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RESEARCH ARTICLE

MaizeNet: A Deep Learning Approach for Effective Recognition of Maize Plant Leaf Diseases

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ABSTRACT The presence of various maize plant leaf diseases has significantly decreased both the quality and quantity of crop production. In order to take the appropriate steps to prevent the occurrence of plant leaf diseases, it is essential to track and recognize such infections during the planting period. However, correct recognition of numerous maize diseases is difficult to achieve because the currently employed automated solutions are operationally complicated or only effective on samples with plain backgrounds. While real-world scenarios are suffering from huge sample distortions like the effect of noise, clutter in the background, and blurring of the leaf regions that increase the complexity of the recognition procedure. To alleviate the above-listed problems, a deep learning (DL) approach called the MaizeNet is proposed for the correct localization and classification of various maize crop leaf disorders. We have presented an improved Faster-RCNN approach that utilizes the ResNet-50 model with spatial-channel attention as its base network for the computation of deep keypoints which are then localized and categorized into various classes. The proposed work is tested on a standard database named Corn Disease and Severity that contains samples from three different classes of maize plant diseases which are captured under diverse conditions such as complex background, brightness, and color and size variations. The MaizeNet model attains an average accuracy score of 97.89% along with mAP value of 0.94, which is showing the effectiveness of our approach for locating and classifying the numerous types of maize leaf infections.

INDEX TERMS Attention, classification, deep learning, faster-RCNN, localization, Maize disease, ResNet.

I. INTRODUCTION

Maize is an essential cereal crop farmed all over the globe. Among the other grain crops, maize has the largest worldwide production, playing an essential part in ensuring food security, feedstock, and energy supply with a growing global population [1]. Maize plays a crucial role as a primary supplier of raw materials for various industrial goods. The extensive use of maize as a primary food source for both humans and animals has resulted in its significant importance. However, despite its high yield potential, the maize plant is vulnerable to numerous illnesses that can result in an annual loss of 6%-10% [2], [3]. Maize diseases are mainly caused by various viruses, viroid, fungi, and bacteria. Typical symptoms

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of infection include discoloration, rot, scab, blight, necrosis, wilt, and deformities, which are used to locate and spot foliar diseases in maize. The most prevalent fungal foliar infections in maize cultivation include northern corn leaf blight (NLB), southern corn leaf blight (SLB), and gray leaf spot (GLS) [4]. Currently, for farmers without specialized knowledge, the precise diagnosis of maize leaf diseases is a vital assurance for maize productivity. Traditional maize disease identification process involves manual inspection of leaves and depends on the knowledge of plant pathology and the experience of agricultural specialists. Misinterpretation of the disease typically results in ineffective pesticide treatments, which not only pollute the environment but also increase the toxic effects on maize. Thus, rapid and accurate methods are required to monitor the maize crop and treat the infections.

Recently, digital technologies including remote sensing, global positioning, and geographic information systems, are widely adopted for plant disease monitoring and forecasting [5], [6]. With the extensive growth in the area of artificial intelligence, automated methods based on computer vision and machine learning (ML) algorithms are progressively replacing traditional plant disease diagnostic methodologies [7]. In recent years, several digital image-based automated plant disease identification methods are introduced as a potential alternative to manual inspection [8]. Initially, ML methods with hand-engineered features were adopted in agriculture to improve decision-making capability. Prior work includes various approaches such as gray level co-occurrence matrix (GLCM) [9], local binary patterns (LBP) [10], scale-invariant feature transform (SIFT) [11], and histogram of oriented gradient (HOG) [12], etc., as feature descriptor for the representation of the images. These approaches extract visual characteristics like shape, hue, structure, and other statistical traits and thus provide a simplified representation of the plant disease [13]. The extracted features are then utilized to train ML models such as decision tree (DT) [14], support vector machine (SVM) [15], [16], and artificial neural network (ANN) [17] framework to perform the categorization of leaf diseases. Despite their ease of use and minimum data requirements, hand-coding feature computation methods entail significant processing time and necessitate human expertise.

Deep learning (DL)-based systems, a subset of ML techniques have recently gained popularity due to their superior ability to identify patterns and perform classification. DL methods such as convolution neural networks (CNN), recurrent neural networks [18], and deep belief networks [19] have been widely employed for different tasks including the agriculture domain such as predicting the yield quantity, plant recognition, and crop disease diagnosis [20], etc. Among others, CNNs are one the most popular approach due to their ability to adaptively learn spatial hierarchies and extract semantic representations from the input samples. The CNN framework is empowered to automatically extract important sample information from the training data without the intervention of human experts and thus allow improved decision-making. Due to such efficacy of the DL approaches, there are widely employed in the area of agriculture. Therefore, in recent works, DLs are extensively applied for various crop disease recognition and classification such as potato [21], apple [22], grape [23], rice [24], tomato [25], [26], cucumber [27] including maize [28], [29], [30], [31], [32]. In a significant number of studies, new CNN architectures such as ResNet [30], AlexNet [33], and DenseNet [28], [34], with transfer learning are used to detect crop diseases. Few studies [35], [36], [37], [38], [39] suggested novel CNN architectures for the detection and classification of crop disorders. These approaches can yield accurate results with minimal preprocessing and computing costs. Additionally, DL-based algorithms outperform other techniques by making use of topological information from the input images and are robust to modifications like rotation, scaling, and translation. Furthermore, with pre-trained frameworks, these algorithms achieve high accuracy in the maize disease identification [28], [29], [30]. Most of the existing methods perform maize disease categorization at the image level, which is captured under controlled lab settings and thus has a high risk of false-positives. As, the dataset generated in a controlled environment is developed with ideal situations like with constant background settings and lack of sample artifacts like noise, blur, etc. Therefore, approaches trained on such data samples when evaluated on images captured in more real-world settings usually result in misclassification with an increased number of false positives. It is critical to locate maize disease spots in field images to attain improved sensitivity (recall-rate). The simultaneous localization and fine-grained classification of maize disease spots can assist agricultural specialists or users in the provision of other critical data like the dimension and region of the lesions, which can also aid in the assessment of the severity of the disease at a higher level and plan treatment accordingly.

At present, DL-based object identification models are continually being developed. State-of-the-art frameworks such as SSD [40], YOLO [41], and Faster-RCNN [42] show robust performance in real-time object localization and classification. Limited studies have been undertaken to perform the complex agricultural operation of both localization and fine-grained categorization in the context of plant disease identification [43], [44], [45]. In [46], Region-based CNN is utilized to govern the precise position and group of the maize disease and achieved satisfactory results. Despite the effectiveness of DL methods, the accurate classification/identification of maize disease using field images is still a challenging task. The researchers have to deal with a number of significant problems while developing a robust model such as data preparation, handling inter/intra class variations, and adverse lighting conditions, including distortion and occlusion [47]. The presence of complex background disturbance also prevents accurate disease identification plants in the real world. Since the background can be quite complicated and obstruct items of interest, fine-grained characteristics of multi-class plant disease might be difficult to identify. Moreover, efficient models with lower computing costs and faster inference speeds are highly in demand for real-time agricultural applications.

In this work, to address the above-mentioned problems, we proposed a DL-based framework namely MaizeNet to perform the complex task of localization and classification of maize disease from field images. Our MaizeNet model is based on the Faster-RCNN network [42] that has shown improved results on various object recognition tasks. We incorporated an improved feature extraction network with an attention mechanism to compute fine-grained characteristics of multiple maize diseases from input samples. The modified backbone network improves the network's ability to extract salient characteristics in the presence of complicated backgrounds and changing environmental conditions. The model simultaneously performs both detection and classification using an end-to-end training strategy and shows effective performance in real environment settings. The distinctive contributions of our framework are as follows:

1) We proposed a Faster RCNN-based framework namely MaizeNet with improved feature computation CNN network architecture for accurate maize leaf disease localization and classification.
2) We added spatial and channel attention mechanisms that learned inter-channel relationships and spatial positioning to extract more robust disease representation from samples having noisy backgrounds and real environment settings.
3) Better detection and classification of disease regions of maize plant leaves due to the high recall ability of the proposed approach because of the inclusion of the Convolutional Block Attention Module (CBAM).
4) We performed huge experimentation on an online accessible database to indicate the efficacy of our approach. The results demonstrate an effective performance of the proposed approach under challenging settings such as the presence of cluttered background, variation in lighting, and distortions.

The manuscript is arranged as follows: Section II examines previous studies related to identifying diseases in plants, specifically maize crop diseases. In Section III, the adopted methodology and detailed architecture of the proposed framework are explained. Section IV presents the details of the selected dataset, implementation, and experimental setup, along with the obtained results and discussion. Lastly, we concluded our work and suggested some future directions in Section V.

II. RELATED WORK

Several methods have been introduced by scientists to locate, classify, and compute the related attributes of various plant abnormalities. For this reason, both the DL and ML approaches are heavily adopted by researchers. In this section, we have provided an analysis of the existing works used for the categorization of corn leaf abnormalities. Initially, conventional ML approaches are adopted for corn leaf disease classification. These techniques use hand-coded keypoints computation approaches along with a classifier to execute the classification task. One such framework was discussed in [16], where the researchers extracted structural keypoints employing a histogram along with the GLCM method to get the feature description of the input images. Then, the SVM approach was adopted to perform the corn diseases categorization task. The work [16] employs the PlantVillage dataset and attains an accuracy of 83.70%. Zhang et al. [48] performed the maize plant disease classification by employing the genetic algorithm to autonomously adjust the kernel method and penalty factor of the SVM classifier. The work [48] gains a classification score of 90.25% over a custom dataset. Further, in [49] an ML approach the Bayesian technique was used to develop a skilled diagnostic model to trace and categorize the corn plant disorders by computing the relevant signs. The work attains an accuracy value of 90% over a custom dataset. Zhang et al. [50] used a segmentation-based method for performing the categorization of maize diseases. For this reason, initially, the area of interest was located by using a segmentation method. Then, the keypoints were extracted based on the textural description of the disease area. Finally, the KNN classifier was used to accomplish the classification task to categorize the given samples into five related categories. The work [50] reports an average accuracy value of 90.30% on a custom dataset. In [51], the authors introduced an adaptive weighting multi-classifier fusion method to recognize the various categories of corn leaf abnormalities. The work categorizes given samples into seven related classes. The method [51] attains an accuracy value of 94.71% on a custom dataset. Another work [52] used a custom dataset to classify the numerous corn leaf diseases via using the SVM classifier with an average accuracy score of 83.2% on a custom dataset. Qi et al. [53] also presented a work to recognize the maize plant diseases where the retinex method was adopted to enhance the visual appearance of the samples. Next, an automotive thresholding technique in R-G gray plane was utilized to capture the structural information of the sample i.e., diseased region, chrominance characteristics and invariant moments, etc. In the next step, the principal component analysis (PCA) was adopted to minimize the feature space. Finally, the categorization task was achieved by employing the SVM classifier by categorizing the samples into three related classes i.e., Common Rust (CR), SLB, and curvularia lunata, respectively. The work [53] has reported an average accuracy value of 90.74% on a custom dataset. The above-performed analysis shows that even though various ML approaches have been proposed in the literature for classifying maize leaf diseases, however, the existing ML approaches are unable to fully capture the structural information of the samples due to their limited discriminative ability.

The robustness and better recall power of the DL approaches have insisted the researchers to test them in the area of the maize plant infections categorization. One such approach was discussed in [29] where a DL model namely the Inceptionv3 was adopted to classify the normal and infected images of the maize plant. Firstly, the augmentation approach was utilized to enhance the diversity of the input samples. Then, the Inceptionv3 model was used to calculate the related keypoints and accomplish the categorization job. The work [29] attains an accuracy score of 95.99% over a custom dataset. In [30], several DL frameworks i.e., VGG-16, ResNet-50, and InceptionV3 were tested for recognizing the numerous types of corn leaf infections. The work used the idea of transfer learning along with the Bayesian hyperparameter optimization to boost the categorization accuracy of the selected models. The work attained an average accuracy rate of 93% for images from the PlantVillage dataset, however, at the cost of increased model complexity. In [54], the work presented an improved LeNet CNN framework comprising a small kernel size for classifying the abnormalities of the corn plant leaves. The technique [54] has reported an average accuracy value of 97.89% on the PlantVillage dataset. In [28], a DL approach namely the DenseNet-121 was analyzed for maize plant disease classification with an accuracy rate of 98.45% on the PlantVillage dataset. Whereas, in [55], the EfficientNet-b0 framework was adopted to recognize the abnormalities of the corn plant leaves. This work is proficient in maize plant leaf abnormality classification with an accuracy value of 98% on a custom dataset, however, requires the evaluation on a complex data sample. Zhang et al. [56] proposed an optimized GoogLeNet framework to categorize the samples into nine different classes of maize abnormalities. The work analyzed various combinations of pooling layers, and activation methods, along with the dropout approaches to reduce the framework parameters. The work exhibits an average accuracy score of 98.9%; however, the work has employed only a total of 500 images for model training and testing which are collected from different sources, such as the Plant Village and Google websites. Therefore, the approach requires the evaluation on a more diverse dataset with a large collection of samples to show its significance. In [57], an improved AlexNet DL approach was presented with expanded and multistage convolution to accomplish the maize plant leaf disease categorization. The work also adopted several preprocessing operations along with the data augmentation phase to eliminate the appearance and diversity of the input samples. This approach has attained an average accuracy score of 98.62% on a custom dataset.

Another approach employing the concept of the multi-activation function (MAF) was presented in [2] where the MAF has used a module in the combination of different activation approaches i.e. ReLU, LeakyReLU, and Tanh, etc., to optimize the classification behavior of the used frameworks. First, several sample pre-processing steps accompanying the DCGAN were adopted to improve the appearance of the input images. Next, different types of DL approaches i.e., AlexNet, VGG-19, ResNet-50, and DenseNet-161 were used by merging the MAF unit. The work has attained the highest classification accuracy of 97.41% for the ResNet-50 model on a data sample collected from two experimental sites; however, the classification results degrade for the noisy images. In [58], the B0-based EfficientNet and DenseNet-121 models were utilized to generate a dense feature set for the identification of maize crop leaves illness. The model combined the computed features for a more accurate representation of the sample before proceeding with the categorization process with an accuracy rate of 98.56%. However, the model was evaluated on samples obtained from the PlanVillage database, and its applicability to real-world scenarios is limited. Zeng et al. [59] proposed a framework named the SKPSNet-50 to identify various maize leaf abnormalities. A nominated kernel module with the swish activation method was used to improve the conventional ResNet50 approach to enhance the keypoints computation ability. This work [59] attains an accuracy score of 92.9% to classify six different types of corn abnormalities on a custom dataset. Ahmad et al. [60] used transfer learning to train five pre-trained DL models to recognize corn disease from images. The models used were InceptionV3, ResNet50, VGG16, DenseNet169, and XceptionNet. DenseNet169 outperformed the other models with an accuracy of 81.60%. Li et al. [61] proposed an improved YOLO-v5 model employing the concept of multi-scale keypoints fusion to locate the infectious regions of the maize plant. A pixel pyramid pooling accompanying the coordinate attention approach was proposed in the base network to enhance the keypoints calculation and categorization results. The work performs well for unseen cases with a mAP of 0.48 on the Kaggle maize leaf disease dataset, however, the performance drops for small diseased regions. In [4], numerous DL approaches like VGG with base 16 and 19, AlexNet, and GoogleNet have tested various combinations of loss methods Softmax, and CosFace to locate the healthy samples from the NLB disease-affected samples. The work has acquired an accuracy score of 99.94% for the GoogleNet model on a custom dataset. Singh et al. [62] also utilized the AlexNet model to classify maize leaf disease using PlantVillage dataset images. The method achieved a 99.16% accuracy rate after training the model using 100 epochs on the PlantVillage dataset. However, the work requires the evaluation on a complicated dataset to better elaborate the robustness of the approach. The attention mechanism (AM) has shown remarkable performance to optimize the feature computation ability of different models. One such framework [31] introduced a model called LDSNet (lightweight dense-scale network) that utilized dense expanded convolutional blocks and coordinated AM technique to identify various corn diseases. The study findings showed an average accuracy rate of 95.40% on the PlantVillage dataset. Yin et al. [63] proposed an enhanced GoogleNet structure to locate the diseased areas of the corn plant leaf. An expended inception block was introduced in the conventional model to optimize the keypoints computation power. Then, the channel AM strategy was used to highlight the significance of inter-channel connections among the calculated features. The work has shown the highest accuracy of 97.12% on a custom dataset. In [64], super-pixels were generated using the SLIC segmentation method, which are then used as input to the CNN to obtain features and perform classification based on the extracted features. This method [64] achieved the highest accuracy of 97.77% using DenseNet121 and a sigma score of 5. In [65], the authors proposed a two-stage semantic segmentation method to estimate the severity of corn leaf disease lesions. The first stage segments the entire leaf portion from the image, while the second stage focuses on identifying and segmenting the disease spots. This method [65] showed an accuracy of 92.37% using a combination of UNet and DeepLabv3+ segmentation approaches.

Moreover, a DL approach was discussed in [32] where a method named the Mobile-DANet was used for corn plant leaf disease categorization. The framework consists of the DenseNet model as the base network containing depthwise separable convolution and the AM blocks. The technique has reported accuracy results of 98.50% on the open maize dataset. Chen et al. [66] proposed a lightweight corn disease identification model namely DFCANet. The method consists of two main components: the dual feature fusion with coordinate attention and the down-sampling modules This method achieved an average recognition accuracy of 98.47%, demonstrating its effectiveness in corn disease identification. Qian et al. [1] introduced a vision transformer approach to recognize different maize leaf abnormalities. First, a CNN framework was employed to compute the keypoints set which were later encoded into a token matrix. The encoder model of the vision transformer utilized a multi-head self-attention approach in the subsequent stage to evaluate the relationship between tokens. The work improves the maize plant disease classification results with an accuracy value of 93.90% on the PlantVillage dataset; however, the results highly depend on the dimension of the token representation, leading to the weakening of the semantic connection among adjacent areas. He et al. [46] proposed the Faster-RCNN approach with the VGG-16 model as the backbone to locate and classify the diseased area of the corn plant leaves. The approach exhibits enhanced classification results, however, it uses a hand-coded engineering approach to locate the affected areas which is a time-consuming activity. The work attains an accuracy rate of 97.03% on the PlantVillage dataset.

The examined literature shows that several efforts have been attempted to identify and categorize corn diseases using different ML and DL models. The accuracy of classifying maize diseases has greatly increased; however, these techniques perform well when used with images that have a clear and static background setting for classifying maize diseases. The effectiveness of current methods is dependent on external factors and suffers when used on photos with cluttered backgrounds that have many visual disturbances, like blurring, distortion, and unbalanced lighting levels. These considerations restrict the practicability of the many corn leaf disease categorizations approaches. Hence, because of the generalization, computation, and process time challenges, still there exists a potential for improvement in the maize plant leaf disease classification performance.

III. MATERIALS AND METHODS

In the proposed work, a DL model namely MaizeNet is presented to identify and categorize the various maize plant leaf abnormalities. More clearly, a customized Faster-RCNN model is presented with the ResNet-50 CNN approach as the base framework. At the start, we generated the annotations of the inspected maize plant images to specifically determine the diseased portion of the dataset images. In the next phase, the generated annotations and images are given to the ResNet50-based Faster-RCNN model. In the MaizeNet model, a reliable set of sample features are computed by the ResNet50 model on which the classification and regression layer of the Faster-RCNN model accomplishes the maize plant leaf disease localization and classification task. A detailed visual depiction of the introduced approach is given in Fig. 1, while the performed steps are elaborated in Algorithm 1.

Algorithm 1 Steps Followed by the MaizeNet for Maize Plant Leaves Abnormalities Localization and Categorization

START
INPUT: TM, Annotation
OUTPUT: Localized RoI, the category of maize plant leaf diseased region, MaizeNet
TM: Total maize images with various abnormalities.
Annotation: Rectangular box localizing the diseased region of maize plant leaves.
Localized RoI: Predicted bounding box specifying the diseased portion.
nMaizeNet: ResNet50-based Faster-RCNN model.
//Data preparation
SampleDimension ← [j h]
// Estimation of the bounding box
Ä ← CalculatingAnchors (TM, Annotation)
// training phase
//Functions
1. ResFRCNN(): employed to measure the keypoints with ResNet50 network
2. IdentifyMazieLeafAffectedArea(): employed to specify the affected samples regions
3. EvaluatFramework(): employed to accomplish the model training
// RESNET-34-based-FasterRCNN approach
MaizeNet ← ResFRCNN (SampleDimension, *Ä*)
[TrainingPart, TestPart ← Database distribution
For each sample c in → TrainingPart
Compute *RESNET50* features → *tm*
End
Utilize *tm* images MaizeNet training:, and calculate time
£oclizeA ← IdentifyMazieLeafAffectedArea (*tm*)
Ap ← EvaluatFramework (*RESNET50*, *£oclizeA*)
// test phase
For each image *C* in → TestPart
a) βC ← Compute features via employing the trained model MaizeNet
b) [*Rectangularbox*, *ConfidenceScore*, *ClassLabel*] ← Predict (βC)
c) show samples with *Rectangularbox*, *ConfidenceScore*, and *ClassLabel*
End
Exit

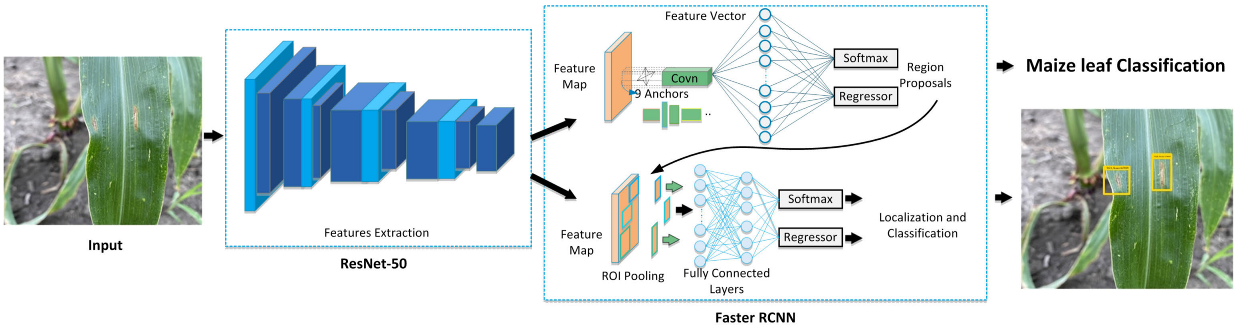

FIGURE 1. A pictorial illustration of the proposed MaizeNet model.

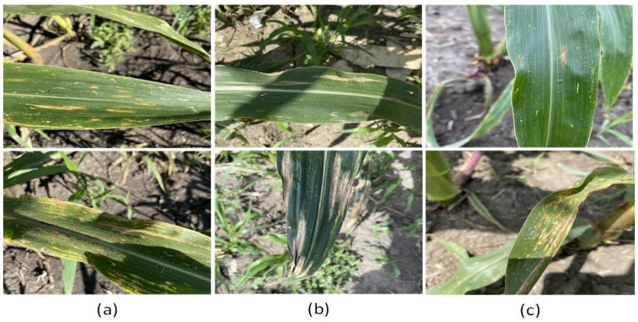

FIGURE 2. Samples from the database showing images belonging to various maize disease classes: (a) GLS, (b) NLB, and (c) NLS.

A. DATASET

The samples utilized in this work for evaluating the proposed MaizeNet method are derived from the online available Corn Disease and Severity (CD&S) [67] database. This dataset is obtained by the Agronomy Center for Research and Education at Purdue University. The images were captured using mobile devices under varying environmental conditions in the field. It comprises a total of 2112 raw samples of resolution 3000 × 3000. The images belong to 3 common maize leaf diseases including NLB, Northern leaf spot (NLS), and GLS classes. A total of 511 samples belong to NLB, 562 samples to NLS, and 524 samples to GLS class. The overall samples in the CD&S dataset are diverse in terms of background conditions containing dead leaves, soil, and weeds and having varying illumination settings, which make it suitable for training the model and performing maize disease localization and categorization in the field. Fig. 2 shows the sample images of the dataset belonging to three different maize disease classes. It can be seen from the figure that the disease spots have varying shapes, sizes, and appearances that may resemble the items in the background, making the accurate detection of disease more difficult in the field. These samples are also challenging in terms of lighting, color, shadow, and intensity variations. We distributed the database into 7:3 for the training and testing process.

B. ANNOTATION GENERATION

For the effective training of the MaizeNet, it is mandatory to precisely determine the diseased areas of the maize plant leaves. For this reason, we used the annotations provided for the dataset created with the help of the LabelImg [42] tool. This tool generates a bounding box around the infected area along with the associated class, from where the computed coordinate's values are stored in a CSV file. The generated file is then passed for MaizeNet training.

C. FASTER-RCNN

In the proposed work, a DL technique namely the Faster-RCNN is employed to automatically locate and classify a number of maize plant leaf diseases. The major reason to choose the Faster-RCNN model over other object detection approaches is that it makes use of convolve filters, which enables it to assess the sample's architecture and construct a trustworthy selection of keypoints from it. The RCNN and Fast-RCNN approaches are operationally more complicated, thus we chose the Faster-RCNN paradigm instead for classifying maize plant leaf diseases. Additionally, RCNN and Fast-RCNN models use manual methods for feature calculation, such as EdgeBox [68] or selective search [69], which makes it impossible to acquire a nominative set of visual keypoints. The Regional Proposal Network (RPN), a distinct component, is introduced in the Faster-RCNN method to effectively address the shortcomings of the RCNN and the Fast-RCNN techniques by the automatic feature computation from the given sample.

There are two key problems associated with the detection and recognition of agricultural leaf illnesses in recognizing the ROIs from the input samples: i) determining the precise infected area from leaves because the affected and normal regions share a great deal of color resemblance. ii) the class corresponding to every designated spot (Fig. 3). The chosen architecture, Faster-RCNN, is better suited to address the aforementioned issues. The RPN component of Faster-RCNN leverages the details of infected part magnitude, color, and structure and assures a greater recall capability by employing a few chosen windows, which improves its ROI localization ability and results in the correct classification of the suspected samples.

D. MaizeNet

In this work, a customized Faster-RCNN model trained on the maize plant leaves is presented that can accurately

FIGURE 3. Sample diseased images from the dataset having a resemblance with healthy leaf.

localize and effectively classify its various abnormalities and is designated as MaizeNet. The classic Faster-RCNN model utilized either VGG16 or ResNet101 approaches as its backbone network for calculating the deep keypoints of the input samples. However, the huge proportion of network parameters in each of these approaches raises the computation expense of the Faster-RCNN. Furthermore, the base architecture of the Faster-RCNN with the VGG16 approach is suffering from the vanishing gradient issue, whereas the ResNet101-based Faster-RCNN model is suffering from a huge computing burden and model overfitting problem as well. To tackle the issues of the existing framework, we have proposed a custom version of the Faster-RCNN model that employs the ResNet-50 and the Convolutional Block Attention (CBA) modules for feature extraction from the maize plant leaves. The ResNet-50 technique has a computational benefit as compared to the backbone architectures since it contains fewer hyperparameters. The MaizeNet framework uses four steps named feature extractor, region proposal networks (RPN), ROI pooling, and categorization to identify and categorize numerous Maize crop leaf illnesses.

1) FEATURES EXTRACTION

In the Faster-RCNN model, a backbone network is used to extract semantic and meaningful representations from the input sample. The extracted representations are then used by the detection head to localize regions of interest and perform categorization. The overall performance of the detection head depends on the learned feature representations [70]. The base model is frequently a CNN approach originally designed for image classification tasks. In existing works, the baseline Faster-RCNN is used with a variety of backbone feature extraction networks such as VGG16, and ResNet101 [71]. According to the study [72], CNN models are more prone to learning irrelevant features in the presence of complex backgrounds during training rather than focusing on important features. Recently, the attention mechanism in CNN networks is incorporated to enhance the focus on target representation learning capabilities from the input during training [73]. Here, we have employed the attention unit in the base CNN to improve the feature representation learning of maize disease spots from the image. This ultimately improves the proposed Faster RCNN model's capability to classify maize infections in the presence of complicated backgrounds and real-world complexities. The attention mechanism is based on a Convolutional Block Attention Module (CBAM) [74]

TABLE 1. Original and modified architecture details of ResNet-50 backbone network.

Block/layer	Original	Modified
Conv1	7×7, 64 3×3 max pool	$[3\times 3, 64]\times 3$ 7×7 Attention
Conv2	$\begin{bmatrix}1\times 1, 64\\ 3\times 3, 64\\ 1\times 1, 256\end{bmatrix}\times 3$	$\begin{bmatrix}1\times 1, 64\\ 3\times 3, 64\\ 1\times 1, 256\end{bmatrix}\times 3$
Conv3	$\begin{bmatrix}1\times 1,\ 128\\ 3\times 3, 128\\ 1\times 1,\ 512\end{bmatrix}\times 4$	$\begin{bmatrix}1\times 1,\ 128\\ 3\times 3, 128\\ 1\times 1,\ 512\end{bmatrix}\times 4$
Conv4	$\begin{bmatrix}1\times 1,\ 256\\ 3\times 3,\ 256\\ 1\times 1,\ 1024\end{bmatrix}\times 6$	$\begin{bmatrix}1\times 1,\ 256\\ 3\times 3,\ 256\\ 1\times 1,\ 1024\end{bmatrix}\times 6$
Conv5	$\begin{bmatrix}1\times 1,\ 512\\ 3\times 3,\ 512\\ 1\times 1,\ 2048\end{bmatrix}\times 3$	$\begin{bmatrix}1\times 1,\ 512\\ 3\times 3,\ 512\\ 1\times 1,\ 2048\end{bmatrix}\times 3$
Conv5	$\begin{bmatrix}1\times 1,\ 512\\ 3\times 3,\ 512\\ 1\times 1,\ 2048\end{bmatrix}\times 3$	$\begin{bmatrix}1\times 1,\ 512\\ 3\times 3,\ 512\\ 1\times 1,\ 2048\end{bmatrix}\times 3$

that adaptively performs feature refinement by learning the inter-channel relations and space-wise positional characteristics. In particular, the CBAM block performs a multiplication of the input keypoints map and the attention maps that are generated by inferring them sequentially along the channel and spatial dimensions from the intermediate feature map.

The suggested backbone architecture comprises a ResNet-50 CNN [75] and a CBAM attention block. The ResNet is a popular CNN architecture that uses identity shortcut connection along with residual links across convolutional layers and achieves high accuracy. Typically, in dense CNN models, all layers pass their computed value into the coming layer, allowing it to calculate more enriching keypoints [76]. However, as the network depth increases, the convergence results get worse due to the gradient disappearance problem. The ResNet architecture contains multiple residual blocks that allow bypassing a few convolution layers during training without affecting performance. The result of the convolution layers is combined with the computed value of the shortcut connections, which decreases the training degradation frequently seen in really deeper networks and overcomes the constraint of adding additional layers. The overall architecture of the ResNet model can be viewed as a group of multiple shallow CNN nets, where distinct architectures are connected together through shortcut connections, and the optimal results are achieved by averaging the outcome of each network. Table 1 displays the detailed layer-wise configuration of the MaizeNet backbone CNN network comprising ResNet-50 with an added attention mechanism. It comprises 48 convolutional layers that are grouped into 5 stages having multiple residual blocks laid on top of each other. The residual block is composed of 3 × 3 convolutional layers, a normalization layer, ReLU activation, and a skip connection. The stacked layers in the residual block offer quick connections that perform identity mapping to accomplish residual mapping.

We added the attention block in the network to filter out the important components from the input in advance so they may be used as the input for the next network. It assists the network to concentrate on disease-affected portions while limiting unnecessary background information and increasing detection performance in real-world cases like varied color, lighting, and intensity. In particular, the CBAM unit consecutively infers the attention map alongside the spatial and channel dimension using the intermediate keypoints map and multiplies the input feature map with the computed attention map to attain adaptive keypoints improvement. The added attention block is lightweight and adds a negligible overhead in the backbone CNN. Moreover, to prevent the loss of important attributes because of down-sampling, we replaced the initial convolution layer with a 7 × 7 filter size with three stacked 3 × 3 convolution layers. In addition, the channel for replaced convolution layers is set to 64 to reduce the computational cost.

2) REGION PROPOSAL NETWORKS (RPN)

The RPN module uses a feature map achieved from the last layer of the CNN network as an input and generates region proposals. Typically, a sliding window is used to generate a defined number of anchors (bounding boxes) taking various scales and aspect ratios on each pixel. To reduce the candidate boxes and obtain the region of interest (ROIs), a bounding box regressor and classification head are applied to determine whether a suspected location belongs to a diseased spot or a background region.

3) ROI POOLING

The RoI pooling layer computes the fixed-sized feature vectors for obtained ROIs from the RPN module. The feature map from the base framework and the proposed region proposals from the RPN module is processed by the RoI pooling layer to compute proposal feature maps.

4) CLASSIFICATION

Lastly, the attained feature vectors are passed through fully connected layers to perform localization and categorization by producing a bounding box for the maize disease-infected regions and its category.

IV. EXPERIMENTAL VALIDATION AND ANALYSIS

This part presents the details of the implementation settings. and various experiments carried out to check the results of the proposed MaizeNet approach. We thoroughly investigated the effectiveness of the MaizeNet approach in terms of maize disease localization and categorization and compared it with other networks utilizing the maize leaf illness data sample.

A. IMPLEMENTATION DETAILS

The suggested MaizeNet framework is executed using Python with TensorFlow and Keras libraries. We employed the pre-trained model on the MS-COCO database, which was then further trained using transfer learning on the maize disease database. The network is trained by employing varying batch sizes, learning rates, and the number of epochs with Stochastic Gradient Descent (SGD) training optimizer to obtain the optimal results. The final parameter settings on which the model attained optimal results are given in Table 2. The Intersection over Union (IoU) value is used to determine the bounding box overlap between the predicted and ground truth and is set as 0.5, which means if the value is greater than the set threshold, the prediction is considered positive.

TABLE 2. Training hyper-parameter settings for the presented framework.

Parameter	Value
Batch size	8
Epochs	35
Learning rate	0.001
Overlap threshold for RoI	0.5
Momentum for SGD	0.9
Weight decay for regularization	0.005

B. EVALUATION PARAMETERS

In this study, the performance of the suggested framework for maize disease identification and classification is quantitatively and qualitatively evaluated using several essential metrics for each experiment. We computed the values of metrics such as precision score (PS), recall score (RS), accuracy (Acc), F1-score (FS), IoU score, and mean average precision (mAP) score for each class. These indicators are computed as follows:

$$PS = \frac{TP}{TP + FP} \tag{1}$$

$$RS = \frac{TP}{TP + FN} \tag{2}$$

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$FS = \frac{PS * RS}{PS + RS} \times 2 \tag{4}$$

Here TP denotes the true positive score, representing total positive samples with correctly classified target disease class. The FP is a false positive score, representing the total negative samples having positive predictions. The FN denotes false negative, showing the number of positive samples with wrongly estimated disease class. Lastly, the TN indicates true negative, representing the samples that the model correctly predicted the negative class. The IoU is the combined ratio of the intersected area of the predicted and ground-truth bounding box in pixels computed for each class i using (5). Whereas, mAP is the average of average precision (AP) score for each i computed at different IoU threshold values.

$$IoU = \frac{TP_i}{FP_i + FN_i + TP_i} \tag{5}$$

$$mAP = \frac{1}{n} \sum_{i=1}^{n} AP_i \tag{6}$$

C. ASSESSMENT OF THE PRESENTED FRAMEWORK

In this experiment, we evaluated the localization and classification performance of the proposed MaizeNet framework for the identification of maize disease regions and their categorization. We performed the experiments using the dataset described in Section III-A.

FIGURE 4. Visual results showing localized and classified disease regions from samples using the proposed MaizeNet model.

1) RECOGNITION PERFORMANCE

The accurate recognition of infected leaf areas is essential to correctly categorize the maize disease using an automated approach. Therefore, we evaluated the localization effectiveness of the MaizeNet framework using maize disease-affected images from the employed dataset. The proposed attention-based Faster-RCNN method uses ResNet-50 with an attention block to extract the deep features from the training images. The obtained localization results are shown in Fig. 4. It can be seen from the reported visual results that the MaizeNet approach can effectively locate target disease spots having varying appearances including shape, color, size, and position. Moreover, Fig. 4 shows that even in the presence of background noise and unwanted objects, such as dirt, corn stalks, and weeds the disease regions are accurately detected and localized. Additionally, despite having varying lighting, orientation, and acquisition angles, our method can effectively perform maize disease recognition. We computed the mAP and mean IoU to estimate the overall localization effectiveness of our approach. These metrics demonstrate the effectiveness of the approach for the detection of target object. We determined the mAP for each category at the IoU threshold value set to 0.5. This implies that when the overlap score between the predicted and ground truth bounding box is greater than the specified IoU value, the prediction result is considered positive. Our technique achieved mAP value of 0.946 and a mean IoU score of 0.913. The identification probability of most ROIs using our technique is more than 93.14%. These findings demonstrate that our MaizeNet framework can precisely locate the infected regions using a location box and outputs the identification probability. The integration of attention mechanism in the network facilitated the detection head in recognizing disease spots with high accuracy, even in the presence of noisy backgrounds such as maize stalks, soil, leaf overlap, and varying lighting conditions.

Although our proposed model achieved high identification accuracy for detecting disease-affected regions of maize plants, however, its performance was affected by some environmental complexities, resulting in false or missed detections. Visual results of such instances are shown in Fig. 5. These misclassifications can be attributed to factors such as the presence of intense light variations, background noise, and high inter-class similarities. Additionally, in some cases, disease symptoms were not clearly visible/differentiable due to low severity levels (early stage) or similarity to other diseases.

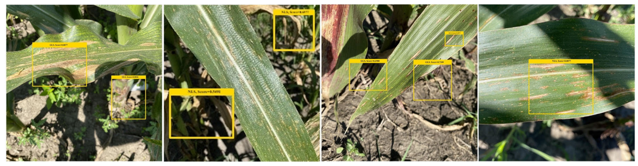

FIGURE 5. Sample visual results of false detection using the proposed MaizeNet model.

TABLE 3. Quantitative evaluation of the proposed MaizeNet model for each class.

Category	P (%)	R (%)	FS (%)	Accuracy (%)
Grey Leaf Spot	0.988	0.979	0.983	0.982
Northern leaf Blight	0.973	0.978	0.975	0.976
Northern leaf Spot	0.979	0.975	0.977	0.979
Grey Leaf Spot	0.988	0.979	0.983	0.982

2) CLASSIFICATION RESULTS

The exact categorization of various disease lesions is crucial to perform the automated identification of maize diseases using real-time field Images. In this section, we reported the categorization results of the introduced MaizeNet framework over 3 common maize diseases by computing metrics i.e., precision, recall, f1-score, and accuracy. Table 3 shows the details of the numeric evaluation results of the MaizeNet approach on each class using the test data. The average recognition ability of the approach for maize disease attained in terms of PS, RS, and F1-score is 0.980, 0.977, and 0.979, respectively. The presented method shows an overall categorization accuracy of 97.91% for all classes. Among all, the highest accuracy is obtained for the categorization of GLS class of value 98.20%. The recognition accuracy for NLB and NLS disease categories is 97.62% and 97.91%.

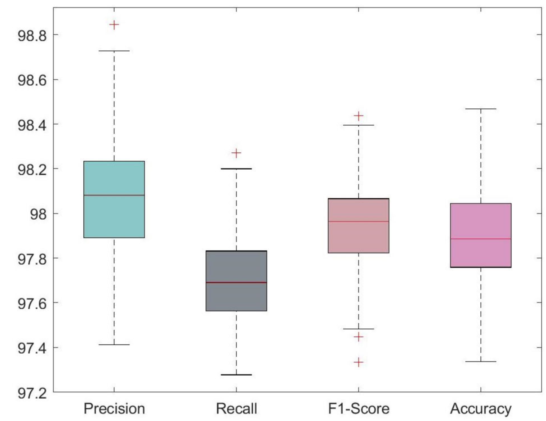

FIGURE 6. Box-plot showing the overall results obtained using the proposed MaizeNet model on the maize disease dataset.

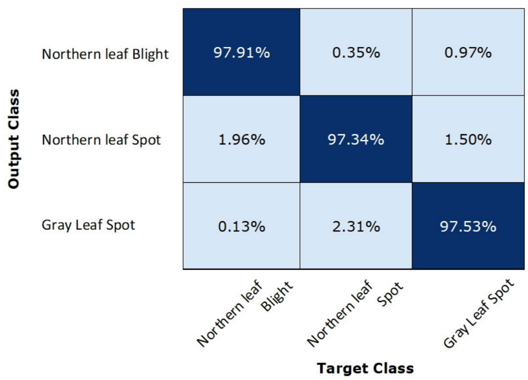

FIGURE 7. Confusion matrix showing categorization results of the proposed MaizeNet approach.

To better understand the performance of our approach, we have presented a boxplot for the computed evaluation parameters in Fig. 6. The boxplot displays the distribution of model categorization output across the database into four quartiles, median, maximum, minimum, and outlier values. The presented results clearly show that our method can accurately recognize and categorize maize leaf diseases in real environment conditions such as noisy background, variation in lighting, and distortions.

To further examine the class-wise recognition performance, we created a confusion matrix to present the details of appropriately and inaccurately categorized samples for each group. Fig. 7 shows the summarized class-wise categorization results of the proposed MaizeNet method against ground truth. The diagonal elements correspond to the percentage of accurate predictions made by the model for each class of test data, while the non-diagonal elements indicate incorrect predictions. From Fig. 7, it can be perceived that our approach correctly categorized the disease classes and attained the true-positive rate of 97.91%, 97.34%, and 97.35% for NLB, GLS, and NLS classes. There were a few misidentifications between NLS and GLS classes. The model sometimes identified the NLS class as GLS and vice versa. This might be attributed to the resemblance of the visual perception of these classes that led to incorrect predictions by the trained model. Overall, based on the reported results on the test set, the suggested framework is effective at differentiating between different categories of maize disease lesions and thus can be applied to perform identification in the actual field environment.

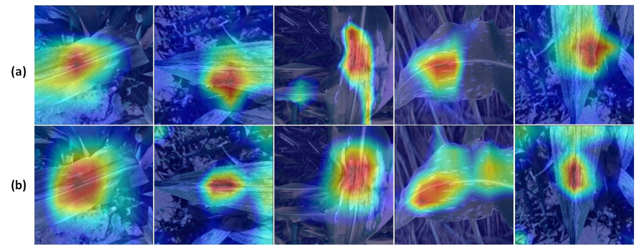

FIGURE 8. Grad-cam visualization results of the proposed approach for maize disease identification (a) without attention (b) with attention.

3) HEATMAP ANALYSIS

To analyze the effect of integration of attention module into the model, we performed a heatmap analysis to visualize the areas of an input image that contributed most to a particular class prediction by the network. We employed Grad-CAM to examine the relevance of specific features in an image. Grad- CAM calculates the gradients of the output class score with respect to the feature maps generated by the last convolutional layer of the network. The results of the analysis are presented in Fig. 8, which shows that our model with attention module learned to concentrate on significant visual features that contribute to accurate categorization outcome. The attention module assists the network to better emphasize the disease lesion area and disregards the background in real-scene images. The presented results of our heat map analysis have shown that the model can effectively recognize maize disease lesions from a visual perspective.

D. COMPARATIVE ANALYSIS WITH DIFFERENT FEATURE EXTRACTION NETWORKS

To perform the automated identification and classification of maize diseases using real-time field images, the model should be able to accurately differentiate between various disease categories in real environment conditions such as the presence of noisy background, different light conditions, and shadows. The extraction of finer-grained characteristics is crucial to accurately detect and recognize the disease in the presence of these factors. We accomplished an investigation to compare the capability of the MaizeNet framework to learn features in comparison with other CNNs as feature extraction for the purpose of maize disease spots localization and classification. For this purpose, other CNN models were taken into consideration such as Alexnet [77], GoogleNet [78], VGGNet [76], ResNet [75], EffcientNet-B0 [79], Inception-ResNetV2 [80] and ConvNeXt [81]. We used transfer learning to train these models and enhance generalization on

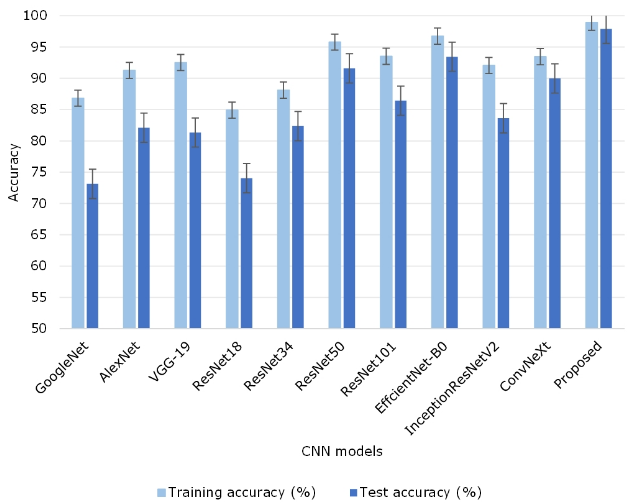

FIGURE 9. **Accuracy of proposed MaizeNet approach using different CNN models.**

unseen data. We initialized these networks using weights obtained on ImageNet [82] and trained them using the maize disease database. The approaches were trained for 35 epochs using mini-batch sizes of 8. We compared the efficacy of these networks in classifying maize disease and evaluated their computational efficiency. Table 4 shows the obtained accuracies of the introduced MaizeNet based on the Faster-RCNN model with different base CNN networks on the maize disease database and respective training parameters. These comparative results are also visually illustrated in Fig. 9. The results demonstrate that the proposed model outperforms other CNN architectures, including AlexNet, VGG-19, GoogleNet, ResNet variants (18, 34, 50, 101), EfficientNet-B0, InceptionResNetV2, and ConvNeXt, on both test and train samples, achieving an overall accuracy of 97.89% with the addition of an attention mechanism. Among other CNN architectures, the AlexNet attained the lowest overall accuracy of 82.12% on test samples for recognizing maize disease. While the other models such as VGG-19, GoogleNet, EfficientNet, InceptionResNetV2 and ConvNeXt attained an average accuracy of 81.34%, 73.12%, 93.43%, 83.62%, and 89.97% respectively. Furthermore, the ResNet50 outperformed other ResNet variants, achieving the highest accuracy of 91.58% for identifying maize disease lesions, while ResNet18, 34, and 101 attained accuracies of 75.04%, 82.35%, and 86.42%, respectively. By further adding an attention mechanism to ResNet50, our framework achieved an overall accuracy of 97.89%, resulting in a 6.31% increase in accuracy for the recognition of maize abnormalities compared to the baseline model. These results validate that the proposed framework precisely extracts the maize disease-related characteristics during training and thus accurately recognizes them from the samples. Moreover, despite the similar visual appearances of disease spots with the surrounding environment such as dead leaves and soil, our approach can correctly differentiate between them. While the competitive models were unable to effectively learn

TABLE 4. **The performance comparison of MaizeNet framework using different CNN networks.**

Models	Training accuracy (%)	Test accuracy (%)	Total trainable Parameter (M)
GoogleNet	86.82	73.12	7.8
AlexNet	91.26	82.11	62.3
VGG-19	92.51	81.33	143
ResNet18	84.91	75.04	11
ResNet34	88.11	82.35	21.5
ResNet50	95.78	91.58	23.72
ResNet101	93.51	86.42	44.5
EffcientNet-B0	96.74	93.43	40.09
InceptionResNetV2	92.05	83.62	54.3
ConvNeXt	93.45	89.97	25.5
Proposed	98.93	97.89	23.91

fine-level characteristics from the samples due to background complexity. This shows that the added attention mechanism assists the network in adaptively learning finer-grained disease attributes through simulating an inter-channel and spacewise position relationship of features.

Table 4 also presents the computational complexity of the MaizeNet model and baseline CNNs in terms of trainable network parameters. The proposed model has 23.91M parameters that are less in comparison to peer networks except for GoogleNet. The GoogleNet CNN has 7.8M parameters, however, it may not be able to effectively capture disease-specific patterns under complex backgrounds and varying conditions such as noise, luminosity, shape, color, and location from the samples which resulted in lower classification accuracy. Whereas, the MaizeNet framework effectively learns the characteristics of diseases under complex field conditions and showed improved detection accuracy. The addition of the attention module in ResNet50-FasterRCNN has significantly enhanced the localization and classification outcomes for maize disease while marginally increasing the number of parameters. Based on these results, we can infer that our framework is computationally efficient and robust for classifying and detecting infected maize leaves.

E. COMPARATIVE ANALYSIS WITH OTHER DETECTION TECHNIQUES

In this part, we presented the evaluation of the introduced MaizeNet framework with other object identification algorithms. This experiment aims to demonstrate the superiority of the presented approach for maize disease detection and categorization. For this purpose, we considered the standard Faster R-CNN algorithm and other popular one-stage object detection algorithms such as the single-shot detector (SSD) [40] and You Only Look Once (YOLO) [41]. We used the same dataset as described in Section III-A for the training and assessment of these techniques. The networks were trained for 35 epochs with a mini-batch size of 8 and an SGD optimizer. The learning rate was set at 0.001 and a dropout value of 0.6. We reported the results in terms of mAP, which is the standard metric used to analyze the performance of object detection algorithms for localization and classification tasks.

TABLE 5. Comparative results with different object detection techniques.

Method	mAP	Inference time(s)
YOLO	0.87	0.19
SSD	0.71	0.34
Faster-RCNN	0.89	0.23
Proposed (MaizeNet)	0.94	0.26

For each category, the mAP is computed as an average of AP of detection when IOU = 0.5.

Table 5 shows the results obtained by evaluating these models for the maize disease recognition task. From Table 5, it is clear that the presented approach acquired the highest mAP value of 0.94. Whereas, the other approaches such as SSD and YOLOv3 algorithm showed a mAP value of 0.71 and 0.87, respectively. Moreover, the comparative evaluation shows that the standard Faster-RCNN algorithm is also unable to accurately recognize maize disease regions from input samples and obtained a mAP value of 0.89. Compared to these algorithms, our method showed a 5% higher mAP than standard Faster R-CNN and it also outperformed the SSD and YOLO algorithms. These results suggest that the comparative methods are unable to accurately locate the disease regions in maize leaves from the noisy background. This ineffectiveness in detecting the infected areas, particularly small and obscured ones, leads to a decrease in the overall identification accuracy. Furthermore, we have examined the inference time of these algorithms, i.e., the time required to process an input sample in order to detect the diseased regions. To compute the inference time, we used the test samples from the dataset and computed the average inference time for an input taken by the model to produce the output. The proposed MaizeNet model has a detection time of 0.26s, which is faster than that of SSD. The identification time of our approach is at least 0.07s slower as compared to YOLO and standard Faster-RCNN, however, the identification accuracy of our approach is significantly higher than these methods. These reported results show that MaizeNet framework is effective for the localization and classification of maize disease regions from the input samples. In our method, the added attention mechanism led the network to learn the different transformations effectively along spatial and channel dimensions and improved the feature information of the target regions. It also enhanced the information of small targets along with overlapped and occluded areas. This assisted the detection framework to identify the target region of interest more precisely, which ultimately improved the overall detection accuracy of the diseased spots in the presence of complex natural conditions.

F. COMPARATIVE ANALYSIS WITH OTHER LATEST METHODS

Here, we presented an assessment of the accuracy of our method for categorizing maize leaf disease with the results from previous studies that used the same dataset i.e., CD&S.

TABLE 6. Comparison with existing methods over the CD&S database.

Reference	Method	Accuracy
Ahmad et al. [60]	Transfer learning using DenseNet169	81.60%
Phan et al. [64]	SLIC method with DenseNet121 CNN	97.77%
Chen et al. [66]	DFCANet CNN	98.47%
Divyanth et al. [65]	UNet and DeepLabv3+	92.37%
Proposed (MaizeNet)	Attention-based Faster-RCNN with ResNet-50 backbone network	97.89%

Table 6 illustrates a comparison of the presented method to the average accuracies obtained using existing methods. In [60], transfer learning was used for training five different pre-trained DL approaches such as InceptionV3, ResNet50, VGG16, DenseNet169, and XceptionNet to recognize corn disease from images. This study assessed the generalizability of employed models under different conditions. The results showed that the DenseNet169 approach performed better than the other 5 frameworks with the highest generalization accuracy of 81.60%. Similarly, in [66], the authors presented a CNN model namely DFCANet comprising deep separable convolution for the classification of maize disease. The method includes dual feature fusion with coordinate attention and down-sampling modules to compute disease representative feature set. This method achieved an average recognition accuracy of 98.47%. In [64], Simple Linear Iterative Clustering (SLIC) segmentation method was initially utilized to generate super-pixels for images belonging to different diseases that served as training data for different DL models such as VGG16, DenseNet121, ResNet50, and XceptionNet. These models were then utilized to classify infectious disease spots on maize leaves into respective classes. The maximum accuracy of 97.77% during testing was obtained using the DenseNet121 network having a sigma score of five and dividing each image into five segments. The work in [65] proposed a two-stage semantic segmentation method based on UNet, SegNet and DeepLabv3+ model to estimate the severity of corn leaf disease lesions. In the first stage, the complete leaf portion is separated using these networks, while the second stage focuses on identifying and segmenting the disease spots within the previously segmented leaf. The proposed method achieved an overall accuracy of 92.37% using UNet and DeepLabv3+ networks. The methods presented in [60] and [66] performed image-level classification that can result in incorrect predictions due to a complex background environment. Moreover, the presence of multiple disease diseases in a sample can result in high false classification for real-world scenarios. On the other hand, the approach presented in [64] and [65] initially performs a segmentation step, which can be computationally complex. In contrast, our method performs both the localization and recognition of maize lesions, achieving an accuracy of 97.89% on the same dataset. The reported result demonstrates the robustness of our proposed model for detecting maize diseases in the field when compared to other methods. This is because our method effectively computes the fine-level disease characteristics along spatial and channel dimensions from the input. As a result, the detection network accurately locates the target region of interest, ultimately improving the overall detection accuracy of diseased spots in complex environmental conditions.

V. CONCLUSION

This work has presented a DL approach called the MaizeNet to localize and categorize various types of maize plant leaf diseases. Clearly, an improved Faster-RCNN approach is presented that utilizes the ResNet-50 model with spatial-channel attention as its keypoints extractor. The work is evaluated using a standard dataset named CD&S to show its effectiveness. This dataset contains images with several sample distortions like noise, blurring, color, light, and size variations. An extensive experimental analysis with the help of different standard evaluation parameters is performed to indicate the efficacy of the introduced work. We have assured through both the pictorial and quantitative results that the MaizeNet model is proficient in locating and categorizing the maize crop leaf disorders with an accuracy of 97.89%. In future work, we are planning to evaluate the proposed approach over other challenging datasets. Moreover, we will explore other DL approaches to further enhance the classification results.

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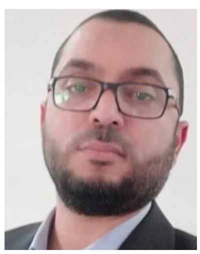

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