CCNet: CNN CapsNet-Based Hybrid Deep Learning Model for Diagnosing Plant Diseases Using Thermal Images

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***Abstract*—Plant disease diagnosis at an early stage enables farmers, gardeners and agricultural experts to manage and control the spread of illnesses in a timely and suitable manner. The traditional methods of plant disease diagnosis are expensive and might need significant manpower and advanced level machinery. In addition to that, conventional methods, such as visual inspections are prone to subjectivity, time constraints and error susceptibility. In comparison to that, computer based methods such as machine learning is accurately predicting plant diseases underscore the need for a transformative approach. However, by focusing solely on visualized contents and thermal images, these methods overlook the potential insights hidden within customer-posted images that may leads to low accuracy. This study is an attempt to addresses these gaps by proposing an alternative methodology which relies on a hybrid deep learning framework called CCNET. The core CCNET is the utilization of the superiorities of Convolutional Neural capsule network models to get better architecture for plant diseases diagnosis. The proposed CCNET effectively amalgamates the strengths of convolutional layers for spatial feature extraction and the sequential modelling capabilities of CNN and CapsNet for capturing temporal dependencies within image data. The performance of the CCNET has been evaluated through rigorous experimentation. The outcomes underscore the remarkable prowess of the proposed model with the accuracy of 94%. When it compared to the conventional methods, the CCNET surpasses all of them in terms of precision, recall, F-Score, and accuracy.**

Keywords*—CapsNet; classification; CNN; feature extraction; plant disease; thermal images

I. Introduction

The agricultural industry holds immense significance for numerous nations globally, serving as a crucial source of sustenance, materials and energy to support the expanding population. Apart from its economic value, agriculture plays a pivotal role in addressing pressing global issues such as climate change, ensuring food security, and promoting sustainable development. As per the Food and Agriculture Organization of the United Nations (FAO), agriculture engages over one billion individuals worldwide and contributes approximately 3% to the overall global gross domestic product (GDP) [1].

However, this sector encounters noteworthy obstacles, including the imperative to augment food production to fulfill the rising needs of the world's growing inhabitants. While concurrently mitigating the environmental impact associated with agricultural practices. Additionally, the prevalence of plant diseases poses a substantial menace to agricultural productivity, leading to crop losses that range from 10% to 40% on a global scale [2]. Plant diseases can cause extensive damage to crop, resulting in significant economic losses for farmers worldwide. Fig. 1 shows the typical leave disease that effect the production of plant. As per the Food and Agriculture Organization (FAO) of the United Nations, plant diseases account for the annual loss of approximately 20–40% of global crop production [3]. An efficient and effective plant disease management system is therefore essential for ensuring the sustainability and productivity of the agriculture sector.

Fig. 1. Leaf disease example adopted from study [5].

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The conventional farm management practices rely on human experts to monitor plants in the field for signs of disease, which can be time-consuming, labor-intensive and prone to errors. However, visual symptoms of plant diseases usually appear several days after infection, indicating that the illness has already disseminated and the quality of yield has declined, leading to significant losses in productivity [4]. Most of the disease control process usually adopted appropriate control measures, such as the utilization of resilient crop strains, farming techniques and chemical treatments. But due to the increasing number of diseases and expensive chemical, this job become quiet hectic and time consuming.

Alternative to the conventional methods, Smart farm management practices, which rely on vision technology and machine learning, have revolutionized plant disease management by allowing for early detection and prevention of crop losses. According to a study [6], smart farm management practices have led to increased agricultural productivity and improved food security in many countries. These technologies are particularly useful in remote areas where access to expert knowledge and resources is limited. By implementing these practices, farmers can detect plant diseases before visual symptoms appear, ultimately increasing crop yields and contributing to the overall economic growth of the country.

The development and adoption of new technologies, including the use of computer science and artificial intelligence, can be better attempt that helps in the timely identification and control of plant diseases. Vision technology, which is widely used in modern smart farm management practices, has the potential to address some of these challenges by processing and analysing images of infected plants to identify disease patterns [7]. However, this approach is limited in that it does not accomplish early detection, presuming that plants are still in the incubation phase prior to the disease's manifestation [8]. This highlights the need for alternative approaches that can detect diseases at an early stage, before visible symptoms appear, to prevent significant crop losses and increase productivity.

However, the variations of diseases at different of plants and temperature discrepancies in the infected plants that are imperceptible to the human eye may require more sophisticated mechanism [9]. The application of thermal imaging as depicted in Fig. 2, in plant disease management has emerged as a promising approach for early detection and control of diseases. By recording the temperature of plants, thermal imaging enables the identification of temperature changes that can indicate the presence of disease. These temperature changes are a result of internal chemical alterations that occur in plants following disease inoculation. Analysing these temperature variations allows for the early detection of diseases before visible symptoms manifest.

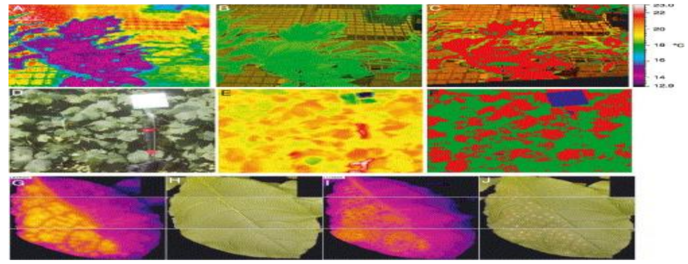

Fig. 2. The Geo-informatics-based view of plant thermal images.

It is concluded that thermal imaging and machine learning technologies have the potential to revolutionize plant disease management and increase crop productivity by predicting and preventing the spread of plant diseases. This research addresses the above discussed gaps by proposing an alternative methodology that is based on hybrid deep learning model called CCNET. The core CCNET is the utilization of the superiorities of Convolutional Neural Network-Gated Recurrent, Bidirectional Long Short-Term Memory and Conditional Random Field models to get better architecture for plant diseases diagnosis from thermal images. The proposed CCNET effectively amalgamates the strengths of convolutional layers for spatial feature extraction and the sequential modelling capabilities of CNN and CapsNet for capturing temporal dependencies within image data.

A. Research Contribution

The key contribution of the proposed research are as follows:

1) The proposed CCNET is an attempt to efficiently diagnosing plant disease by using thermal images that perform detection at early stage before visible symptoms appear that is not tackled in the previous literature to prevent significant crop losses.

2) The utilization of advance level deep learning methods such as CNN and CapsNet provide better identification as compared to machine learning algorithms that are based on static similarity measures.

3) Experimental evaluation on thermal imaging and comparative analysis with benchmark methods has proved that the performance of proposed CCNET surpasses the existing works by obtaining an accuracy of 94 %.

The rest of the paper is organized as follows: An overview of the relevant research is presented in Section II. The proposed CCNET is briefly described in Section III. The experimental evaluation and discussion has been discussed in Section IV. The conclusion and future work are given in Section V.

II. RELATED WORK

The utilization of digital images for the categorization of plant diseases presents a significant hurdle. However, advancements in machine learning techniques, particularly deep learning, have facilitated the identification, detection, and diagnosis of plant diseases. In the article [10], a combined model is proposed that merges two pre-trained convolutional neural networks (CNNs), specifically VGG16 and VGG19, to classify images of healthy and diseased leaves for the purpose of diagnosing plant diseases. CNNs are employed due to their capacity to overcome the technical intricacies associated with the classification of plant diseases. Nonetheless, CNNs pose a challenge in terms of hyper parameters, necessitating manual identification of specific architectures to attain optimal performance. To tackle this challenge, the paper utilizes the orthogonal learning particle swarm optimization (OLPSO) algorithm to optimize the hyper parameters by determining the optimal values instead of relying on traditional trial and error methods.

In another work, specifically focuses on charcoal rot, a fungal disease that affects soybean crops globally and is transmitted through soil [11]. In their study, the authors propose a unique 3D deep convolutional neural network (DCNN) that directly incorporates hyper spectral data and provides meaningful physiological explanations through model interrogation. Their proposed model achieves an impressive classification accuracy of 95.73% and an infected class F1 score of 0.87 when analysing hyper spectral images of both inoculated and mock-inoculated stem samples. By employing an explainable deep learning model, the study not only achieves high accuracy but also provides valuable physiological insights into the model's predictions, thereby increasing confidence in the reliability of these predictions.

The work of study [12] provide a comprehensive overview of the existing literature on neural network techniques that are employed for processing image data in the detection of crop diseases. They claim that predictions are particularly relevant for precision agriculture and research applications that utilize automated phenotyping platforms. The goal of this survey is to enhance the performance and accuracy of deep learning in detecting plant diseases, with the potential to significantly impact sustainable agriculture. Hyper spectral imaging has emerged as a potent tool for plant disease identification, but its effectiveness heavily relies on the choice of deep learning models. Convolutional neural networks (CNNs) have been identified as the most promising models for diagnosing and predicting crop infections.

TABLE I. COMPARATIVE ANALYSIS OF THE EXISTING RESEARCH METHODS

Reference	Methodology	Data Set	Accuracy	Limitations
[15]	Support Vector Machines (SVM)	Thermal images	90%	The study was only conducted on wheat crops under moisture stress conditions, which limits the generalizability of the findings to other crops and growing conditions.
[16]	Support vector machine (SVM), Gaussian kernel and Random Forest	High-resolution thermal image	82%	Only evaluates model accuracy for detecting decline, not effectiveness of management interventions, and is geographically specific.
[17]	Feature weighted random forest (FWRF)	27 olive orchards	92%	Study's insights on olive orchards affected by Xf and Vd outbreaks in 2011-2017 Italy and Spain may not apply to other regions or timeframes.
[18]	Multiple Linear Regression (MLR)	IoT-sensed crop Dataset	91%	Restricted to blister blight in tea plants, doesn't address other diseases, and relies on IoT sensor accuracy for environmental data.
[19]	Dual-stream hierarchical bilinear pooling model	Field-obtained dataset	84.71%	The study only demonstrates accuracy in identifying plants and diseases on a specific field dataset, with uncertain generalizability to other crops or datasets.
[20]	14-DCNN	147,500 images of 58 different healthy and diseased plant lea.	91.79%	Does not discuss the real-world application and the limitations that the proposed model may face when deployed in the actual environment.

Gadekallu et al. [13] emphasizes the importance of ensuring a consistent supply of healthy food for the growing global population, as well as the economic significance of agriculture in developing countries. To overcome these challenges, their study focuses on harnessing the power of machine learning models to classify tomato diseases, with the aim of proactively addressing agricultural crises. Their research utilized a publicly available dataset from plant-village to train and evaluate their model. They employed a hybrid approach that combines dimensionality reduction method. The extracted features were then fed into a deep neural network for the classification of tomato diseases. To demonstrate the effectiveness of their proposed model, they compared their work with traditional machine learning techniques, showcasing its superior performance in terms of accuracy and loss rate metrics.

The utilization of automated approaches, such as machine learning and deep learning, for the prediction of plant species and diseases has been explored in the work of study [14]. In addition to this they also proposed a novel multi-task learning strategy, which leverages shared representations between these related tasks to enhance overall performance. Their proposed approach utilizes a multi-input network that incorporates raw images and transferred deep features extracted from a pre-trained deep model to predict both the plant's type and disease. An end-to-end multi-task model is developed, enabling the simultaneous execution of multiple learning tasks by integrating Convolutional Neural Network (CNN) features and transferred features. This approach has the potential to address the challenges associated with plant species and disease prediction by providing accurate predictions, reducing the time and cost required for manual prediction, and guiding decision-making processes in the context of sustainable agriculture.

From the above discussion, it has been concluded that, instead of traditional diagnosis methods that are hectic, expensive, and time-consuming, machine learning models perform better disease diagnosis. However, the detection of diseases at an early stage is still challenging. By foreseeing and halting the development of plant illnesses, thermal imaging, and machine learning technologies hold the promise of revolutionizing plant disease management and boosting agricultural output. This research tries to fills the gaps of previously mentioned literature by giving an improved architecture by utilizing the advantages of Convolutional Neural Network-Gated Recurrent, Bidirectional Long Short-Term Memory, and Conditional Random Field models.

III. Materials and Methods

This section discusses the proposed CCNET's core methodology, which is composed of data collection, pre-processing, feature extraction, and final classification. Fig. 3 depicts the diagrammatic flow of the proposed CCNET.

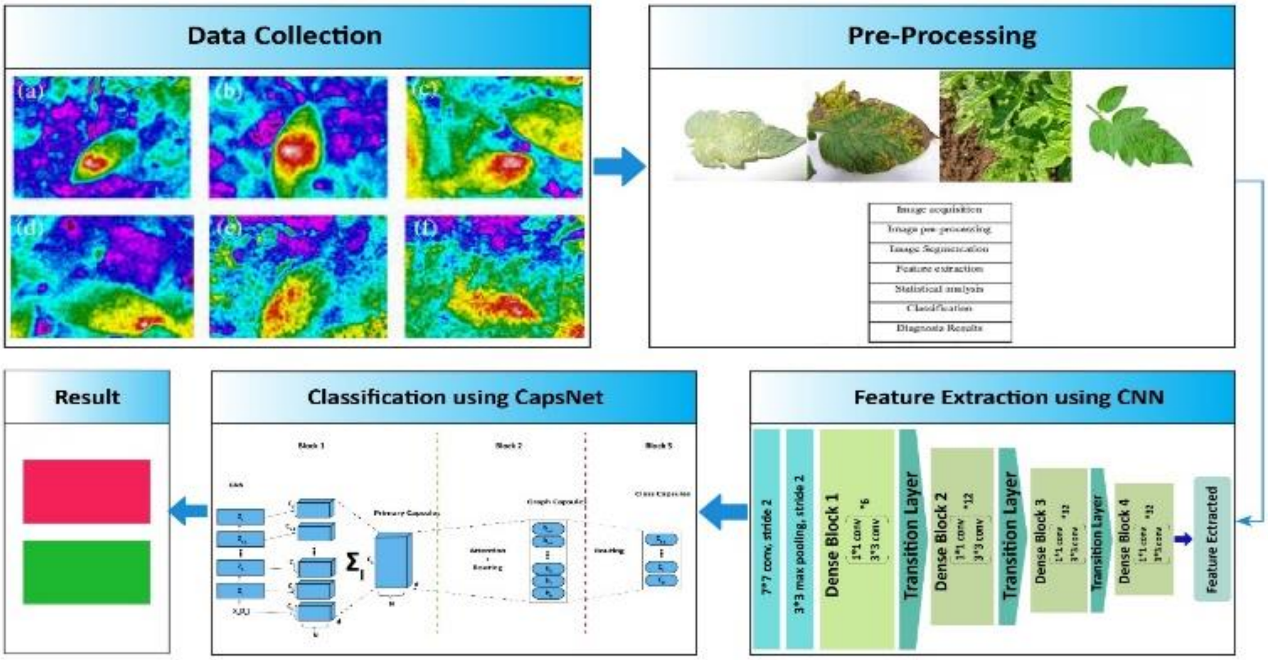

Fig. 3. The CCNET architecture for plant disease detection.

A. Data Collection and Description

In this research, thermal image-based datasets that are publicly available on the Kaggle repository have been used. The first dataset, DS-I, encompasses roughly 87,000 RGB images of plant leaves, categorized into 38 distinct health-related classes. Offline augmentation techniques were employed during its construction to ensure both authenticity and diversity. A separate collection comprising 33 test images was also established solely for predictive purposes. Another dataset that is DS-II, has 1132 images that focus on corn and maize leaf disease, derived from reputable sources like Plant Village and Plant Doc, meticulously tailored to address issues related to corn or maize leaf diseases.

The last dataset is DS-III, which contains 1401 images of rice leaf diseases. This dataset holds particular significance for regions characterized by low to lower-middle-income economies, where rice is crucial to food security. This dataset serves as a comprehensive compilation of crop leaf images, offering researchers in the agricultural science domain an opportunity to utilize it for further examination and exploration. The availability of such a dataset can facilitate the development of robust and precise models, aiding in the detection and classification of crop diseases and empowering farmers to identify such diseases at an early stage, thereby mitigating potential crop yield losses.

B. Pre-processing

After the formation of the dataset, the very next phase is the pre-processing. Algorithm 1 outlines the proposed pre-processing procedure. Initially, images are resized to a consistent dimension of 256x256 pixels. Pixel values are normalized via min-max normalization, representing pixel (x, y). Each image is randomly rotated within a defined angle range, and random horizontal or vertical flips are applied. A random zoom transformation is also employed. Additionally, images are converted to grayscale. Data is then organized into batches and shuffled using a randomized seed for training randomness assurance.

Algorithm 1: The Data Pre-Processing

```
def preprocess_image(image):
 resized = resize(image, (256, 256))
 normalized = (resized - np.min(resized)) / (np.max(resized) - np.min(resized))
 rotated = rotate(normalized, random.uniform(-30, 30))
 flipped = np.fliplr(rotated) if random.choice([True, False]) else np.flipud(rotated)
 zoomed = zoom(flipped, random.uniform(0.8, 1.2))
 grayscale = rgb2gray(zoomed)
 return grayscale
random.seed(42)
preprocessed_data = [preprocess_image(image) for image in original_data]
random.shuffle(preprocessed_data)
batches = [preprocessed_data[i:i+batch_size] for i in range(0, len(preprocessed_data), batch_size)]
```

By applying these pre-processing steps, the dataset is prepared in a format that can be effectively utilized for training deep learning models. Resizing the images ensures that the models can handle images of different sizes, while normalization and data augmentation techniques help enhance the dataset's diversity and reduce overfitting [21]. Finally, batching and shuffling the data enable efficient model training.

C. Feature Extraction

There exist too many deep learning models that are used for image based feature extraction. However, convolutional neural networks (CNNs) are the most demanding due to their exceptional ability to capture hierarchical patterns and spatial dependencies in images [22-26]. In the proposed CCNET, the CNN model starts with the convolution operation, where the dot product is calculated between input image patches and adaptable filter weights, uncovering specific attributes within localized areas as shown in Fig. 4. Subsequently, the Pooling operation comes into play, particularly Max pooling. This technique is renowned for its efficiency, selectively highlighting the highest value within a predefined window, distilling the essential information while retaining the core of the data. The process culminates with flattening, a transformative step that restructures pooled feature maps into a streamlined one-dimensional vector. This sequence effectively transforms raw images into compact yet enriched features, crucial for subsequent analytical processes.

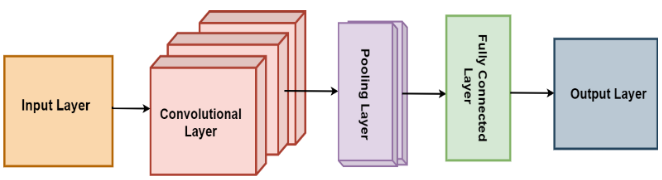

Fig. 4. The feature extraction workflow using CNN.

D. Classification

In comparison to the traditional CNN, Capsule Networks (CapsNet), is an alternative architecture for image classification. CapsNet was introduced by Geoffrey Hinton and his colleagues in 2017 [27-34] and was designed to address some of the limitations of CNNs, especially when it comes to handling spatial hierarchies, pose variations, and viewpoint changes. The CapsNet is a layered network in which the first layer of a Capsule Network typically consists of primary capsules. Each primary capsule is responsible for detecting a particular visual feature along with it numeric values in an image. Instead of using convolutional layers like CNNs, Capsule Networks use a combination of convolutional layers and capsules. These capsules output a vector representing a specific feature's presence along with its pose information. Whereas the pose estimation layer handles variations in the pose (position, orientation, etc.) of the detected features. Each capsule outputs a vector representing the probability of the feature's presence and pose parameters (such as position and orientation). The architecture is shown in Fig. 5.

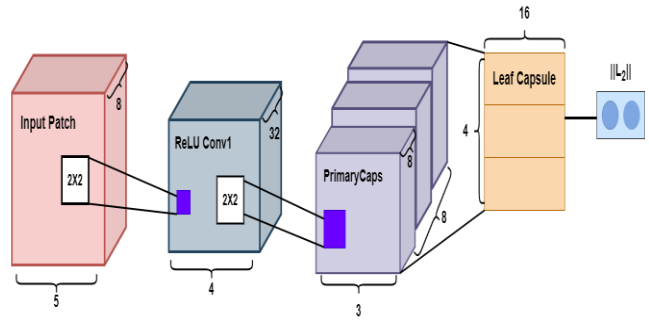

Fig. 5. The typical CapNet architecture for thermal image classification.

One of the key innovations of CapsNet is the routing algorithm. This algorithm aims to find the agreement between capsules in one layer and capsules in the subsequent layer. It ensures that capsules with similar features and poses "agree" with their predictions. This process helps to establish a more coherent and dynamic representation of hierarchical features. In addition to this, dynamic routing involves iterative updates of the coupling coefficients between capsules in different layers. This process encourages capsules that agree to have higher coupling coefficients, while capsules that disagree have lower coefficients. It allows the network to learn better feature hierarchies and spatial relationships. The final layer of capsules is used for classification. Each capsule in this layer represents a specific class, and the length of the capsule's output vector indicates the probability of the image belonging to that class.

IV. Experimental Results

This section thoroughly examines the experimental analysis and evaluates the proposed methodology. The proposed CCNET has been evaluated on three different datasets already discussed in the data collection section. It has also been compared with three baseline techniques and five machine learning models to test its accuracy and efficiency through a series of rigorous experiments.

A. Baseline Method

The following baseline reference models have been considered for comparison and evaluation of efficiency.

1) Banerjee et al. [24]: This study employed thermal imaging technology to capture images of wheat crop canopies and aimed to estimate the leaf area index (LAI) under varying moisture stress conditions. Their method was based on Maximum Likelihood Estimation, Box Classifier, and Support Vector Machines.

2) Poblete et al. [25]: They employed a Feature Weighted Random Forest (FWRF) classification model on olive orchards affected by specific outbreaks (Xf and Vd) in a limited timeframe and region might restrict the generalizability of its findings to other areas and time periods.

3) Zhiyan Liu [26]: This study focused on IoT-sensed crop fields, specifically addressing blister blight in tea plants with the utilization of multiple linear regression (MLR).

B. Results

Fig. 6 shows a comprehensive overview of the experimental results of CCNET on three distinct datasets—DS-I, DS-II and DS-III. On DS-I, the CCNET achieved 0.92 accuracy, 0.91 precision and 0.90 recall indicating that the model is enough capable to correctly predict plant disease. Whereas for DS-II, the accuracy remains high at 0.93, signifying the model's consistent ability to make accurate predictions across different datasets. In the last, the accuracy on DS-III is 0.94, indicating that the model remains robust in different plant health contexts. Whereas, the precision score is 0.92, suggesting that the model effectively predicts plant diseases without excessive false positives. Based on this measure, the predicted ROC curve is also demonstrated in Fig. 7 to clearly mention the superiority of CCNET.

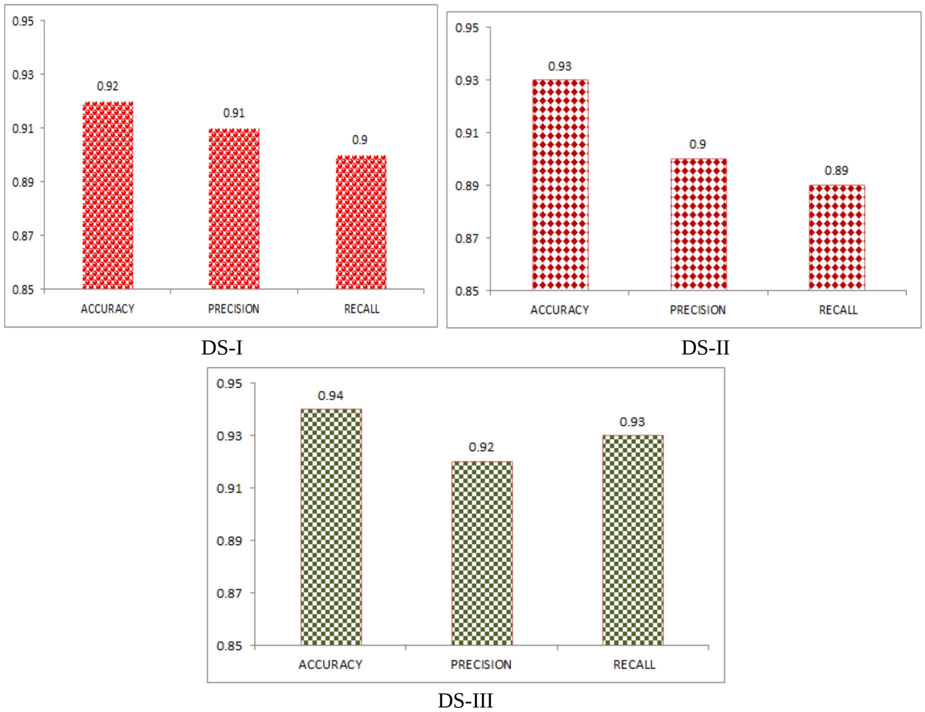

Fig. 6. Experimental results of CCNET in terms of precision, recall and accuracy.

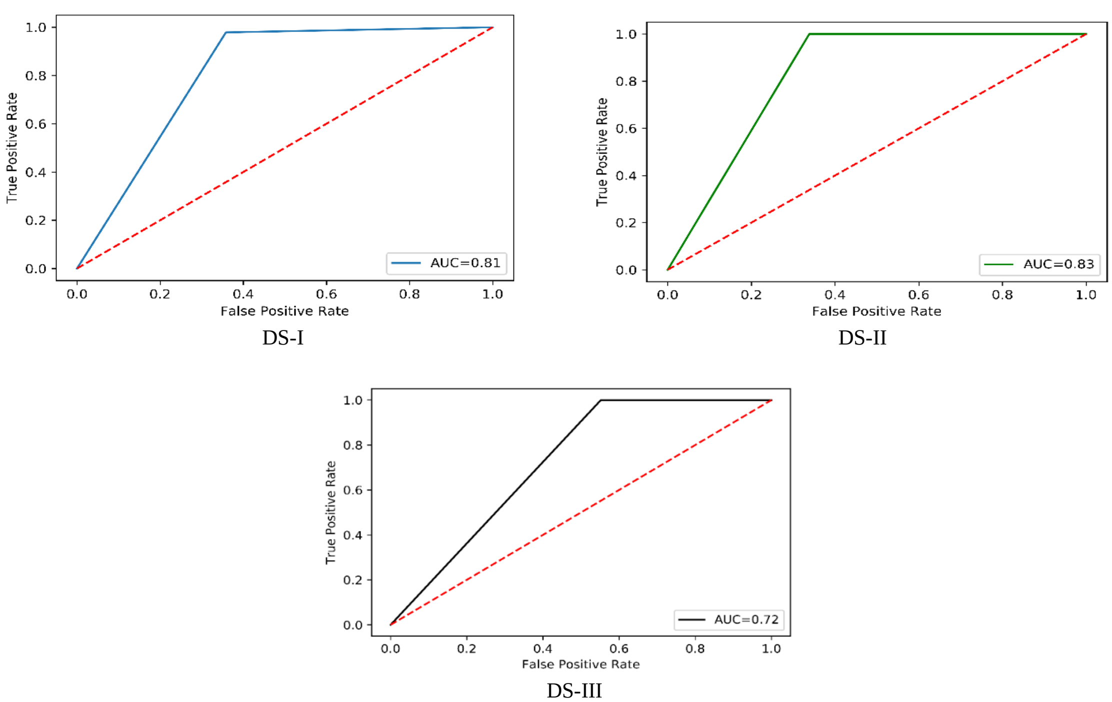

Fig. 7. ROC curves on DS 1, DS II and DS III.

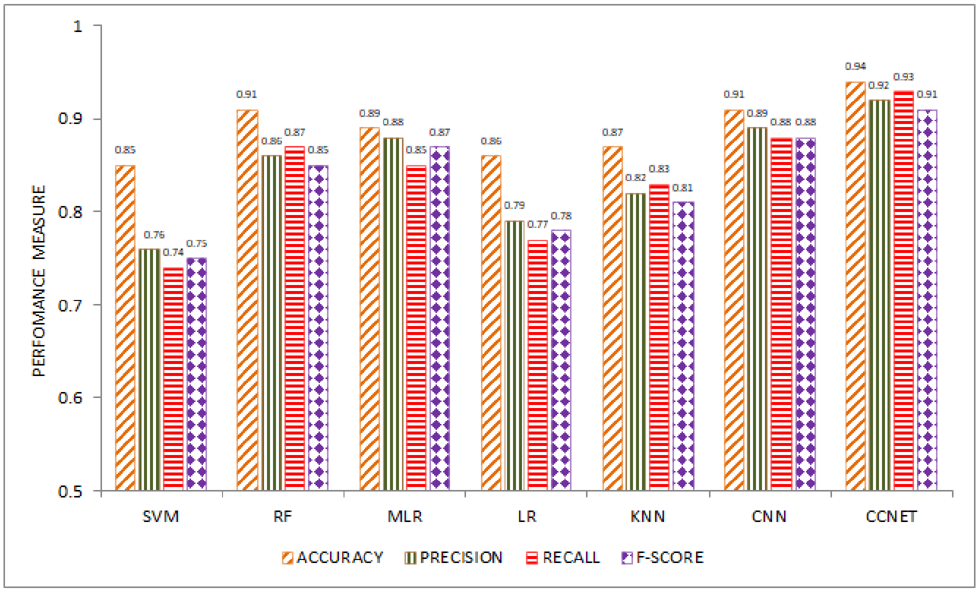

Fig. 8. Comparison of CCNET with machine learning models.

Fig. 8 presents a comprehensive comparative analysis between the proposed CCNET techniques and with standard machine learning model. The graphical values show that CCNET achieves a remarkable performance with 0.92 precision, 0.93 recall, 0.91 F1-Score and 0.94 Accuracy. This results shows that the CCNET gets a significant fraction of correctly identified positive instances in relation to the total actual positive instances.

In the last experiment, a thorough comparison of the CCNET with baseline methods was conducted by using DS-I, DS-II and DS-III to assess the accuracy. The graphical demonstration at Fig. 9 shows the superiority of the CCNET by beating the baseline with the variation of 6%, 7% and 9% respectively.

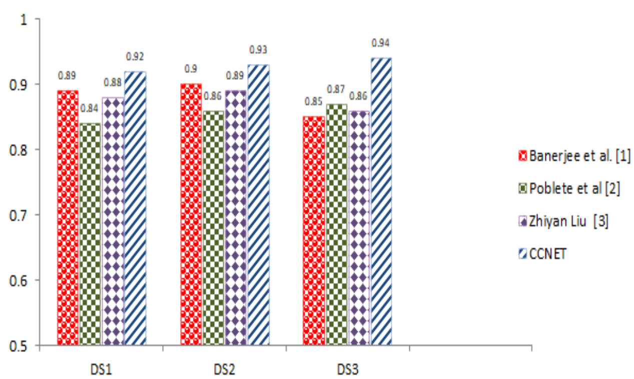

Fig. 9. Experimental analysis of CCNET with baseline models.

V. Conclusion

Plant disease diagnosis at early stages enables farmers to manage and control the spread of diseases in a timely and appropriate manner. Traditional methods for diagnosing plant diseases are costly and may necessitate a large number of personnel and sophisticated equipment. In addition, conventional methods, including visual inspections, are subject to subjectivity, time constraints, and error susceptibility. Whereas, the machine learning models based solution are limited to thermal images and leads to poor accuracy. In this research, a new model CCNET based on deep learning model has been proposed. The key steps of CCNET are data collection of thermal images, feature extraction and CapsNet based final classification. The evaluation of CCNET has been performed on three different datasets. The experimental results and comparative analysis provides a compelling evidence of the significant potential CCNET. The results demonstrate that the CCNET gets high accuracy with the value of 0.94, 0.93 and 0.92 on three different datasets and beat the base line methods with the variation of 6%, 7% and 9%. Looking forward, future research should concentrate on integrating multiple imaging modalities, such as hyperspectral or multispectral data, to further heighten disease detection accuracy. Expanding the training dataset to encompass a broader range of diseases and addressing class imbalances will bolster the model's generalization and robustness. Additionally, incorporating contextual information, developing interpretability techniques, and optimizing the model for real-time implementation are pivotal areas for advancement.

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