed model's good performance. Similarly, Sood and Singh [2] also used deep learning-based classifiers to differentiate between wheat rust and healthy wheat classes. The dataset was collected and preprocessed to get valuable results with two different deep learning models, ResNet50 and VGG16. The proposed approach gained a classification accuracy of 99.07% using the VGG16. Wheat diseases that are caused due to fungi like leaf and stem rust, yellow rust, septoria, and powdery mildew cause harm to wheat production annually. To control the spread of these diseases Genaev et al. [23] presented a CNN method based on the EfficientNet technique. The dataset of 2414 images named WFD2020 was generated. The accuracy achieved was 94.2%. Kumar and Kukreja [24] presented a method for the automatic detection of wheat mosaic virus, which is very harmful to the crop. A visual object tagging tool was used to label the mosaic virus. Mask-RCNN with backbone ResNet50 was used for the detection task on a dataset of 15,536 wheat images that were collected manually. Each leaf was segmented, and mosaic virus disease was detected with 88% and 97% accuracy, respectively. Safarijalal et al. [25] presented a method to detect three major wheat diseases (brown-rust, yellow-rust, and healthy leaves) and suggested ways for automatic pesticide spraying to the plants. It used different object detection methods for plant identification like other versions of YOLO and efficient net-B0. For object detection, YOLO-V4-tiny gained the best results with a 19% mAP while high accuracy of 99.72% and 0.794 Gigaflops for disease detection using EfficientnetB0. An efficient navigation system implemented on the UAV was built. Most of the methods discussed here are very efficient in the classification and detection of disease recognition, but all these have a limitation. It is known that due to some environmental conditions, new diseases may outbreak, or a system may get trained on a few diseases, and to add a new disease, one must retrain the whole system. Although traditional deep learning models are very efficient, this imitation makes it worth moving to new methods. Secondly, a huge amount of data is required for each class efficiently set in the training data. This makes the deep learning model computationally expensive and time taking. This limitation can be solved using continual learning-based methods.

C. FEW-SHOT LEARNING

Few-shot learning (FSL) is a technique that does not need a large amount of training data. The trained model can be extended with new classes by incorporating prior knowledge and without retraining the model with the entire dataset. Many researchers have successfully applied FSLbased methods. In agriculture, FSL methods have been used for plant disease and pest classification as discussed by Li et al. [26], Nuthalapati et al. [27] and, Gomes and Borges [28]. A recent study on the analysis of fungal plant diseases in five different plant species were conducted by Itziae et al. [29], for 17 different diseases. Siamese network and triplet loss were used during training while feature extraction was done using a metric learning-based approach. The overall performance was the gain of an F-score of 6% on other traditional methods of few-shot learning. Argeso et al. [30] used FSL for the classification of plant diseases on the PlantVillage dataset. The dataset consisting of 38 classes was split into a source domain with 32 classes and a target domain with 6 classes. In the source domain, fine-tuning of the Inception V3 network was performed to learn abstract leaf features. FSL was accompanied by Siamese networks, Triplet loss was applied and collated with traditional fine-tuning. The FSL method surpassed the traditional fine-tuning, which achieved 18.0% and 72.0% accuracy for 1 and 80 images per class, respectively. The author argued that using Siamese networks with Triplet loss might learn unseen plant leaves and diseases with tiny datasets, with a decrease in training data requirements and surpassing traditional learning approaches for small training sets. Triplet loss was also employed by Uzhinskiy et al. [31] with one shot learning technique for plant disease detection and moss species identification in five different crops. The dataset consisted of 935 images of 25 classes belonging to four crops e.g., cotton, wheat, corn, cucumbers, and Grapes.

TABLE 1. Related work for wheat disease classification.

Study	Method	Dataset	Results	Few-Shot Learning	No. of Classes
Machine Learning-Based Methods					
S. Ramesh et al. [16] (2018)	Feature Extractor: Histogram of Oriented Gradients, Classifier: Random Forest	Manually collected	70.14% accuracy	No	Diseased and normal plants
A. S. Tulshan and N. Raul [17] (2019)	Feature Extractor: Gray level co-occurrence matrices (GLCM), Classifier: KNN	Dataset of 75 images	98.56% accuracy	No	Seven diseases
M. Azadbakht et al. [19] (2019)	ν-SVR with other four machine learning architectures	Canopy level Wheat leaf rust data	RMSE=8.5% with ν-SVR	No	Wheat leaf rust
I. H. Khan et al. [18] (2021)	PLS-LDA Model	Hyperspectral images of Healthy and powdery mildew wheat	85% accuracy	No	powdery mildew disease in wheat
H. Khan et al. [20] (2022)	Feature Extraction: Histogram of Oriented Gradient (HOG), Local Binary Pattern (LBP), Hue-Moment (HM), Color Histogram (CH), Haralick Texture (HT). Classifier: Random Forest Classifier	1050 images collected from field	99.8% accuracy	No	Yellow and brown rust (2)
Deep Learning-Based Methods					
A. Hussain et al. [21] (2018)	AlexNet	Four Class dataset	84.54% accuracy	No	stem rust, yellow rust, Powderly mildew, and normal.
M.A. Genaev et al. [23] (2021)	CNN with EfficientNet	WFD2020	94.2% accuracy	No	stem rust, yellow rust, Powderly mildew, leaf rust, and septoria.
S. Sood & H. Singh [2] (2020)	ResNet50 and VGG16	Collected from Kaggle, Google, manually collected	99.07% accuracy using VGG16	No	leaf-rust, stem-rust, and yellow rust.
A.V. Uzhinskiy et. al [31] (2020)	Siamese Network with triple loss, MobileNetV2	Manually collected data on different plants and diseases	98% accuracy	Yes	Four crops cotton, wheat, corn, cucumbers, and grape have 25 classes
D. Argüeso et al. [30] (2020)	Siamese Network	Plant Village dataset	90% accuracy	Yes	38 classes of different plants
L. Goyal et al. (2021) [22]	A convolutional model, VGG16 and ResNet50	LWDCD2020	97.88% accuracy	No	10 classes
H. Mukhtar et al. [33] (2021)	MobileNetv3 as Feature Extractor, Siamese Network	CGIAR, Collected field Images of 11 classes	92.2% Accuracy	Yes	11 wheat diseases
B. Safarijalal et al. [25] (2022)	EfficientNet B0	Manually collected wheat disease dataset	99.72% accuracy	No	Yellow rust, brown rust, and healthy leaves
D. Kumar and V. Kukreja [24] (2022)	Mask-RCNN	15,536 real-time gathered images	88.19% and 97.16% for leaf and mosaic virus segmentation	No	Mosaic Virus class

The proposed method used MobileNetv2 as the base network and the Siamese network with triple loss as the one-shot network. The overall achieved accuracy by MobileNetv2 for plant disease detection was above 97.8% for most category classifications.

As a result, it was determined that the fusion of the Siamese network and the triplet loss function could lead to achieving good results for classification tasks with a limited amount of training data. L. Chen et al. [32] used FSL for the plant disease classification using different datasets. A local feature matching conditional neural adaptive processes (LFM-CNAPS), and a dataset with different species were introduced. The proposed method obtained 93.9% accuracy on the above-mentioned dataset. H. Mukhtar et al. [33] presented a wheat disease identification network that used a one-shot learning technique. The objective of the experiments was to propose a lightweight system that may operate on a mobile phone. For this reason, MobileNet was used as the feature extractor. The proposed network was trained on the PlantVillage dataset. The entire one-shot network was trained using 440 images. Each of the two input images was encoded using Siamese networks, after which the absolute difference between both was measured and similarity scores were calculated. MobileNetv3 model obtained around 96% accuracy, while the entire one-shot network scored greater than 92% accuracy, 84% precision, and 85% recall. TABLE 1 presents a brief overview of related work done so far on wheat disease classification.

III. DATASET

In this study, three datasets are used. PlantVillage [3] dataset which has approximately 20k labeled images of 15 categories. The second one is the plant disease dataset named CGIAR Computer Vision for Crop Disease dataset, available on Kaggle.[4] This dataset consists of around 1450 images and three classes i.e., normal, stem rust, and leaf rust. The third dataset is collected from Google that consists of 80 images for every 18 classes of wheat diseases. All images were searched based on the disease name. Out of these datasets, PlantVillage and CGIAAR datasets are used for pretraining and finetuning of EfficientNet, respectively while the manually collected data will be used for training and testing of the few-shot network. FIGURE 3 presents a pictorial representation of these diseases.

IV. PRELIMINARIES

The Support Set and Query Set: The main idea behind few-shot learning is to train a model on a small number of "support" examples of a new task or concept, this is called a support set. And then use this knowledge to generalize to new "query" examples which are called a query set. This approach allows the model to adapt to new tasks quickly and efficiently, without the need for large amounts of labeled data. Siamese Network: We have used the Siamese network approach for our few-shot learning architecture. Siamese networks are a particular form of neural networks that have two or more identical subnetworks or branches that share the same architecture and weights. In the proposed FSL architecture, the feature extractor for support and query set is the same network that will be discussed in upcoming sections.

[3] https://www.kaggle.com/datasets/emmarex/plantdisease

[4] https://www.kaggle.com/datasets/shadabhussain/cgiar-computer-vision-for-crop-disease

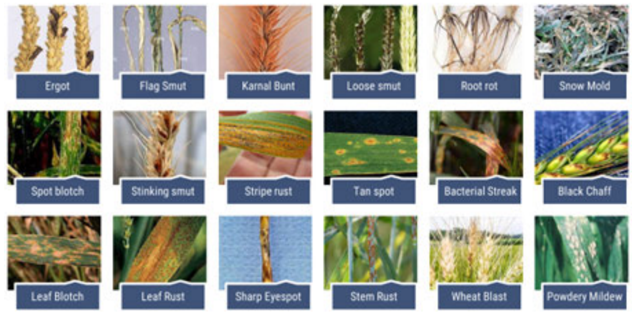


FIGURE 3. Samples from manually collected dataset from Google with 18 classes.

V. METHODOLOGY

Our network consists of three main components, an efficient net as a backbone network for feature extraction, a similarity score calculator, and a dense layer with a softmax unit.

A. PREPROCESSING

First, input images are fed into feature extraction units to obtain image encodings. Encodings are feature vectors obtained from an input image. There are two sets of images used in a few-shot network, a support set and a query set used for training and evaluation purposes, respectively. These encodings are used to calculate the difference between the reference/support images and the query image by using the attention-based similarity calculation module. Lastly, the probability score is calculated using a dense layer with a softmax unit. We have utilized EfficientNet for feature extraction because it is accurate with a smaller number of computations. This few-shot network is referred to as the Siamese network as the same feature extractors are used for the query set and support set. Training of a few-shot-based network is done using the mentioned feature extractor and the other two modules. FIGURE 5 is a graphical representation of the proposed few-shot learning-based network.

B. SUPPORT AND QUERY SET

For using few-shot learning, the data is divided into a support set S, and a query set Q. It is generally studied using N-way-K-shot classification. It means to classify N classes using K number of instances, and this set refers to as a support set. It includes the number of images that are employed to learn how to execute the specific task. The query set contains examples of the same classes that are used to evaluate the performance of the task. In FSL, these sets together make

FIGURE 4. Support set and query set.

tasks that are used for training purposes and none of the tasks contains overlapping classes. In FIGURE 4, there is an example representation of these tasks. In this figure, a 3-way-2-shot classification task is represented, which means in every task, there are three classes with two examples each.

C. EFFICIENTNET

EfficientNet is a convolutional neural network architecture and scaling technique. With a set of predefined scaling coefficients, the EfficientNet scaling algorithm adjusts network breadth, depth, and resolution consistently. Scaling up the CNNs by adding more layers cause an increase in computational complexity and training time, whereas efficient net proposes a simple and effective scaling-up method using compound coefficients in a more accurate manner. Moreover, these architectures are scalable to the underlying device they are heading to. For example, if the computation resources are increased by 2N, then network depth, width, and image size can be increased by α^N, β^N, and γ^N, respectively where α, β, and γ are constant coefficients discovered from the initial small model. The argument behind the compound scaling method is that if the input image is larger, the network will require additional layers to expand its receptive field and channels to gather more fine-grained features on the larger image. Specifically, we have used EfficientNetB0, which consists of an input layer of size 224*224*3 and 18 convolutional layers, including 1 conv3*3, MBConv1 with a kernel of size 3*3, six MBConv6 with kernel size 3*3, nine MBConv6 with kernel size 5*5. Finally, a dense layer of 1024 units are applied to get the feature vector. This architecture is adopted from [34]. Along with EfficientNet, which is a sequential architecture, we have added skip connections between the two adjacent blocks to give it a residual effect. In the case of sequential architecture, some of the features are lost in the feed-forward process. Similarly, for deeper networks, these residual connections serve as a way to solve vanishing the gradient problem as mentioned in [35]. For both sets, support, and query, Efficientnet is used as a feature extractor thus forming a Siamese network-style structure for our FSL architecture.

D. IMAGE ENCODINGS

Image encoding refers to the feature map of the given image. A series of image encodings belonging to the support set is represented as $S = \{s_t\}_{t=1}^{M} \epsilon R^{M\times d}$. The query set images are also fed to the feature extractor with the generated encoding as $Q = \{q_t\}_{t=1}^{N} \in R^{N\times d}$, where M and N are the numbers of encodings of support and query set respectively and d is the dimension of vectors. The final feature vector obtained from the EfficientNetB0 model was used to calculate the absolute difference between the support set and the query set. The image encoding obtained from the model is of the size 1024 column vector. This column vector is generated by using the dense layer at the top of the network.

E. ATTENTION BLOCK

As the support set contains different images of different classes, we aim to reduce the computational complexity of the entire model. Therefore, we are not using the simple distance mechanism. Instead, we have used an attention-based mechanism for calculating the similarity between encodings of both support and query sets. Our attention block consists of two sections:

1) ATTENTION SIMILARITY CALCULATION

Two types of encoding vectors s_i and q_j obtained from the feature extractor module, represent i^{th} and j^{th} elements of encoding S and Q, respectively. The similarity score is based on the combination of additive and multiplicative similarity functions introduced by Y. Shen et al. [36]. It has combined tri-linear, an additive similarity function, and ReLU, a multiplicative similarity function, to form a t-trilinear similarity function. Attention function $\phi(s_i, q_i)$ is represented as follows:

$$s_i^t = \mathrm{Re}\,LU\,(W_1 s_i + b_1) \tag{1}$$

$$q_i^t = \mathrm{Re}\,LU\,(W_2 q_i + b_2) \tag{2}$$

$$X_{ij} = \phi(s_i, q_i) = \omega_x s_i^t + \omega_y q_i^t + \omega_{xy}\left(s^i \circ q^i\right)_t (3) \tag{3}$$

where W_1 and $W_2 \epsilon R^{d\times d}$, b_1 and $b_2 \epsilon R^{d\times 1}$, ω_x, ω_y, $\omega_{xy} \epsilon R^{d\times 1}$ are trainable weight vectors associated with each encoding and $\circ$ denotes the Hadamard product. Similarity score matrix $X_{ij} \epsilon R^{M\times N}$ is generated through the trilinear similarity function with input vectors s_i and q_i using an activation function ReLU.

2) RELEVANT INFORMATION GENERATION

After getting the attention vector from the Attention Similarity Calculation function, it was normalized to pass further to the next unit of the Siamese network. The normalized form of the similarity score matrix is referred to as the attention weight matrix represented as $\mathrm{A}\epsilon R^{M\times N}$, and it is calculated as:

$$\alpha_{ij} = \frac{\exp(X_{ij})}{\sum_{k=1}^{N} X_{ik}} \tag{4}$$

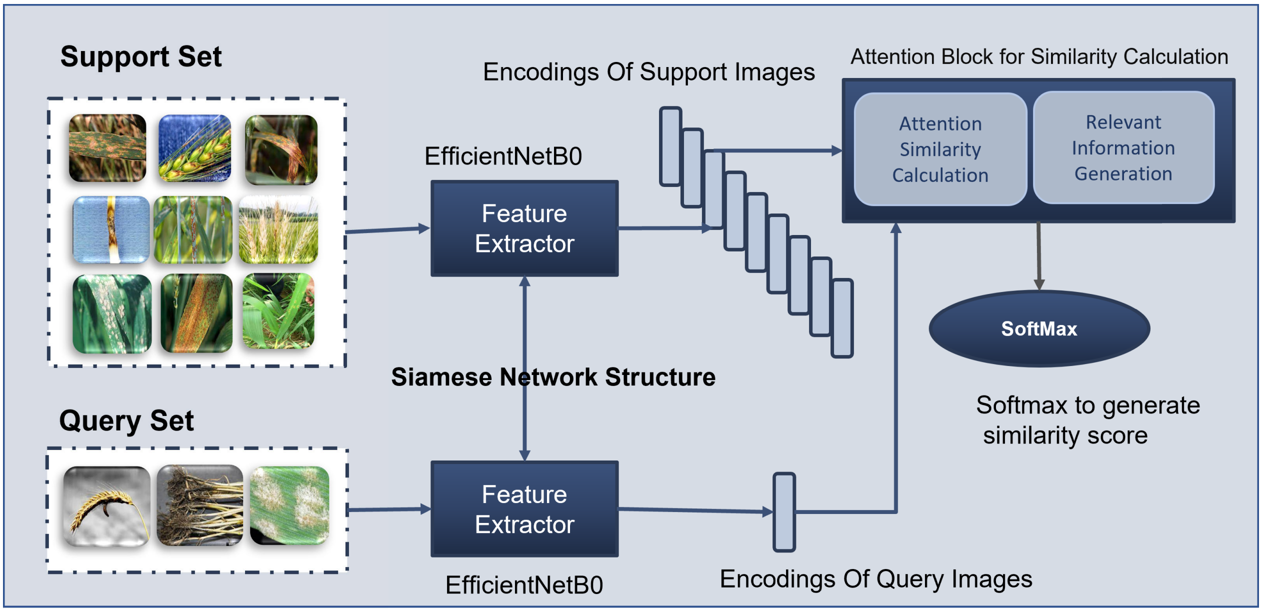


FIGURE 5. Architecture diagram of a Few-shot Learning-based network.

where α_{ij} represents the attention weight matrix calculated for each element of the attention similarity score.

F. SOFTMAX CLASSIFICATION

Finally, after computing the attention-based similarity, an output layer with a softmax unit was utilized to determine the probability of encodings related to each class. The output of softmax is obtained by using the following equation:

$$\sigma(z)_i = \frac{e^{\alpha_i}}{\sum_{j=1}^{K} e^{\alpha_j}} \tag{5}$$

Where α_i are the elements of the vector obtained from the attention block, K is the total number of classes present and $\sum_{j=1}^{K} e^{\alpha_j}$ is the normalization factor that ensures the output to be 1.

VI. EXPERIMENTATION

We conducted experiments to illustrate the effectiveness of the suggested few-shot network. The EfficientNetB0 was used for feature extraction after its fine-tuning. We demonstrated the findings of fine-tuning EfficientNetB0 and a few-shot network for disease identification. The experimentation was carried out in the below-mentioned steps:

A. TRAINING SETUP

A 1080 Ti Nividia GPU-enabled machine with 16GB RAM was used for training and fine-tuning the EfficientNet model. All the experiments are performed using the Python language and Pytorch platform. We have experimented with EfficientNetB0 by applying different values of hyperparameters to get the optimal solution.

B. DATASET PREPROCESSING

The dataset gathered from internet sources is of different resolutions and sizes. All the images must be of the same size. Moreover, images gathered from internet sources contained some background noise. Therefore, the background was removed from images for training as well as testing. Color thresholding, edge detection, etc. was used to remove the background using the OpenCV library. Then all images were resized to 224×224 to be used for EfficientNet Model. Further, some classes had a smaller number of instances as compared to others. These images were augmented using different techniques like random rotation, random translation, cropping, scaling, hue or saturation changing strategies, etc. After applying these preprocessing techniques, the next step was the training of both the feature extractor EfficientNet and the few-shot learning network. Moreover, we tested our model on a 5-way-5-shot, 5-way-1-shot, 3-way-3-shot, and 3-way-2-shot dataset sample. Before passing to the feature extraction, these samples were formed for both support and query sets.

C. EFFICIENTNET TRAINING

Pretraining of the EfficientNetB0 model was done by using different hyper-parameter values, and the best model was recorded to be used for fine-tuning. Firstly, the PlantVillage dataset was split into train, test, and validation data in a ratio of 70, 15, and 15%, respectively. Adam optimizer with a learning rate of 0.0001 got pretraining accuracy of about 98.5% with a weight decay of 0.001 and a dropout of 0.1 with a batch size of 128 and a validation accuracy of 97.3%. After pretraining, the model was further fine-tuned for domain-specific learning on the GCIAR dataset with 98.98% training accuracy and 97.2% validation accuracy. Now, Adam was used as an optimizer with a learning rate of 0.0003 and weight decay of 0.1 while dropout was 0.2. Cross Entropy (CE) was employed as the loss function was calculated using:

$$CE = -\sum_{c=1}^{N} y_{o,c} \log \left(p_{o,c}\right) \tag{6}$$

where N denotes the number of classes, y denotes the correct class c for observation o and p denotes the predicted probability on observation o for class c. While different experiments were done in both cases using different learning rates and batch sizes to get the results. Both pretraining and fine-tuning were done with 3500 and 3000 epochs, respectively.

D. FEW-SHOT NETWORK TRAINING

After successful training of the backbone network, we trained our few-shot network. First, the input images were divided into a support set and a query set. We used different learning methods like 3-way-2-shot classification means at a time support set consisted of three classes with two samples each, 5-shot-1-way and 5-shot-5-way learning. Forty instances of each class of dataset gathered manually and preprocessed was used for training purpose. In this model, the trained EfficientNet model was used as a feature extractor. Firstly, the features of each image from each set were extracted. Then the attention module takes the embeddings and calculates the similarity score between the two sets. After the softmax layer classifies the query set data, the negative log-likelihood of the actual class via Adam optimizer was calculated using the following equation:

$$\text{loss}(\theta) = -\sum_{i=1}^{n} \left(y_i \hat{y}_\theta + (1-y_i)\log\left(1-\hat{y}_{\theta,i}\right)\right) \tag{7}$$

where $\hat{y}$ is the predicted probability. 40 images of the preprocessed dataset were used for training and 40 were used for testing the model. The reason for using this loss function is that due to a small number of samples the model needs to learn to classify new samples with limited information. As there are only a few instances per class, NLL loss will give optimum results. The learning rate of 0.001 with a weight decay coefficient of 0.0001, and dropout of 0.2 was used during training to avoid overfitting. The model was trained for about 150 epochs and final results were generated using the query set.

VII. RESULTS AND DISCUSSION

We have presented a few-shot learning method for disease classification in wheat crops. As discussed earlier, most of the work done in the agriculture field is based on traditional machine learning or deep learning which needs a considerable amount of data and these methods cannot accommodate new classes because new classes are recognized by the model only if it is retrained. While agriculturists or farmers need a system that can accommodate new classes, hence the cost of making a new system every time can be reduced.

TABLE 2. Results obtained by few-shot network.

Samples	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
3-way-2-shot	92.22	90.15	90.26	90.20
3-way-3-shot	92.30	90.22	90.27	90.24
5-way-1-shot	92.63	90.85	91.01	90.92
5-way-5-shot	93.19	91.35	91.52	91.43

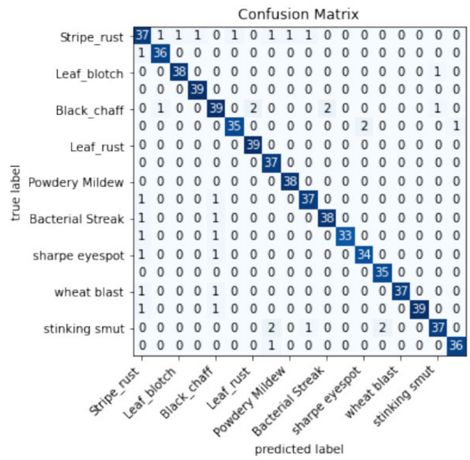
TABLE 3. Comparison of the latest FSL-based methods with our proposed one.

Study	Dataset	Results	Few-Shot Learning	No. of Classes
A. Hussain et al. [21] (2018)	Four Class dataset	84.54%	No	stem rust, yellow rust, Powderly mildew, and normal
M.A.Genaev et al. [23] (2021)	WFD2020	94.2%	No	stem rust, yellow rust, Powderly mildew, leaf rust, and septoria
A.V. Uzhinskiy et. al [31] (2020)	Manually collected data on different plants and diseases	98%	Yes	Four crops (cotton, wheat, corn, cucumbers, and grape) with 25 classes
D. Argöeso et al. [30] (2020)	Plant Village dataset	90%	Yes	38 classes of different plants
H. Mukhtar et al. [33] (2021)	CGIAR, Collected field Images of 11 classes	92.2%	Yes	11 wheat diseases
Proposed few-shot learning-based network	Plant Village Dataset, CGIAR Dataset, 18 diseases dataset collected from Google	93.45%	Yes	18 wheat diseases

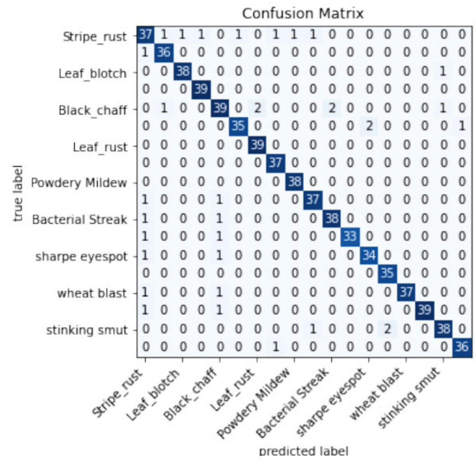
We have presented our methodology and experimental work performed on different datasets. Our few-shot network that utilizes EfficientNet as a backbone and attention mechanism to calculate similarity scores between the support and query set was evaluated using 3-way-2-shot, 3-way-3-shot, 5-way-1-shot and 5-way-5-shot learning with 92.22%, 92.30% 92.63%, and 93.19%, respectively. The highest accuracy was obtained when we used more examples per shot for the proposed method. The confusion matrix for each experiment was recorded and presented in FIGURE 6. We have used different metrics for representing our results. A complete overview of results obtained by using different sampling techniques of our manually collected dataset is given in TABLE 2. It can be seen that our proposed model has performed well on the collected dataset.

A. COMPARISON WITH STATE-OF-ART

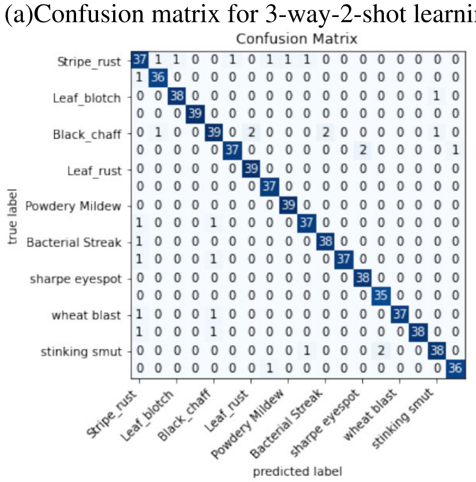
Our results are not directly comparable to other research. However, TABLE 3 presents a brief comparison of our approach with other approaches discussed in the literature review section to give insight into how we have contributed to the classification of wheat diseases. It can be seen that



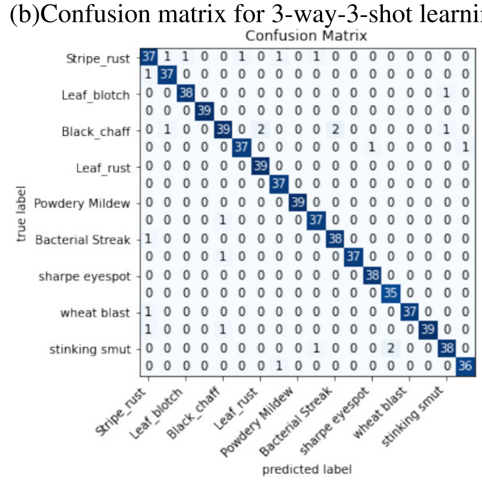
(a)Confusion matrix for 3-way-2-shot learning.



(b)Confusion matrix for 3-way-3-shot learning.



(c)Confusion matrix for 5-way-1-shot learning.



(d)Confusion matrix for 5-way-5-shot learning.

FIGURE 6. Confusion matrix for different samples.

most of the research has applied only machine learning-based methods for the classification of wheat diseases and these methods fail to classify new classes. For few-shot learning-based methods, few studies have less scope (classify a smaller number of diseases). There are studies for example [33] that have used one-shot learning instead of few-shot learning for the classification of different wheat diseases. However, our research is based on few-shot learning with a wider scope of wheat diseases. Our presented method has one more advantage that it is lightweight due to the use of Efficientnet and has the potential to be used for different mobile devices [34].

Our proposed architecture is trained over 21450 total images of 18 different wheat disease classes while in the query set, there were 40 images of manually collected datasets from Google. The above TABLE4 highlights an important observation that prior FSL-based studies used larger training and testing datasets as compared to our proposed methodology. However, in the realm of few-shot learning, our model has surpassed existing approaches that relied on thousands of images for evaluation. Despite using only 40 images, our model achieved a significantly higher accuracy of 93.45% as mentioned in Table 3. This remarkable improvement in accuracy underscores the effectiveness of our approach, showcasing its ability to excel in scenarios with limited training data. Thus, by employing a smaller amount of data, the training process became more efficient and required less time to complete with less consumption of computational and memory resources. While during the inference phase,

TABLE 4. Comparison of dataset sizes used in wheat Disease Classification Studies.

Study	Method	Training Sample	Query Set
H. Mukhtar et al. [33] (2021)	local feature matching conditional neural adaptive processes (LFM-CNAPS)	61,527 images	12,668 images
A.V. Uzhinskiy et. al [31] (2020)	Siamese network based on the distance metric with a triplet loss function	48,775 images	9,755 images
D. Argöeso et al. [30] (2020)	FSL methods based on siamese networks	40,000 images	10,000 images
Proposed model	few-shot learning-based network	21,450 images	40 images

with fewer data points to process the model performed predictions more quickly. The improved utilization of resources has also reduced the inference latency. As a result of the reduced data requirement, our proposed model stands out as resource-effective. Furthermore, when combined with its computational effectiveness and time efficiency, the model becomes more effective. In contrast to the existing approaches that utilized larger datasets but achieved lower accuracy, our proposed architecture demonstrated that high accuracy can be achieved with less amount of datasets and fewer computational resources. Due to the use of few-shot learning with an attention mechanism a small number of training samples are required, hence computational cost is reduced. This cost-effectiveness makes it an advantageous choice for wheat disease classification tasks, providing an affordable solution without compromising performance.

VIII. CONCLUSION

The proposed research demonstrates a few-shot learning-based network for wheat disease classification. 1) The proposed network achieved accurate detection of wheat diseases with a minimal amount of data. 2) Moreover, EfficientNet as a feature extractor gained very good accuracy on two training datasets, Plant Village and CGIAR Crop Disease dataset. 3) The feature extraction ultimately gained good results, which in turn proved to be very helpful in a few-shot learning network. 4) The proposed network gained an accuracy of 93.19% on the dataset of manually collected 18 wheat diseases from Google. 5) The network has been carefully designed using an attention mechanism to lower the computational requirements. In the future, this network can be integrated with a mobile or edge device to be used by end-users. Furthermore, the proposed system can be extended to other crops and plants.

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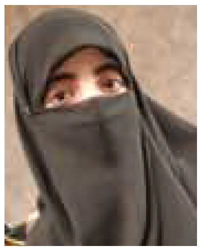

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