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RESEARCH ARTICLE

An Early and Smart Detection of Corn Plant Leaf Diseases Using IoT and Deep Learning Multi-Models

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ABSTRACT Plant leaf diseases have various causes, leading to severe disorders. The early and accurate detection and classification of these diseases are fundamental for fostering healthy crop production. In recent years, smart agricultural systems have garnered significant attention due to their capability to enhance efficiency by deploying sensor networks and Internet of Things (IoT) devices that collect and analyze environmental data. However, traditional plant disease detection methods are manual, time-consuming, and often need help handling the data's complexity and dynamism. These manual methods do not use heterogeneous data to make better decisions. Corn holds significant importance yet it faces numerous diseases that include main three diseases such as blight, common rust, and grey leaf spot. The advancement of computer technology has led to a pivotal focus on corn leaf diseases classification application based on deep learning. Convolutional Neural Networks (CNNs) have revealed remarkable achievements within Precision Agriculture (PA) due to their ability to enhance information. To this end, this work introduces a CNN-based architecture, the Multi-Model Fusion Network (MMF-Net). Its primary objective is to classify diseases within the realm of PA. MMF-Net integrates multi-contextual features using RL-block and PL-blocks 1 & 2, thus effectively combining different model streams trained on heterogeneous data. The RL-block uses spatial range to process coarse grained images to convolve the local context, while PL-block 1 extracts fine-grained global context by expanding the perceptual area of images. PL-block 2 deals with real-life environmental parameters as features. The extracted features are syndicated using multiple classifiers that ensemble three individual blocks at the decision level to improve the accuracy. After fusion, it uses adaptively the majority voting scheme to generate the final decision probability score of the base model. Multiple experiments are conducted involving the corn leaf diseases dataset and a real-life numerical dataset, generating an impressive 99.23% accuracy in the classification of corn leaf diseases. Overall, MMF-Net provides a promising and smart solution to identify plant leaf diseases in PA effectively.

INDEX TERMS Precision agriculture, corn disease, sensors, pest control, CNN, decision level fusion, multi-model, MULTI-context, AlexNet, VGG-16, ResNeXt, heterogeneous data.

I. INTRODUCTION

Precision Agriculture (PA) aims to enhance crop production in challenging and multifaceted environments. In recent years, there has been a rise in various plant leaf diseases, resulting in a decline in the average potential crop yield and food availability. However, traditional plant leaf disease diagnosis methods have some deficiencies, such as human fatigue, and are time-consuming and labor-intensive [1]. The other leading causes are seasonally unstable environmental

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conditions and climate changes. It hinders crops' average growth, ultimately reducing the yield [2]. Crops can also experience damage on plant leaves that depend on crop types, sensitive physical properties, water logging, drought, low soil fertility, insects, viruses, weeds, and the presence of pathogens [3]. Disease-ridden plants tend to show different abnormalities and unique noticeable patterns such as cuts, wounds, marks or lesions on fruits, flowers or leaves. Plant leaves are the primary source of these abnormalities, and most disease symptoms appear on leaves at early stages [4]. At early stages, the detection and prevention of plant leaf diseases are fully developed and of great significance. In totality, this effective treatment and knowledge may lead to experiencing fewer complications, which play an essential role in growing at the excessively appropriate rate. So, the right decision can assist farmers in accurately achieving higher crops at the appropriate times and locations [5]. Therefore, an accurate and automatic plant leaf disease detection and classification system ensures a high yield that eludes manual detection procedures in the field. It can also help conserve land resources and improve farmers' profits [6].

Deep learning (DL) models have achieved remarkable progress in agricultural applications by identifying plant diseases. Numerous standard schemes of DL are built, trained and tested on the collected data for detection. Convolutional neural networks (CNNs) play a crucial role in enhancing the performance of various tasks by detecting salient content. Still, they might be unable to determine visual attention due to the lack of explicit representation of prominent features [7]. These models eliminate the need for feature engineering by effectively capturing data in a more representative format. They are designed to extract intricate features from input images and then integrate these extracted features to create an automatic image-based classification system [8]. The ground theory of proposed approach is to understand the theoretical concept of botanical knowledge about how diseases affect plant tissues and leverages the inherent capabilities of CNN architectures. The main phenomena marked as visual symptoms appear at different location of leaves, including discoloration, lesions, spots and other abnormalities that exhibit spatial patterns and textures. The proposed approach is designed to recognize spatial features at different scales, capturing local basic features and complex global structures. It can synergy between theory and technology contribute to distinguish between healthy and diseases leaves. The most common image-based features in any CNN detection model are edges, corners, ridges, regions of interest/blobs, shapes-based, etc. The automatic analysis of images using image processing techniques is challenging due to several characteristics such as complex background, minor lesion portion, image illumination, and presence of multiple disease spots on leaves [9]. CNN networks have been employed to identify these patterns within images, indicating diseases in afflicted plants' images. It also incorporates global and local object features, considering the overall appearance of objects and their parts as distinct components [10]. A comprehensive investigation was conducted to demonstrate the entire process of detecting and categorizing diseases in plant images. The classification process encompasses two main stages: training and testing, which encompass tasks such as input acquisition, pre-processing and feature extraction [11]. The PA is more critical in any developing country for improving agricultural production with the support of many intelligent technologies such as IoT, cloud computing and data analysis with DL models. Combining Deep learning and the Internet of Things has opened up new ways in human life.

The basic principle of using the IoT and deep learning multi-models in the context of early plant diseases detection is to develop an autonomous system that should be pervasive and ubiquities. Multimodality system is also remove erroneous condition at some distinctive condition. The advantages of early diagnosis of plant leaf diseases using autonomous system enable to identify the subtle changes in leaf images with minimum human interference. Early detection allows farmers for timely intervention and minimizes the spread of diseases only where and when necessary that enhance the quality and quantity of food production. It helps in capacity with higher crop yields for precise monitoring and farmers can optimize the use of resources that can minimizes the input cost. Consequently, it would be commendable to research CNN-based classification systems, including the IoT paradigm in the agricultural domain, for detecting diseased plants. Thus, plant leaf disease surveillance can be characterized by extracting visual features from 2D digital images and measurement of complex growing contextual environmental factors [12]. A fabulous improvement has been made by collecting high-level contextual information from various sources like IoT sensors and images that may be utilized to effectively increase the progress in modern recognition systems in the agriculture industry. Thus, due to their portability, embedded and mobile devices are more favorable than computers or servers in agricultural fields. In addition to this, commercial agricultural tools are so classy to get revenue. So, a new low-cost technology with CNN variant would be an optimum solution for diagnosing plant leaf diseases that speed up the work [13]. Furthermore, CNN-based approaches and fusion techniques have advanced standing that fuses multiple forms of agricultural data, resulting in widespread research for early plant disease diagnosis control systems. It will support the protection of plant leaves from diseases that comprehend yield growth [14]. The complexity of customary plant leaf disease detection architecture has made it more challenging to streamline agricultural operations. Most of these approaches are built on variant of CNN architecture. However, the low-level visual features may not be a superior solution for higher accuracy and CNN does not provide high-level semantic features for accurate plant leaf disease classification. In addition, the captured images might need help with background clutter and illumination variation. For this reason, our research focuses on getting contextual and real-life parameters for the high performance of any customary plant leaf disease detection system when deployed in real-world settings. Such limitation highlights the need for techniques to enhance the accuracy and robustness of these models to handle the various complexities and variations encountered in practical applications. In the context of this situation, the proposed research will explore the following research questions:

RQ1. How can we improve the accuracy of the plant leaf disease detection model in real-world scenarios? This remains our main research question.

RQ2. Related to RQ1, which techniques are effective for improving the accuracy of the plant leaf disease model? The effectiveness of the said techniques is to be evaluated quantitatively.

RQ3. Related to RQ2, if the fusion of multi-contextual features is selected as an effective technique, what are the main challenges and how to address them?

RQ4. Related to RQ3, how can our proposed fusion architecture be trained on heterogeneous datasets?

The main objective of this work is to develop an automatic and smart solution for a classification system in PA that supports the improvement of classification accuracy of different plant leaf diseases in real-world scenarios. Thus, we explore the syndication of pre-processed visual and real-life multi-contextual features with a fusion mechanism. The desire is to get one robust multi-model network of three sub-networks based on RL-block and PL-blocks 1 & 2 feature representation inspired by end-to-end variant forms of CNNs. To capture different levels of detail, individual CNNs are trained exclusively for specific multi-scale details. This is achieved by resizing the training images with one CNN dedicated to the object level and the others focused on the part level. MMF-Net incorporates heterogeneous data, including the image's pixel values and environmental parameters. RL-block and PL-block 1 provide more discriminative local and global level features, such as edges and patterns for background stacks around that are sent to the recognition part as feature maps. PL-block 2 is considered for attaining environmental-based features such as temperature, humidity, and air pressure and soil moisture. That wealth of data can be leveraged to optimize crop growth and identify plant diseases. The robust selected features are passed to multiple classifiers for decision-level fusion. The fusion of multi-contextual features based on image and numerical data is a versatile single-fused interpretation that may boost the system's accuracy. Interestingly, this strategy has two different forms of design that learn features correspondingly before fusion and then fuse three paths to form a single result. After decision-level fusion, it integrated the salient information linearly, significantly improving results. The ultimate detection process returns a recognition label for each testing image. The main steps involved in MMF-Net are depicted in Figure 1. The integration of IoT and CNNs in context of plant leaf diseases detection system faced some challenges.

- Quality of data collected by IoT devices change rapidly due to different climate and soil type.
- An autonomous corn leaf diseases detection system in real-world required enhanced accuracy.
- Implementation of corn leaf diseases system with different classifier using ensemble method.

The rest of the paper is arranged as follows: Section II discusses the related work. Section III explains the proposed methodology. Experimental details are expounded in Section IV. The performance evaluation and results of the proposed network is shown in V Finally, we end up with conclusions in Section VI.

II. RELATED WORK

The latest trend in using various deep learning models has presented promising results for plant leaf disease detection. The fusion of features approaches used for plant leaf disease detection is a significant challenge for researchers. Several CNN models have been presented in the literature for classifying plant leaf diseases. The authors proposed a (PD R-CNN) discrimination algorithm of decision fusion based on multiple features on crop surfaces. The algorithm uses an R-CNN computer vision processing model that can identify crop surface lesions and analyze the growth of cucumber seedlings. It reduced the workload effectively and distinguished crop diseases during the occurrence of pests [15]. The authors focused on determining the best DCNN classification model that fuses the features of seven one-dimensional CNN models for five disease-grading classes of rice leaf samples. The sample number was increased by using data augmentation and amplification techniques. This proposed model was compared with different CNN models, and machine learning techniques showed that the results of fused features were significantly better in accuracy [16]. An IoT-based model was deployed to recognize crop diseases in the wild. It adopted CNN as the backbone to extract discriminated features from in-field crop disease samples or images. Contextual parameters are collected from image acquisition sensors that reduce false positives to build a deep, fully connected network for crop disease classification [17]. It presented a fine-grained visual classification model with a cross-stage partial network backbone, cross-level fusion, and three parallel subnetworks. This multi-stream hybrid architecture can distinguish interclass discrepancies for identifying crop categories [18]. A two-stream deep fusion architecture was employed for automatic detection and classification. It was based on CNN-SNM and CNN softmax pipeline to infer classes. Its results achieved better accuracy and lower false positives than others [19]. Features were extracted from hyper-spectral and chlorophyll fluorescence images and end-to-end fused to detect the hazardous substance. Fusion used low, middle, and high-level information to improve accuracy [20]. A multi-source feature-level fusion method sped up the training process by transfer learning for integration. The multi-model fusion method identifies the features to retain the critical information. It used R-CNN and ResNet34 models to classify six types of diseases [21]. Efficient Net B7 deep learning architecture is used for transfer learning to get features from digital images. These features were down-sampled by Logistic Regression to identify the most discriminant traits with the highest constant accuracy [22].

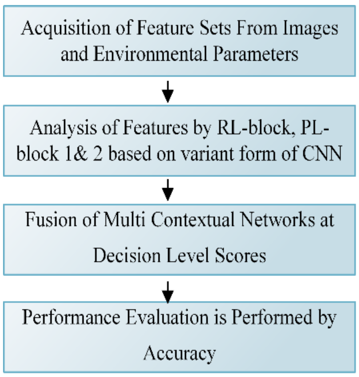

FIGURE 1. Main steps involved in MMF-Net.

SCNN-KSVM and SCNN-RF are used to classify, but a shallow CNN cannot extract enough information from the image dataset. The experiments were carried out on three different datasets and outperformed other pretrained deep models, which showed that combining two shallow CNN models was a positive attempt [23]. Two sub-networks were provided with more discriminative feature segmentation separated from the background and used to increase the classification accuracy. Then trained the model with early and later fusion to get the final feature information that was semantic–level spot features [24]. A dilated inception embedded attention module for extracting the multi-scale features strengthening the performance of DISE-Net was proposed. These modules learn the inter-channel relationship for input feature maps that dense the connection strategy for model building. The dataset of maize with all small leaf spots was made by the authors [25]. Two automatic CNN models for learning and extracting features were fused to identify infection in the input images. RL learnt the significant features of the attention mechanism in the 5-fold cross-validation [26]. VGG19 extracted deep features using the pretrained model, and partial least squares regression fused parallel extracted features. PLS projection method selected the best discriminant features for final recognition plugged into the tree classifier [27]. Another novel approach was proposed. This novel work uses multiple features to improve the classification accuracy and reduce computational time. Hu-Moments, local-Binary-Pattern, Color-Histograms and Haralick features are considered for training and testing. Two classifiers were used for fusion at the decision level, but the random forest was more accurate than the decision tree classifier [28]. A comparison between different multi-fusion techniques for detection and classification is shown in Table 1.

The authors considered an urgent need to develop a rapid protocol that evaluates disease severity accurately. Three networks were used to assess the severity of apple diseases. Apple leaf images were segmented into different backbone portions. Then, PSPNET with MobileNetV2 network was applied to the affected and segmented leaves [29]. An effective loss-fused CNN network was proposed to identify the area with diseases of its type on plant leaves. This system better combines two different loss functions to predict the model's final layer [30]. However, there still needs to be a sufficient gap in this field to improve the accuracy of classifying any disease using machine learning algorithms.

III. MULTI-MODEL FUSION NETWORK

The autonomous proposed approach holds significant potential for early detection of corn leaf diseases that have proactive diseases management strategies towards enhance crop yields. Once a potential issue is identified, farmers can take prompt action, such as targeted pesticide application, to prevent the spread of the disease. This proactive approach can contribute to better overall disease management and higher crop yields. We proposed a multi-model fusion network (MMF-Net) based on RL-block and PL-blocks 1 & 2 with an embedded modified CNN parameter. For multi-category plant leaf disease detection, an efficient and smart solution is proposed by integrating three parallel individual sub networks through the inexpensive RL-block, PL-blocks 1 & 2 inspired by the deep learning framework of CNNs. In MMF-Net, simple shapes, edges, and boundaries are automatically extracted as rich features in the initial layers. In contrast, high-level features such as complex shapes and complete objects are extracted from deeper layers. These different sets of features from different layers are fused at the decision level to improve the performance. MMF-Net was an integration analysis scheme with a feed-forward neural network with a plant leaf disease detection application. The training was performed on the heterogeneous dataset, a fusion of multi-contextual features of images and environmental parameters at the decision level. Specialized sensors capture environmental conditions surrounding the corn plants. Transmit data from sensors to system for analysis using multi-models architecture combining with image processing. Analyzing images and environmental data to detect patterns indicative of diseases by training the model. The architecture of the designed framework is shown in Figure 2.We improved the accuracy of the trained classifier by choosing environmental parameter features such as temperature, humidity, and air pressure and moisture level. A good compromise was present between semantic and spatial, global and local representation in images and numerical datasets. The last convolution layer in the fused network responded to the predicted results. Finally, the trained model was deployed anywhere to provide end-user services, where the test image was converted into the required dimensions and normalized environmental parameters. Input is evaluated by assessing the intensity level of the environment and performing plant leaf disease detection by a trained classifier. The trained model

TABLE 1. Comparison between different multi-contextual fusion and IoT techniques used for plant leaf disease detection and classification.

Year	Model	Category	Dataset	Algorithm	Classes	Classifier	OA(%)
2022, [15]	PD R-NN	Cucumber	CNKI	R-CNN	6	FInference Rules	99.95
2021, [16]	DCNN	Rice Plant	Selfmade	CNN	5	Nadam Algo	98.58
2020, [17]	MCFN	Different Crop	Selfmade	CNN	77	SF	97.50
2021, [18]	MCF-Net	Different crop species	CropDeepv2	CNN	60	GP	96.2
2022, [19]	Two-stream	Eggplant	Selfmade	CNN-SVM, CNN	9	SF	98.9
2022, [20]	CNN-S	Rice Plant	L-VIS/NIR, S-VIS/NIR, L-Chl-FKC, S-Chl-FKC	SVM, CNN	5	Cross-Entropy loss	94.7
2022, [21]	Proposed Model	Tomato Leaf	PlantVillage,Selfmade	Mask R-CNN, ResNet34	6	SF	98.9
2022, [22]	Hy-CNN	Grape Plant	PlantVillage	ENet B7	4	ENet B7	98.7
2020, [23]	SCNN-KSVM, SCNN-RF	Apple, Grape, Maize	PlantVillage	CNN, RF	4	SVM	99.0
2020, [24]	LSA-Net	Apple	Images provided by Apple Research Institute	CNN	3	SVM	89.4
2022, [25]	DISE-Net	Maiz	Selfmade	CNN	5	SGD	97.12
2020, [26]	Residual-CNN	Tomato	PlantVillage	CNN	4	SF	98.0
2021, [27]	PLS	Tomato	PlantVillage	VGG19	3	ESD Classifier	91.67
2020, [28]	FGVR	Reality objects	Selfmade	ResNet50+LSTM	Muliple	-	97.74
2022, [29]	PSNet, Unet	Apple	PlantVillage	VGG,MNV2	5		96.41
2021, [30]	Proposed Model	Potato,Tomat o	PlantVillage	CNN	5	SF	98.93

Remark: The used abreviations have the following meanings: CNN (convolutional neuro network), SVM (super vector machine), LR (logistic regression), RF (random forest), DT (decision tree), SF (softmax funtion), MNV2 (mobile network v2), EN (Efficient Net B7), GP (Gaussian probability) and FInference Rules (Fuzzy Inference Rules).

can process incoming data and providing quick feedback to farmers for timely decision.

A. LAYERED ARCHITECTURE OF RL BLOCK

In deep learning, CNN is a multilayer extraordinary design that extracts rich different patterns automatically from images to produce features for decision. We developed the RL-block with the cardinality concept of width dimension. "Cardinality" adjusts the width of convolutional layers with residual knowledge by changing the training parameters. Furthermore, cardinality is considered an essential property for getting better results instead of going deep [10]. The learning patterns were based on aggregated feature maps derived from the "16" multilevel branches. For passing significant details extracted in the initial layers, residual or skip connections were employed to collect simple shapes like edges and boundaries or feature maps. RL-block used residual-like connections with different spatial ranges of "16-cardinality $\times$ 4 d" for convolving to learn the hierarchy of multi-scale feature aggregation from coarse-scale image-like edges in an orderly fashion. In the first convolutional layer, we used 32 inputs with kernel size "7 $\times$ 7" and stride = "2" which produced 64 feature maps followed by a subsampling of the max pool layer with stride = "2". This stride value states the movement of a sliding window. There were four modules piled up by adding Conv2-x, Conv3-x, Conv4-x, Conv5-x, consisting of residual blocks, in each module, there were two convolutional layers with kernel size "3 $\times$ 3" and pad = "2". After each convolutional layer, a batch normalization layer and a ReLu function were present. Finally, a global average pool layer was added. It formed 34 convolutional layers, with one first convolutional layer and the final fully connected layer. Therefore, we call it RL-block as presented in Figure 3 (a), a block of skip connection with two convolutional layers (b). A block of skip connection for RL-block with 16-cardinality is shown in Figure 3 (c).

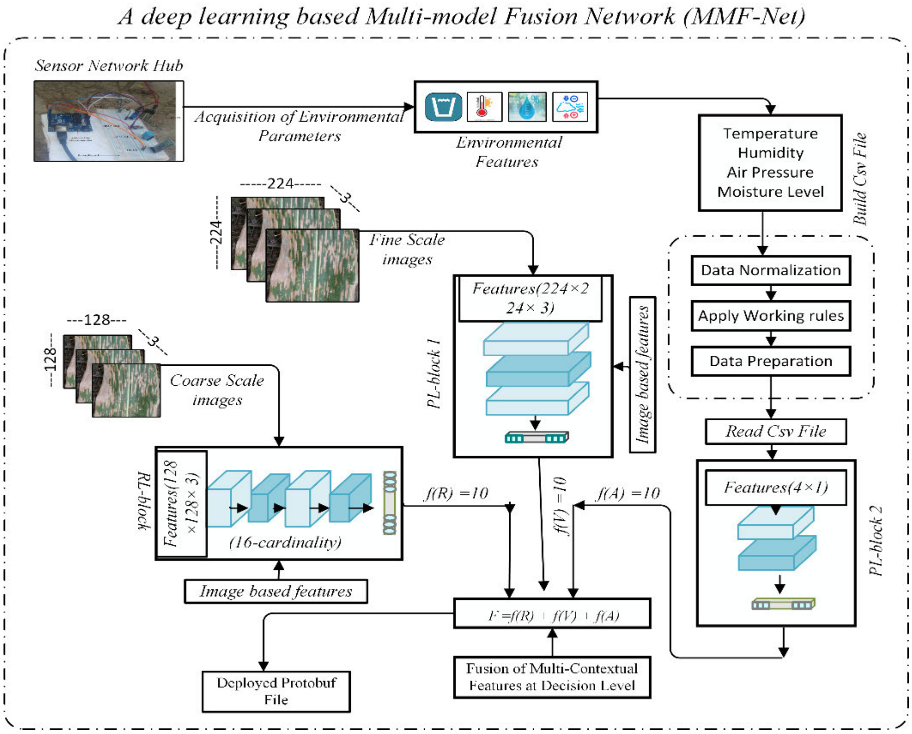

FIGURE 2. Detail architecture of the MMF-Net, which comprises decision-level fusion of heterogeneous data features.

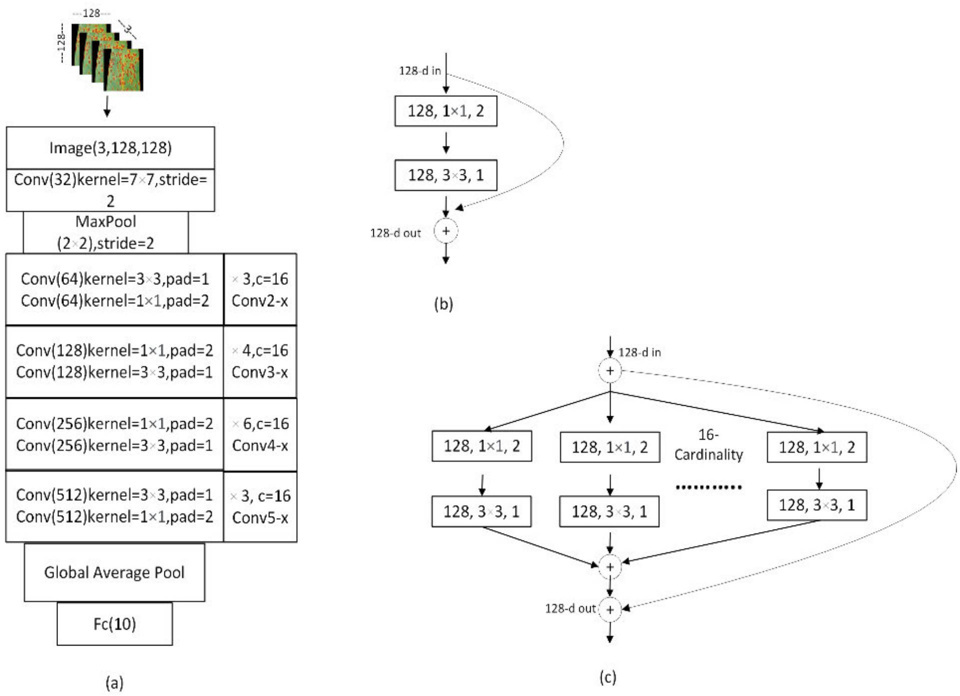

FIGURE 3. Layered architecture of RL-block based on ResNeXt model. In this model, the convolutional layers are shown as channels, filter, pad (a), and a block of skip connection (RL-block) with two convolutional layers (b), a block of RL with cardinality-16 (c).

B. LAYERED ACHITECTURE OF PL-BLOCK 1

The PL-block 1 is used to extract fine-grained features in diverse channels by reducing noise in fine scale images with a dimension of "$224 \times 224 \times 3$". The network filters finer granularity level information from the image's perceptual area which is to be expanded. The input images are passed through a stack of convolutional layers. The architecture's evaluation study is done by increasing the layer depth to 16-19 weight layers with a very small filter size of "3 × 3" which substantially improves the prior architectures. This small filter size captures the notion of up-down and left-right center with padding necessary for keeping the same resolution of intermediate outputs. In this architecture, 13 convolutional and 3 dense layers with activation function "ReLU" are used. At the end, the final layer has an output, which is equal to the number of classes that need to be identified. In this configuration, we used a "1 × 1" filter as a linear transformation followed by non-linearity. The spatial padding of the convolution stride is 1 pixel, which preserves the spatial resolution after convolution. Spatial max-pooling layers are carried out over a "2 × 2" pixel window. At the end, the three fully connected layers follow the heap of convolutional layers. Soft-max layer is used for generating the final results. The architecture of PL-block 1 (left) is shown in Figure 4.

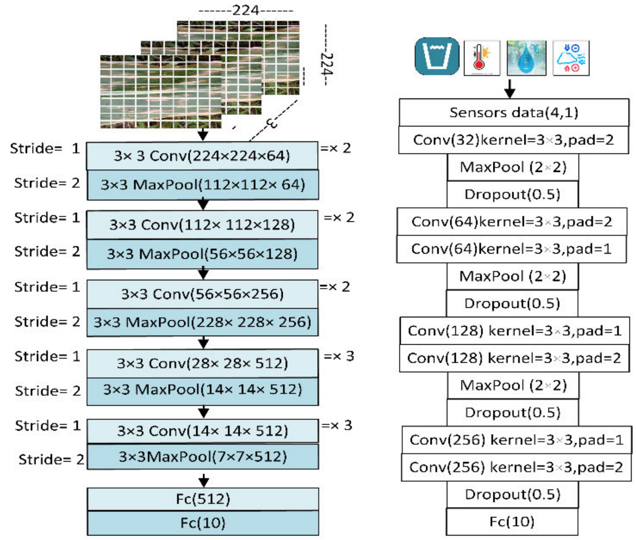

FIGURE 4. Layered architecture of PL-blocks 1 & 2 based on the variant form of VGG-16 and AlexNet-8. PL-block 1(left) and PL-block 2(right).

C. LAYERED ARCHITECTURE OF PL-BLOCK 2

CNN is a very renowned feed-forward architecture. There are three types of CNN such as 1D, 2D, and 3D. In 1D CNN, the kernel slides along only one dimension, which is favorable for real-time and time-series data [31]. Therefore, we trained our plainly learning model on a real-time numerical dataset by using 1D CNN based on AlexNet model [7]. It achieved significant features on a trivial dataset by applying some function to the input values coming from the receptive field, each neuron computes the output values. It consisted of seven layers of convolutional layers and one fully connected layer to reduce overfitting by using dropout layers. Tensor with two dimensions was created as input. The first dimension represents the total number of features in one record. We found that more meaningful features were present in the form of neural responses at higher layers than at lower layers. The last layer converted neural responses into classification scores. We used a small convolutional window shape of "3 × 3" with "pad=2" or "pad=1". First, Conv layer with input 32 was followed by a max-pooling layer with a convolutional window shape of "2 × 2". To overcome the overfitting problem, we added the dropout layer after each max-pooling layer. After the last dropout layer, there was only one fully connected layer before decision-level fusion with 10 outputs. The architecture of PL-block 2 (right) is shown in Figure 4.

D. MULTI-MODEL FUSION OF MULTI-CONTEXTUAL FUSION

In order to solve the plant leaf disease detection problem, fusion is a process to integrate multi-contextual features for improving the performance of classification models of multi-classes. It can be found that decision-level and feature-level fusion methods are effective for improving the classification results and increasing the accuracy of any classification application. From the existing literature, decision-level fusion is more favorable when the training datasets are different [32]. Therefore, the proposed multi-model intends to optimize the multi-stream network with decision-level fusion of two different datasets: one is publically available and the other is built according to the local environment. It is considered as one, the stream carries image features according to standards, and two, and the stream has environmental and contextual features. Both streams independently gather various feature maps during training and fuse at the end. It is a linear combination of probability-based multiple classifiers that fuses multi-contextual features at the decision level. This multi-model is responsible for getting the final decision results by mixing up the probability scores. Finally, the classifier produced 4 final probable classes for the 4 definite labels. Let V be an input dataset that has d(n) sample images, for the sample image d(j) ∈ V, where j = 1, 2, 3, 4, ...n, the output was generated by Conv-1 for one sample image is shown mathematically as in (1), where x^1 is the resultant features of Conv-1 with training factors, weights and bias.

$$x^1 = \sigma\left(\sum\nolimits_{i=1}^{n} d_i^1 \times w_i^1 \times b^1\right). \tag{1}$$

For ResNeXt-34 model

$$f(R) = x^1 + x^2 + x^3 + \ldots + x^k. \tag{2}$$

The resultant output after "k" Conv layer is obtained by putting the value of Eq. (1) into Eq. (2) accordingly

$$\begin{aligned} f(R) = \sigma&\left(\sum\nolimits_{i=1}^{n} d_i^1 \times w_i^1 \times b^1\right) \\ &+ \sigma\left(\sum\nolimits_{i=1}^{n} d_i^2 \times w_i^2 \times b^2\right) + \ldots \\ &+ \sigma\left(\sum\nolimits_{i=1}^{n} d_i^k \times w_i^k \times b^k\right). \end{aligned} \tag{3}$$

For AlexNet-8 model.

$$f(A) = x^1 + x^2 + x^3 + \ldots + x^k. \tag{4}$$

The resultant output after "k" Conv layer is obtained by putting the value of Eq. (1) into Eq. (4) accordingly.

$$f(A) = \sigma\left(\sum_{i=1}^{n} d_i^1 \times w_i^1 \times b^1\right) + \sigma\left(\sum_{i=1}^{n} d_i^2 \times w_i^2 \times b^2\right) + \ldots + \sigma\left(\sum_{i=1}^{n} d_i^k \times w_i^k \times b^k\right). \tag{5}$$

For VGG-16 model.

$$f(V) = x^1 + x^2 + x^3 + \ldots + x^k. \tag{6}$$

The resultant output after "k" Conv layer is obtained by putting the value of Eq. (1) into Eq. (6) accordingly.

$$f(V) = \sigma\left(\sum_{i=1}^{n} d_i^1 \times w_i^1 \times b^1\right) + \sigma\left(\sum_{i=1}^{n} d_i^2 \times w_i^2 \times b^2\right) + \ldots + \sigma\left(\sum_{i=1}^{n} d_i^k \times w_i^k \times b^k\right). \tag{7}$$

Final result after decision-level fusion of multi-contextual model's outputs is shown in (8).

$$F = f(R) + f(A) + f(V). \tag{8}$$

IV. EXPERIMENTAL DETAILS (A CASE STUDY)

In precision agriculture, plant leaf diseased datasets are more challenging for detection and classification because of the nature of the domain-specific images having inter-and intra-claseses variances. So, corn leaf diseased datasets are considered as a case study to apply the proposed MMF-Net for accurate recognition of the diseases.

A. DATASET ACQUISITION

This section covers the experimental setup of developing MMF-Net that includes different steps to put on for plant leaf diseases detection and classification. Corn leaf diseased datasets are available online, but a Sensor Network Hub (SNH) setup is built for the acquisition of real-time datasets. Thus, we trained multi-model based multi-contextual fusion at decision level, and then deployed for testing.

Corn leaf disease dataset: "Plant Village" dataset contains over 50,000 leaf images of healthy and unhealthy plants of 14 crop species, and 38 types of plant diseases [33] but it contains only 4188 images of corn leaf diseases. Corn leaf diseases dataset can be increased by using different techniques of augmentation. There are three corn leaf diseases such as blight, common rust, grey leaf spot, and one healthy form, as shown in Figure 5. Various portions of the leaf were taken with full light, rotated to 360 degrees to get more data images, and cropped unnecessary background with the leaf tip pointed upwards at the experimental research stations. In this dataset, plant pathologists labelled the plant leaf disease for identification. For training, the proposed architecture used the corn leaf disease image dataset with around 4,188 images. Total number of images of a specific type in the corn leaf disease dataset are shown in Table 2.

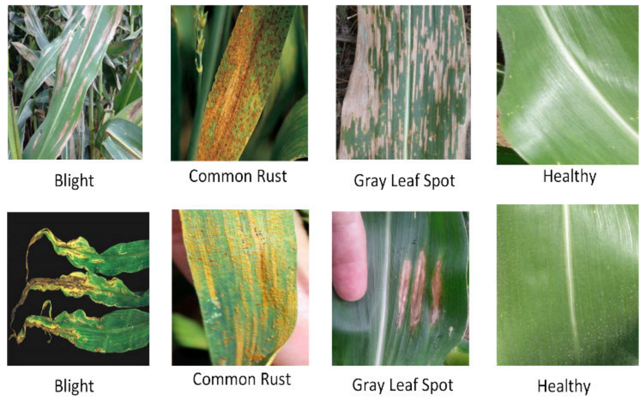

FIGURE 5. Sample images of corn plant leaves from Plant Village dataset.

TABLE 2. Corn leaf disease dataset separated from Plant Village.

Corn leaf diseases name	Number of images
Blight	1145
Common Rust	1306
Gray Leaf Spot	575
Healthy	1162
Total	4188

Real-Time Dataset: For getting the real-time environmental parameters, we built a SNH with electronic components and low-cost sensing device that detects changes in its surroundings. SNH is utilized to sense environmental factors such as soil moisture level, temperature, atmospheric pressure, and humidity, which act like a hub to collect the data from the field to make a numerical dataset. All four sensors and "Bluetooth Module" are wired up to Arduino microcontroller for sensing field data. All sensors except the soil moisture sensor are connected to digital pins. A program code in Arduino software (IDE) for getting sensor data on a serial monitor is uploaded. At this time, we ran PLX-DAQ software that copied sensor data from a serial port and transmitted it into Excel file (csv) for saving record entries to form the numerical dataset. The utilization of IoT sensors (SNH) for data collection in the context of corn leaf disease detection is a critical aspect of the proposed approach that is shown in Figure 6. For data acquisition, we deployed SNH in different sites of corn plants locally at different time intervals, day and night. We executed the experiment by sensing the real-time environmental information. We obtained four climate factors at low, medium, and extreme ranges in different weather conditions. It was recorded for 40 days (100/day) to build the numerical dataset for further use, which is around about 4,000 records. We used a working range of environmental parameters for corn leaf disease classification that was designed after learning from related literature [34] and local pathologists. Local pathologists suggested

TABLE 3. Working rules applied for corn leaf disease environmental parameter-based features.

Disease Name	Class Id	Temperature Range (°C)	Atmospheric Pressure Range (hPa)	Soil Moisture Range (%)	Humidity Range (%)
Blight	0	23 – 35	900 - 1250	75 – 82	> 80
Common Rust	1	6.8 - 22.9	335 - 990	65 – 79	60 – 82
Gray Leaf Spot	2	21 – 29	390 - 989	70 – 80	50 – 70
Healthy	3	>40	745 – 1300	75 – 85	55 – 70

environmental parameters' working ranges according to the local climate. These working rules are shown in Table 3.

Data Normalization & Preparation: Numerical environmental-based data must be normalized before the training process because it might contain varying degrees of units, noise and missing values. Normalization is a preprocessing technique applied to change the values of numeric columns into a common scale without changing the range of values, then it is used for further decision making. Normalization is required only when the input dataset has different feature ranges [34]. Therefore, we applied min-max data normalization technique on real- time numerical raw dataset because our numerical dataset has different feature value ranges. It reconstructed our numerical dataset into a reformed shape which will increase the decision-making performance. For this purpose, we used the sklearn package and "transform ()" function for data normalization. Both datasets are separated randomly into training and testing datasets with 75-25% ratio. The language function "train_test_split ()" was used to split at this ratio. It meant the training dataset contained 3,141 images and the same numerical records. The testing dataset consisted of 1,048 images and the same numerical records. The quality of the dataset was not compromised for getting better recognition results. Table 4 shows the sample data of the numerical dataset.

TABLE 4. Environmental parameter-based numerical sample dataset collected by SNH module used for corn leaf disease classification.

Record No.	Temperature	Humidity	Soil Moisture	Air Pressure
1	26.00	59.00	97.00	449.14
2	26.00	50.00	97.00	448.00
3	28.00	45.00	94.00	456.00
4	28.00	43.00	94.00	490.45
5	29.00	42.00	94.00	978.00
6	24.00	39.00	80.00	1001.00

B. MULTI-MODEL TRAINING

In this phase, it is needed to construct a multi-model network by using two different types of datasets for developing a trained classifier. Initially, the diseased images are resized into "128 × 128×3" and "224 × 224×3" dimensions for the RL-block and PL-block 1. The field numeric datasets of

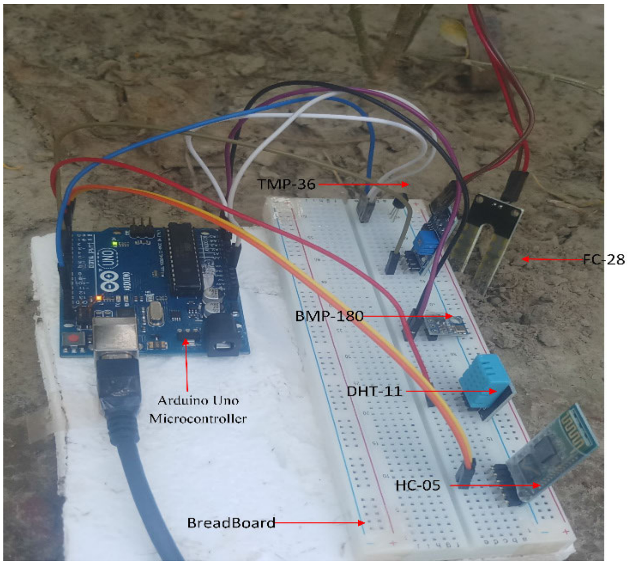

FIGURE 6. SNH with HC-05(Bluetooth Module), TMP- 36 (Temperature sensor), DHT-11 (Humidity sensor) and FC-28 (Soil Moisture sensor), and BMP-180 (Air pressure sensor).

shape "1 × 4" are used for PL-block 2. The whole dataset is divided into batches and covers every sample in each batch. After completing this process with all data examples for all batches, one epoch is concluded. In this work, we divided the image and numeric datasets into "32" batch sizes with "50 epochs". After 45 epochs, our proposed multi-model starts to converge and tends to be stable at "50 epochs". This plant leaf disease detection task is accomplished through three stream training models independently. Three sets of final features, extracted from the last fully connected layer and generated "10" outputs at the last fully connected layer, are used as input for the "softmax layer". Each model is generated decision weights from the accurate classification rate and obtained top-4 possible classes from the probabilities which are computed by softmax layer. The multiple softmax layers of three independent streams are used to obtain the top-4 possible classes. Online diseases dataset are classified according to the classification labels and environmental parameters features are classified according to the working range. After learning, each classification category is corresponded to each other of the online and environmental parameters dataset. Before decision-level fusion, the number of outputs from each softmax should be equal. The weighted average ensembling were accomplished through "Voting-Classifier()" function with soft voting parameters that predict class membership probabilities. We used the "Cross entropy" loss function because its value was always towards positive for multiclass and it did not slow down the learning process. The model is optimized with paramount values of weight by using an optimizing function "AdamOptimizer" with a learning rate "1e-4". At the end, the initialized learning parameters were saved to form the weight file of the trained classifier.

V. RESULTS

The main complexity is to find the effective techniques for improving the accuracy of plant leaf disease detection system in real-world scenarios that would be operational on heterogeneous datasets. As a result, we reconnoiter the online pre-processed and real-life features for decision level fusion for developing a smart solution of plant leaf diseases detection in PA. We are integrating three parallel stream architectures for plant leaf disease classification and learn end-to-end learning parameters with forward propagation of three stream models. To evaluate our multiclass proposed architecture, performance metrics are discussed in terms of "accuracy". To improve the accuracy, we fused multi-contextual features at the decision level and performed an appropriate experiment by changing the architecture, batch size value, and total number of epochs. The training accuracy started from 96.85%, 97.80% to 98.48%, and 99.23% at the first to 50 epochs. After every epoch, different model streams are evaluated to test the testing images and numerical data and print the loss and accuracy curves. The training vs test accuracy and training vs test loss learning curves of RL-block and PL-blocks 1 & 2 before multi-contextual fusion at decision level are shown in Figure 7 (1^{st} and 2^{nd} Column) with 97.80% and 98.48% accuracy respectively. The training vs test accuracy and training vs test loss learning curves are plotted after fusion of multi-contextual features at the decision level and represented in Figure 7 (3^{rd} Column) with 99.23% accuracy. After combining the heterogeneous data, the final accuracy of our proposed multi-model network was improved by 0.75%. The proposed multi-model got better results after multi-contextual fusion at decision level with accuracy 99.23% on heterogeneous datasets. In addition to this, the performance of a recognition model can be described by a table named as confusion matrix. It is a very effective tool that can examine all probable results on test data, where the true values of a recognition model are known. The confusion matrix with the true label and predicted label for corn leaf disease dataset and numerical dataset before fusion with 50 epochs as shown in Figure 8 (a, b, c). The confusion matrix with the true label and predicted label for corn leaf disease dataset after decision-level fusion with 50 epochs as shown in Figure 8 (d). The overall accuracy on testing dataset instances separated from images and numerical dataset is shown in Table 5. In the final confusion matrix, after fusion of multi-contextual features, presenting, the total "Predicted" classes were 1,048 out of which 8 were predicted incorrectly. The fused unified model has an accuracy of 100% for the healthy class, above 99% for 2 classes, and over 98% for 1 class. Classification accuracy of "Blight", "Common Rust", "Gray Leaf spot", and "Healthy" have reached 99.30%, 98.77%, 100%, and 99.31%, respectively and found that the fusion of multi-contextual at the decision level of three stream models was a natural way to find adapted features, that improved the significant performance of the proposed framework. Table 6 shows the total testing dataset instances.

We proposed a multi-model feature extraction network (MMF-Net) that integrates with RL-block and PL-blocks 1 & 2. It is trained on images and numerical datasets that perform classification better in determining the correct condition of plant leaf disease with great accuracy. Accuracy is the ratio of correctly predicted instances to the total number of input instances. Here, the combination of cardinality and plainly learning can investigate its performed accuracy by comparing it with various CNN models which were used for corn leaf disease classification. These models used the same dataset with the different number of classes. MMF-Net is significantly ahead of the six CNN approaches, with the highest accuracy of 99.23%. It can be seen from Table 7, AlexNet [35] has only 0.07% lower accuracy than our model, but this model can classify only one disease to one healthy class. Table 7 shows the comparative accuracy with total number of images dataset. All the cited models had small sample size except one given [37] but the proposed framework has higher accuracy than others instead of small dataset instances due to the fusion of images and environmental features at decision level. The effectiveness of the proposed strategy in detecting corn leaf diseases is increased by using field sensors and images at the same time. Its comparison to other methods shows the evaluation results and accuracy of various deep learning models for early corn leaf disease detection system. Table 7 has shown improved accuracy of proposed method in identifying diseases symptoms by reducing false positives and negatives as compared to traditional methods which are subjective, time-consuming, and less sensitive to early stage symptoms. On the other side, based on our results, it can be seen from Table 7, our proposed framework has great robustness and well predicts three corn leaf diseases with one healthy class. It is proven that our proposed framework has better performance with a high diagnosis accuracy. The potential limitation in timeliness is not issue due to cloud computing facility. Implementing a plant leaf diseases detection system in practical field management involves a combination of technology deployment, data collection, and decision making processes. Enable continuous monitoring of the field. Set up necessary IoT infrastructure with camera to collect data from the field. Implement real time data streaming from IoT devices to the central monitoring system by using online edge computing. Set up alerts or notifications for

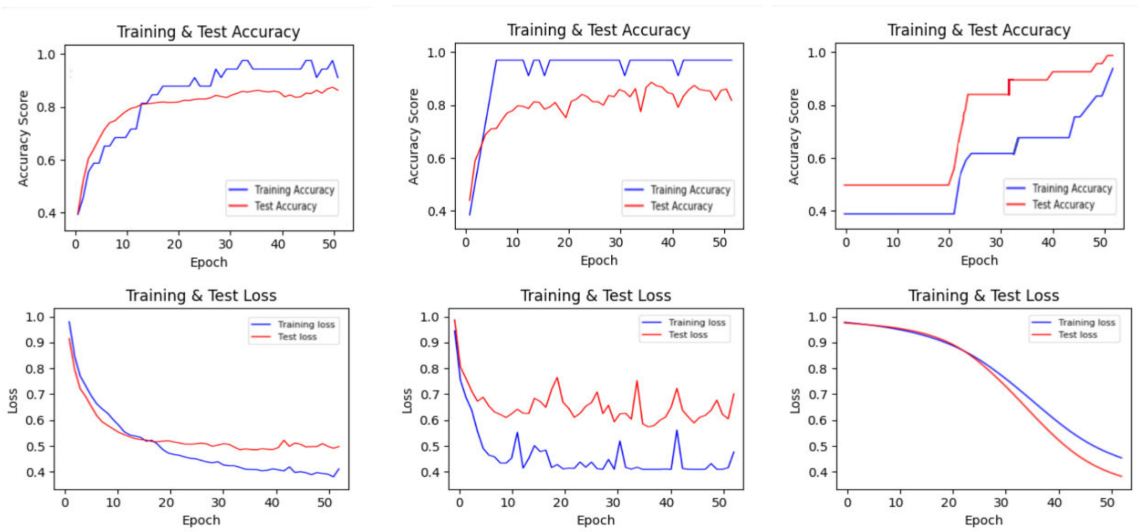

FIGURE 7. (In the 1st Column) Training vs Test Accuracy and Training vs Test Loss for corn leaf disease image dataset by using RL-block before fusion. (In the 2nd Column) Training vs Test Accuracy and Training vs Test Loss for numerical dataset by using PL-block 1 before fusion. (In the 3rd Column) Training vs Test Accuracy and Training vs Test loss for multi-contextual dataset of corn leaf disease after fusion of decision level.

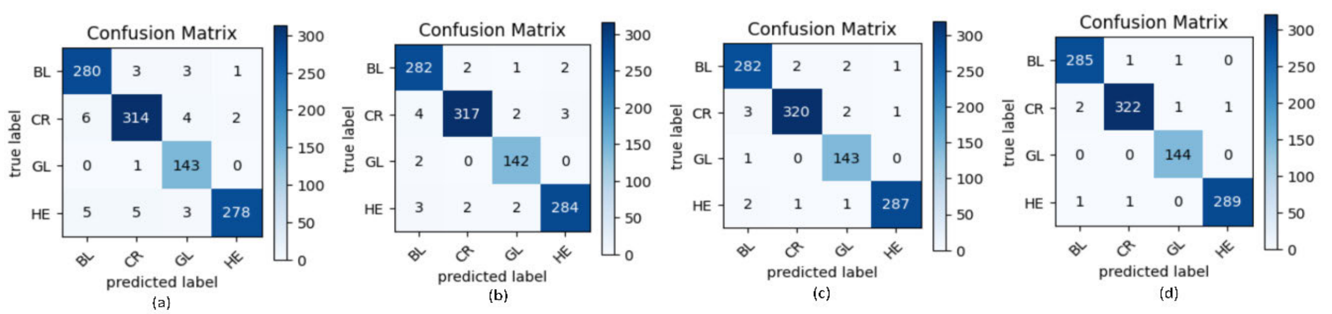

FIGURE 8. Confusion matrix generated by three stream models based on corn leaf disease dataset with ratio (75-25) before decision-level fusion with multi-contextual features. The total number of epochs are 50 for training the individual model stream. Confusion matrix (a) is based on the corn leaf disease image dataset of Plant Village with coarse scale dimensions (coarse scale features) before fusion. Confusion matrix (b) is based on the corn leaf disease image dataset of Plant Village with fine scale dimensions (Fine scale features) before fusion. Confusion matrix (c) is based on the environmental parameters (Features) dataset collected from corn fields before fusion. Confusion Matrix (d) generated by the proposed model after multi-contextual fusion based on multiple features when the total number of epochs are 50. In every confusion matrix figure, where BL stands for Blight, CR stands for Common Rust, G stands for Gray Leaf Spot and HE stands for Healthy.

TABLE 5. Overall accuracy on testing dataset instances separated from images and numerical dataset.

Dataset	Dimension	Dataset	Accuracy
Images with coarse-scale features before fusion	128 × 128 ×3	Plant village	96.85%
Images with fine-scale features before fusion	224 × 224 ×3	Plant Village	97.80%
Numerical environmental-based features before fusion	1 × 4	Numerical	98.48%
Multi contextual features after fusion	10-4	Both	99.23%

immediate response to detected diseases. Integrate the disease detection model with a user friendly interface accessible to farmers. Generate reports or visualizations to communicate the status of the crops.

A. LIMITATIONS AND FUTURE WORK

Some limitations associated with implementing MMF-Net which are discussed as: Other important environmental aspects that may play an important role for getting high

TABLE 6. Total testing dataset instances separated from Plant Village with true & false positive rate.

Corn leaf disease	Total Number of Instances	Correct Predicted Instances	Wrong Predicted Instances	True Positive Rate (%)	False Positive Rate (%)	Overall Accuracy
Blight	287	285	2	99.30	0.70	99.23%
Common Rust	326	322	4	98.77	1.23	
Gray Leaf Spot	144	0	0	100	0	
Healthy	291	289	2	99.31	0.69	

TABLE 7. Comparison of different CNN models used for classification of corn leaf disease on the Plant village dataset while the classification classes are different.

Paper	Publisher	Year	Model	Classes	Input Images	OA (%)
[35]	Springer	2020	AlexNet	2	2292	99.16
[36]	CSSE	2020	Proposed CNN Model	4	4354	98.15
[37]	IEEE	2022	ResNet152 (CNN)	4	15408	97.49
[38]	MDPI	2022	GLS_net(MaskRCNN)	4	3852	94.1
[39]	Springer	2021	DenseNet121(CNN)	4	4188	91.49
[40]	Elsevier	2022	CBAM	3	-	98.44
MMF-Net (Our proposed model)				4	4188	99.23

prediction results are not considered. For real-time prediction, internet availability and online mechanism with edge computing are not handled yet. The need for further improvements in the proposed approach are:

- More advancements in algorithms are required through regular updates with incorporating more diverse datasets to enhance accuracy, efficiency, and processing capabilities.
- Further integration of additional data modalities, spectral data, and genetic information can provide a more comprehensive understating of plant health.
- An online notification system with edge computing can improve the on-site efficiency of the system.

VI. CONCLUSION

Our target is to develop a multi-model network with the fusion of multi-contextual networks that is automatically exploited with the CNN strategies with some variant forms. This is a general idea based on the integration of RL-block and PL-blocks 1 & 2 with width cardinality and environmental parameters for learning effective feature sets that are fused at the decision level. These feature sets are identified at the global and local level for effectiveness of the proposed modeling accuracy. The proposed model helps to select learning parameters for receptive fields to look at feature maps at different layers. In addition, a deep multi-model network is designed to fuse the contextual features of 1D as well as visual features of 2D CNN and is generating potential results for plant leaf disease detection and classification in any application. The experiment results proved that MMF-Net with fused features is considerably better than without fused feature methodology in terms of accuracy. MMF-Net is able to recognize corn leaf diseases with an overall accuracy of 99.23% and the improved accuracy is due to training on the combination of heterogeneous datasets. Finally, we explored the fused detection features to establish a more accurate, stable, and comprehensive plant leaf diseases detection model. Such a model could be an operative solution to classify diseases in agriculture or health sectors and be utilized in real-world IoT applications.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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