RESEARCH PAPER

A Robust Plant Leaf Disease Diagnosis Approach Using Hybrid CNN and Capsule Networks

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ABSTRACT
Disease of plant leaves plays a critical role in enhancing food security and agriculture. This paper recommends that the SE-SK-CapResNet which has been improved in terms of classification and detection networks may be utilized to improve the deep learning methodology applied in the diagnosis of plant leaf diseases. In the case where the Xception model is implemented with the dataset of plant leaf disease, it can be used to integrate the functions of feature extraction and classification and imprint them on the capsule-residual network. High precision and speed of the reproduction of the abnormality with the aid of the algorithms of the object recognition provided with the help of the YOLO are possible due to the fact that the spots related to the disease could be found in the leaf images. The enhancement in usability and deployment: Development of authenticated interactive web front-end in Flask. The enhanced system is precise, unaffected to image distortions, and real time recognition of numerous datasets with regard to plant diseases compared to CNN-based algorithms. The efficiency and the credibility of the surveillance and the consistency of the structure are demonstrated in reference to the agricultural diseases based on the experiment results.

Keywords: Plant leaf disease detection, Capsule network, Residual network, Xception model, YOLO, Deep learning, Image classification, Object detection, Flask framework..
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INTRODUCTION

Plant diseases have scientific significance because they affect production, quality of crops, and food security.Early and correct diagnosis of plant diseases is of importance. Deep learning and CNNs can specifically be used to classify and detect the plant leaf diseases. According to Dhaka et al. [1], deep CNN outperform human ratings when it comes to image recognition of plant diseases based on the photographic properties of leaves. Generally, in a thorough study of the plant disease in the identification of the methods, CNN-based methods were more accurate and scaled on data sets [2].

Deep learning models have been successfully used in some studies in the agricultural sphere. DeChant et al. [3] applied deep learning and real-field image in finding the northern leaf blight in maize in several areas. According to Li et al. [4], the main challenges of plant disease detection with the deep learning-based approach are image rotation, image occlusion, and the loss of the spatial information in the feature extraction. Due to the existence of such constraints, the traditional CNN models are not necessarily incompatible with the complex agricultural environments.

Xiao et al. [5] have invented a CNN-based method of strawberry disease diagnosis with potential accuracy. Moreover, they discovered that CNNs require huge datasets and data augmentation to solve the variation of angles of the leaf and manifestations of the disease. To improve the resilience, spatial perception, and real-time diagnosis of diseased leaf of plants, this paper supplements CNN-based solution with intricate classification and detection frameworks and capsule network with residual topologies.

Literature Survey

Life cannot survive without greenery. Climate change poses a great threat to plant species because of its environment impact. In order to save the plant diversity, a number of experiments have been carried out. In the

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majority of the works done on plants, species and diseases are identified using photos. Deep learning algorithms are effective and are being applied in the identification of plant species research.

The article developed a Multi-Division Convolutional Neural Network (MD-CNN) model of a plant recognition to address an agricultural issue in which the species of plants would be recognized. The deep features that are extracted are derived depending on the Convolutional Neural Network where the photos of the plants are divided into nxn equal portions. PCA determines the effectiveness of deep characteristics. The effective properties are then pooled together to make SVM classification.

The deep-based method was tested on Flora The Flavia, Swedish, ICL, Foliage, Folio, Flower17, Flower102 and LeafSnap datasets. The results of these experiments were 100, 100, 97.87, 98.03 and 94.38 in Flavia, Swedish, Folio, ICL, Foliage, Flower17, Flower102 and LeafSnap respectively [6].

It is quite frequent that the plant leaves diseases manifest themselves and there is a need to analyze them and implement deep learning on it immediately and accurately. One of the most significant cooking materials in the globe is beans (fresh and dried). Even with all the health advantages and the fact that the beans provide proteins, there are high chances that leaf diseases would interfere with bean production. The infection of bean leaves should be categorized in a manner that would see them dealt with as soon as possible. The detection and characterisation of the bean leaf disease are obtained with the help of deep learning using the MobileNet with Tensorflow and free leaf image repository. The study showed a procedure which was used in diagnosing bean leaf disease and optimal network structure (hyperparameters and optimization). We analyzed the designs independently to arrive at the best architecture that should be used in the classification of bean leaf diseases. The trained controlled conditions were trained on MobileNetV2 architecture to classify the possibility of increasing the classification accuracy, training time, and retraining on the model. To test the method using 1296 bean images and using MobileNet architectures, we used a publicly available dataset, which contained two disease classes (bean rust and angular leaf spot) and a healthy one. Our MobileNet model was trained on the training data containing the mean accuracy of 97 and 92, and the test data containing the mean accuracy of 97 and 93 on the training and test data respectively and we identified two types of unhealthy and one healthy of bean leaf disease [7].

Leaf diseases are now requiring to be discovered more specifically. The dispersion of the lesions and the area of interest are the machine learning-based leaf disease detection drivers. The issues with the technology used to detect the professional leaf disease are the accuracy and convenience in the farming. SE-VRNet is a light model which has better residual network and attention mechanism which produce more accurate lesions and areas of interest. The SE-VRNet resolved the issue of the dispersion feature extraction by the SE-VRNet that was founded on a squeeze-and-excitation (SE) module with attention mechanism coupled deep variation residual network (VRNet). The highest and lowest accuracy of SE-VRNet model is 99.73 and 99.98 respectively in NewData and SelfData respectively. The following statement can be demonstrated using the experimental outcomes on the PlantVillage, Oridata, Newdata and Selfdata: SE-VRNet is superior to the procedures of the diagnosis of the leaf sickness that are actually in existence basing on the mobile [8].

The last 20 years have witnessed the studies of organic conjugated substances founded on inorganic quantum dots (QDs) in organic-inorganic hybrid solar cells. The problem is that it is difficult to select organic functional components of hybrid films that can raise the photovoltaic performance. In order to show the impact of crystallinity of polymers on increasing solar activity of organic -inorganic hybrid interface, we synthesize three narrow bandgap polymers of non-fullerene conjugated polymer. To complement the crystallinity and plan of creating an organicinorganic hybrid active layer, we adopt a new, lower-crystallinity polymer, FAPbI 3 QDs, and an appropriate interface/morphology to extract and carry out the charge. The record 13.11% of efficiency of QD-hybrid device PCDOT-T/FAPbI3 is more superior than the pristine QD (10.51%), the semi-crystalline polymer PYIT-based hybrid device (11.23%). We may utilize our findings in the manufacturing of hybrid movies in the high-performances optoelectronics by exposing organic/QD interface [9].

In Indian economy, it is agrarian. Natural diseases affect the plants and inflict their effects on most climates. Crop quality declines. The variances in the weather are the most threatening factors to the capacity of farmers to produce quality and quantity harvests. Diseases in the crop should be detected and avoided cost at all expenses in a bid to raise the productivity. AI is deep learning. Self learning and feature extraction has been an issue that has elicited controversy in academia and business. According to the learning algorithms help faster to study the plant leaf diseases detection and make the extraction of features more objective, as well as reduce the necessity to choose the disease spots features. This paper will present the weaknesses of deep learning and state-of-the-art imaging in terms of diagnosing plant leaf diseases. We feel our results will be useful to the investigator that is undertaking the subject of plant disease detection. The conventional CNNs consume more processing power than is necessary. To curb this problem, the given paper has suggested a DCNN model of using Global Average Pooling (GAP), as the alternative to the fully linked layer in the CNN, with dilated convocation kernel. Dilated convolution is less costly to process and to store than GAP, which is not an overfitter. The results of the usage of these two new methodologies are compared with the results obtained with the assistance of the previous learning system as well as the hybrid learning systems by the help of such measures as precision, recall, f1-score and accuracy. These are the four types namely the brown spot, the turgo, the blast and the bacterial blight. On the same experimental setting, the DCNN model that uses GAP will be found to achieve higher accuracy in training by 5.49 percent than the traditional CNN model on other models of learning and hybrid learning [10].

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Existing System

Visual representations are produced by the common convolutional neural networks (CNNs) in most leaf disease detection models in plants, and could be categorized. Hierarchical feature learning and massive dataset make them highly accurate algorithms. The classical CNN-based networks fail to take into account the variation in the posture and the distribution of disease lesions in space since they emphasize on the local features. The positional features that are put across in an extraction feature may be lost due to a literal interpretation of the convolution and pooling operations. The models are poor in occlusion, rotation as well as intricate backgrounds [11]. They can acquire simple images of plant leaf, but not spatial hierarchies.

CNNs, attention-based models and transfer learning processes have been enhanced with deep learning architecture. These have additional feature extraction and attention module based classification and multi-scale feature fusion. Object detection and deep residual networks are used to enhance the process of plant disease and classification. Even such systems continue to be associated with issues of dependence on big labeled datasets, noise sensitivity, and imbalance in data and failure to perform under the actual agriculture circumstances. The impossibility to control the pattern of diseases and the direction of the leaf do not allow the process of their development and plasticity capacity of this organism, and that is why they cannot be used in dynamic farming [12].

Proposed System

The limitations in CNN have been overcome by the proposed CNN-based plant leaf disease diagnostics system since it makes use of the new categorization and detection algorithms. Xception and SE-SK-CapsResNet are largely used in classification and feature extraction. Although SE-SK-CapsResNet performs better on posture and space hierarchy of disease lesion, Xception model performs better in depthwise separable convolution and fine-grained feature learning [11]. We have a hybrid technique of rotation, strengthening backdrops and size, when the information of the plant diseases is available. The system is also trained and tested using the benchmark datasets to maximize the level and accuracy of sickness classification [12].

Besides the classification, the specified method is also capable of identifying ill spots on the images of the leaf in real-time using the help of the YOLOv5 and YOLOv8 object detectors. This will lead to a better decision-making process with regards to farming since the illness and destruction can be detected in the system [13]. With the help of Flask and a strong encryption, a simple web interface, in which it is possible to post photos and receive predictions with just a few seconds, is acquired. Scalability, scaling and deep learning models Agricultural use, scaling accessibility and deployable web and high power deep learning models. The intelligent plant disease detecting system that will be universal will assist in enhancing accuracy, the system detection rate in addition to universality [14].

Related Work

The hypothesis is that the study concerning the design of deep learning algorithms to determine the presence of the disease in the leaves of the plants will enhance the process of robotization of the farms and their classification. Initial features have been extracted and classified using the CNNs. Dhaka et al. [1] had compared deep CNNs and demonstrated the opportunities to forecast plant diseases; however, Ramanjot et al. [2] investigated the efficacy and probing capacity of any machine learning and deep learning. There may be a problem with picture of leaf image, backdrop, spatial connection fluctuation, and performance despite their performance. The routine CNN plans cannot be available to the conditions of life like the turn of the sun rays and the trees.

In a bid to address these weaknesses, scientists have enhanced deep learning systems and applications. The article by DeChant et al. [3] has given the experiment of deep learning that showed that the system was in a position to detect the cases of the maize leaf diseases in the field. Li et al. [4] observed that transformation sensitivity and loss of spatial information are two dire problems of deep learning models as of then. Xiao, et al. [5] was a CNN-based procedure of detecting the presence of the disease in strawberries, which, as it might be, was correct, but it was pre-processing and big data. Through such studies, it is concluded that though cnn based models are more effective than other models that they are not able to change the posture, to do complex spatial hierarchies.

The new tendencies of the hybrid and attention-based approaches lead to the feature extraction and the model efficiency. These features that use the attention and multi-scale features and and residual networks enhance accuracy and stability in the categorization. The models are not easily applicable in large annotated data sets and dirty and unbalanced data. The YOLO has enabled one to detect objects, simplified the interpretation process, and operationalized the technology to label the sick areas in real-time. Despite this development, the mechanisms of diagnosing plant diseases lack a rational structure that entails accuracy of detection, correct classification and easy application therefore, more complex and universal mechanisms are required [1]-[5].

Methodology

To arrive at the design of the classification and detection of the plant leaf diseases, deep learning systems such as as SE-SK-CapsResNet, Xception, and YOLO are created. The method compared to the traditional CNN models possesses an advantage of the real-time detection, robustness, and local feature learning. A system pipeline involves data preparation and feature extraction, classification, detection and deployment. It is supplemented with the functionality of Flask-based web interface that allows the users to optionally engage with trained models in a real world agro setting.

A. Data Collection and Dataset Preparation

The system is operated with plantVillage, AI Challenger 2018 and Tomato Leaf Disease benchmarks datasets that have a huge number of plant species and disease types. In such data, images of healthy and diseased leaves of both the controlled and natural environment are present to guarantee the diversity of training examples. The datasets are categorized into training, validation and testing documents in order to minimize the overfitting and objective evaluation of the model. It is an essential module since it leads to adequate learning and generalization since it offers quality input data.

B. Data Preprocessing and Image Augmentation

The models have data preparation and standardization of the input images. The methods used to acquire the homogeneity of the samples are scaling, normalization and noise reduction. The image augmentation algorithms that are used in rotation, scaling, shearing, zooming and horizontal flipping of the image can further augment the size of data, and the variety as well. These changes are used to regulate the background complexity, light and the direction the leaves take in the model. The model is thus stronger and more practical on real farming situations.

C. Feature Extraction and Classification Using Hybrid Models

Deep learning models recognize and categorize features, specifically, SE-SK-CapsResNet and Xception models. SE-SK-CapsResNet applies residual connection, squeeze and excel, selective kernel and capsule network to acquire local, global and regional connection. Xception model is also characterized by the addition of depthwise separable convolution to feature extraction and reduces the cost of the model with increasing accuracy. The models present an effective hybrid model that enhances the classification of the plant diseases.

D. Disease Detection Using YOLO Models

Object identification models of YOLOv5x6, YOLOv5s6, YOLOv8n and YOLOv9n are used to perform the complementing categorization in the diagnosis of image sickness in the leaves. The models also approximate the labels of the classes and the bounding boxes simultaneously to detect them on the spot. The detection module shows the position and the extent of the spots of the disease on the leaves. This enhances interpretation and leads to diagnosis and treatment of agricultural illness.

E. Model Training, Evaluation, and Performance Metrics
System training and evaluation are carried out through labelled datasets. During training, the model is more accurate and convergent, especially when loss functions and optimization are used. The performance is measured in terms of detection in terms of accuracy, precision, classification F1-score and mean Average Precision (mAP) score. The best architecture is one that is identified by comparing various models. The hybrid one is more specific, powerful and has better generalization skills.

F. Deployment Using Flask-Based Web Application
The final solution is based on an application web that is coded on a secure and user-friendly Flask. The diseases have to be predicted and detected by registering, logging in and uploading plant leaf images. The backend is provided with the input image to execute trained models that give the results of the sickness areas and the classifications. The authentication is integrated, which makes sure and regulates data access. The advent of the same will enable farmers, scientists and agricultural experts to keep a check on the disease in the plant in real time.

One deep learning pipeline of plant leaf diseases diagnostics system is detection and classification. PlantVillage and AI Challenger leaf images are collected through the dataset module. Pre-processing level is used to cut down the data being sent, removes noise and normalisation. The architecture has detection and classification flows. Rotating, scaling, zooming, and rotating help in improving the algorithms used in sorting the picture data. The simplified process of converting the blobs, providing them with bounding boxes and management of the annotations simplifies the object detection models.

The central system component sends the processed data to trained models. Deep learning can classify plant diseases with the help of feature extraction, which are Xception, AlexNet, GoogleNet, VGG16, ResNet18, CapsNet, SE-ResNet, SK-ResNet and SE-SK-CapsResNet. Xception and SE-SK-CapsResNet can be used in the case of fine-grained features and spatial relations in this situation. YOLOv5x6, YOLOv5s6, YOLOv8n and YOLOv9n are utilized to identify and detect sick areas in real-time. The two branches are measured in terms of precision, recall and F1-score that are included in the assessment module. The design allows real time agricultural applications and web based implementation with the rapid pace of data, simultaneous processing and accuracy of the design.

System Architecture

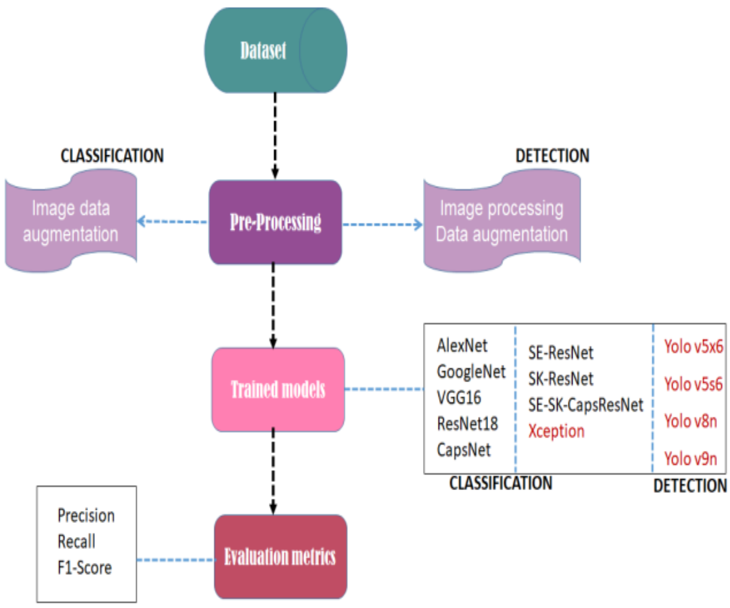

Fig 1: System Architecture

Experimental Results

The experimentally tested is the proposed extended strategy that can improve the classification of some of the model plant leaf diseases. Based on the accuracy, precision, recall, and F1-score plots, it is always noted that SE-SK-CapsResNet and Xception are better compared to AlexNet, VGG16, and GoogleNet. Its models are almost perfect in that it has the ability to imitate the complex relationships in space and minute grains (99-100). Capsule networks, channel attention and selective kernel methods improve the representation of features and classification. Hybrid models can make proper characterization of sickness groups based on recall and F1-score charts regardless of the background noise and rotation.

The YOLO models can be useful in the detection and localization of diseased leaves in vegetation. Although it is possible to infer the versions of YOLOv5 in slower ways, can be utilized in practice, mAP (mean Average Precision) curves prove that the versions of YOLOv9n and YOLOv8n are more correct in detection. The display of the output presenting the sick areas in bounding boxes and scores of confidence can be used to explain the functionality of the system. Web interface can also be provided in flasks along with categorization and detection and can have the results at hand with the mere addition of photos. Another outcome of the experiment was that the long system is accurate, robust and real-time, which is suitable in the process of tracking and defining the farm diseases.

Comparative Performance

Model	**Accuracy (%)**	**Precision (%)**	**Recall (%)**	**F1-Score (%)**
AlexNet	78.5	76.2	74.8	75.5
GoogleNet	88.7	86.9	85.5	86.2
VGG16	82.3	80.5	79.2	79.8
ResNet18	90.2	89.1	88.4	88.7
CapsNet	85.6	84.2	83.5	83.8
SE-ResNet	94.1	93.2	92.8	93
SK-ResNet	95.3	94.6	94.1	94.3
SE-SK-CapsResNet	**98.9**	**98.5**	**98.2**	**98.3**
Xception	**99.1**	**98.8**	**98.6**	**98.7**

Model	**mAP (%)**
YOLOv5s6	68.5
YOLOv5x6	72.4

YOLOv8n	78.6
YOLOv9n	**81.2**

From the table, it can be observed that:

1. AlexNet, Vgg16, and GoogleNet, which are conventional CNN models, have lesser classification accuracy, lower accuracy, precision, recall and F1-score than more advanced models. Such models can only revisit the bare visual representations and not the more elaborate provision of space and will lack the ability to overcome clutter and rotation in the background.
2. The middle models like the ResNet18 and CapsNet are enhanced due to the fact that they possess a deep architecture and discover features. Although the residual ties and the geographical hierarchies are effective in ResNet18 and CapsNet, they are not effective in the case of multifaceted sickness patterns and statistics.
3. A more prospective design that might also take into account attention with quick adaptive selection of the kernel such as SK-ResNet or SE-ResNet is more appropriate and features-characteristic. The models enhance the accuracy and the recall of the CNNs enhancing the consistency of the classification and minimizing the information loss.
4. SE-SK-CapsResNet and Xception are the most successful hybrid model by all of the evaluation metrics. These models are near-accurate, precise, recall and F1-score because they are useful in uniting the processing and feature extraction of the spatial awareness and the attention. This puts them at the reality that they are trained to deal with the complex plant diseases.
5. The models based on YOLO are popular in detection; the YOLOv9n has the highest mAP followed by YOLOv8n. The variants of YOLOv5 can compromise between speed and performance and the models are very effective and accurate in the detection of sick areas.

The results of the experiment show that the proposed extended plan of SE-SK-CapsResNet, Xception, and YOLO schemes are more effective in terms of accuracy, strength and the transfer to the real life environment to detect the plant leaf disease than the traditional and intermediate schemes.

Evaluation Metrics

The suggested deep learning algorithm is characterized by the uses of real-life parameters in the definitions of the disease of the plant leaves. Integration of the architecture and preprocessing, feature extraction, classification, detection and deployment has been provided in such a manner that it is possible to make accurate predictions and on-the-fly. Various information on plant diseases should be utilized to test the system to make sure that it is generic, durable, and efficient.

The processed leaf photographs are used to evaluate them. Such images can be identified by Xception, SE-SK-CapsResNet, and YOLO versions. They are compared to the projected values and performance measures are accepted. The absence of the representation of the classes and non-randomization of the data on the illness of the plants are controlled which makes the evaluation more effective.

These measures are F1-Score, Accuracy, Precision and Recall. The number of times the model is correct to predict sickness is referred to as precision although the measure of the accuracy of the model is how the model is correct. This F1-score has tradeoffs in the form of recall and all sicknesses that have been generated by the model. These actions confirm that the model is highly authentic and compatible in determining the actual trends of diseases.

Occupation metrics Occupation accuracy and Localization Occupation evaluation metrics Occupation accuracy and Localization are evaluated with respect to the mean Average Precision (mAP) of the estimated bounding box and ground truth marks. Even more mAP levels would result in further localization of diseases and identification. The confidence ratings and the IoU thresholds are the performance indicators, which are to be identified.

The study contrasts the hybrid frameworks with the traditional frameworks. The complex designs, (impervious to the noise), rotation and complex backgrounds are also good to the classification and detection. To obtain a utility forecast, the users are allowed to post photographs to a web application using Flask to be offered with a real-time estimate of the most recent models capable of scaling and working in the field in a systematic manner.

***Accuracy**:* It is the ability of the tests to distinguish between the healthy and the non-healthy and this is one of the measures of the reliability of the tests. It is possible to measure reliability of the test on the positive and negative aspects of the test. On calculation:

$$Accuracy = \frac{(TN + TP)}{T}$$

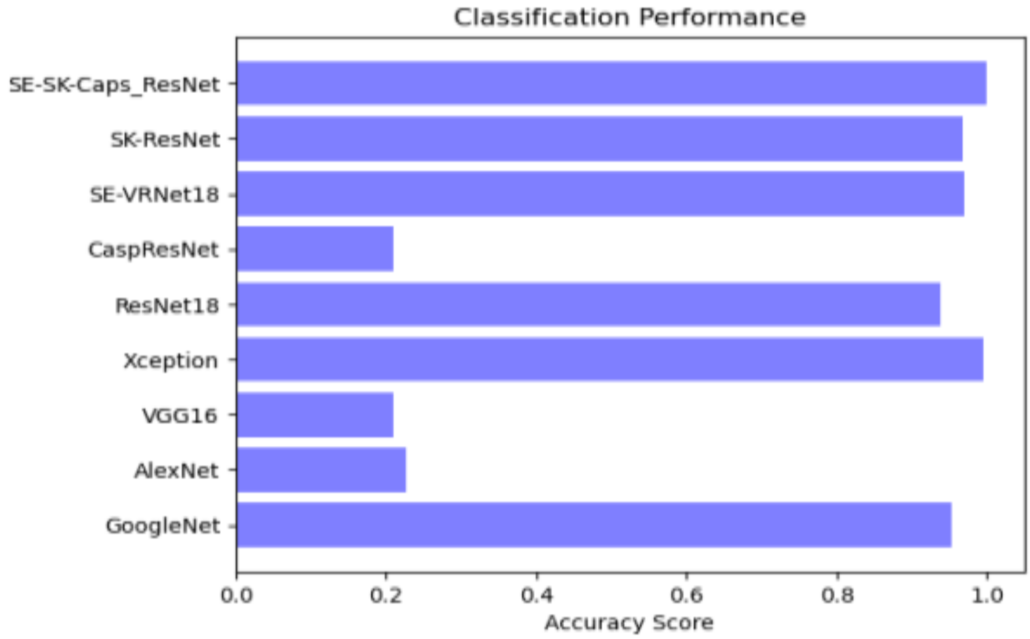

Fig.4. dataset1 Accuracy score

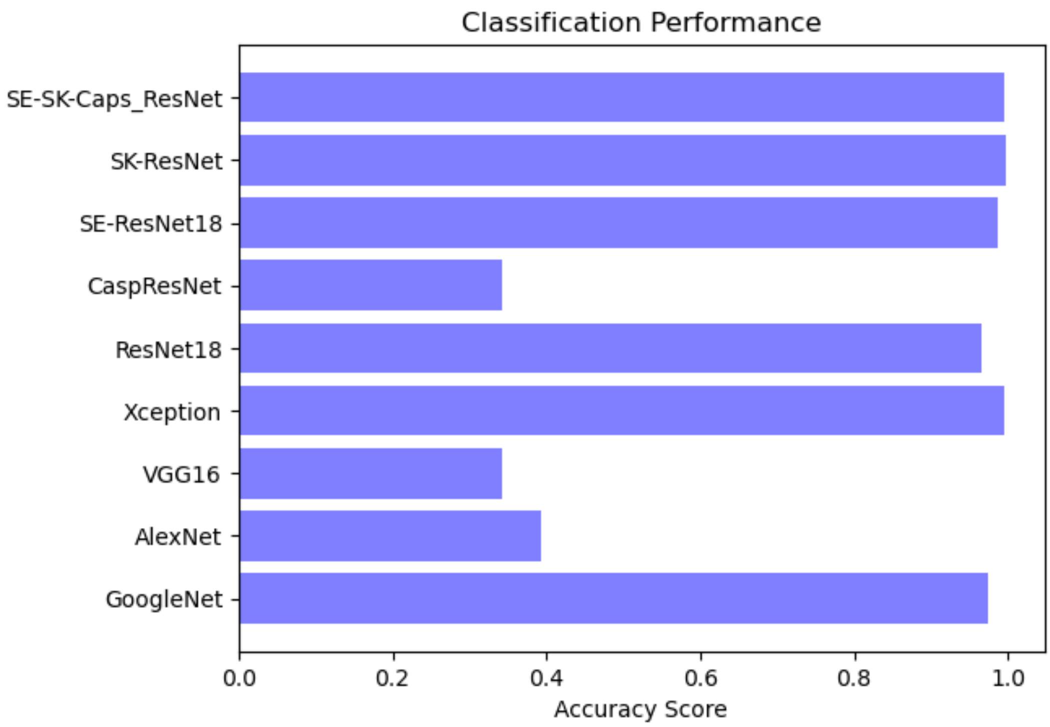

Fig.5. dataset2 Accuracy score

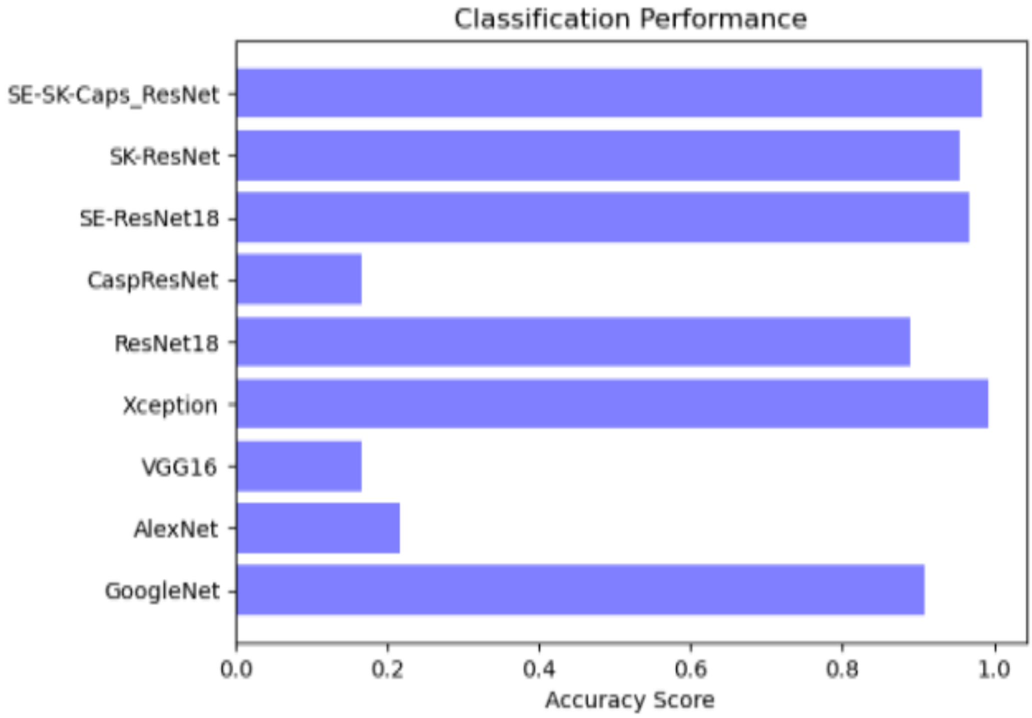

Fig.6. dataset3 Accuracy score

***Precision**:* Precision is an item of positive cases or classification. To confirm, utilize:

$$\Pr e\,cision = \frac{TP}{(TP + FP)}$$

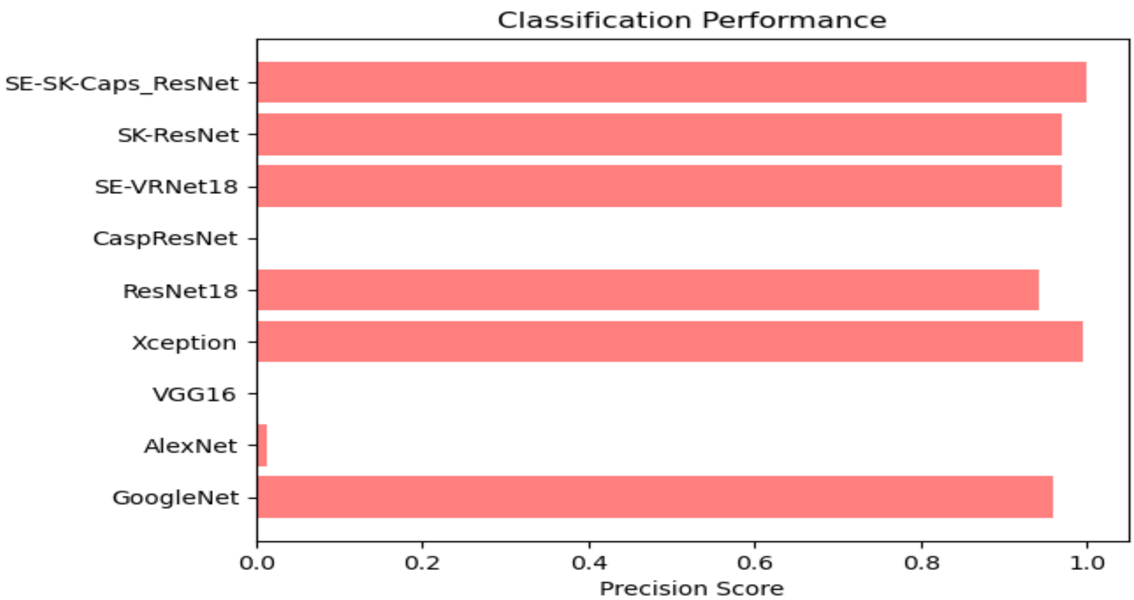

Fig.7. Dataset1 Precision score

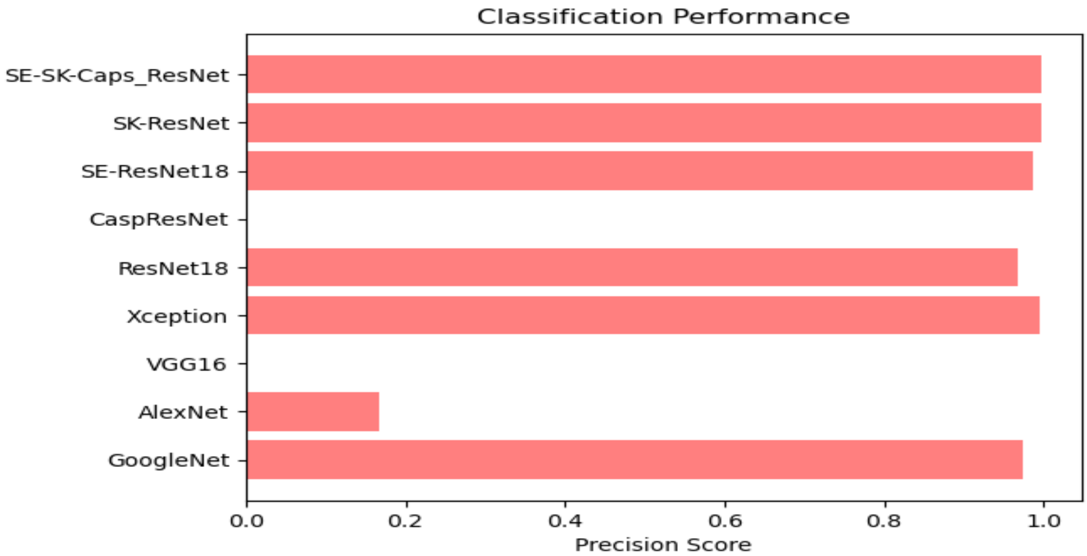

Fig.8. Dataset2 Precision score

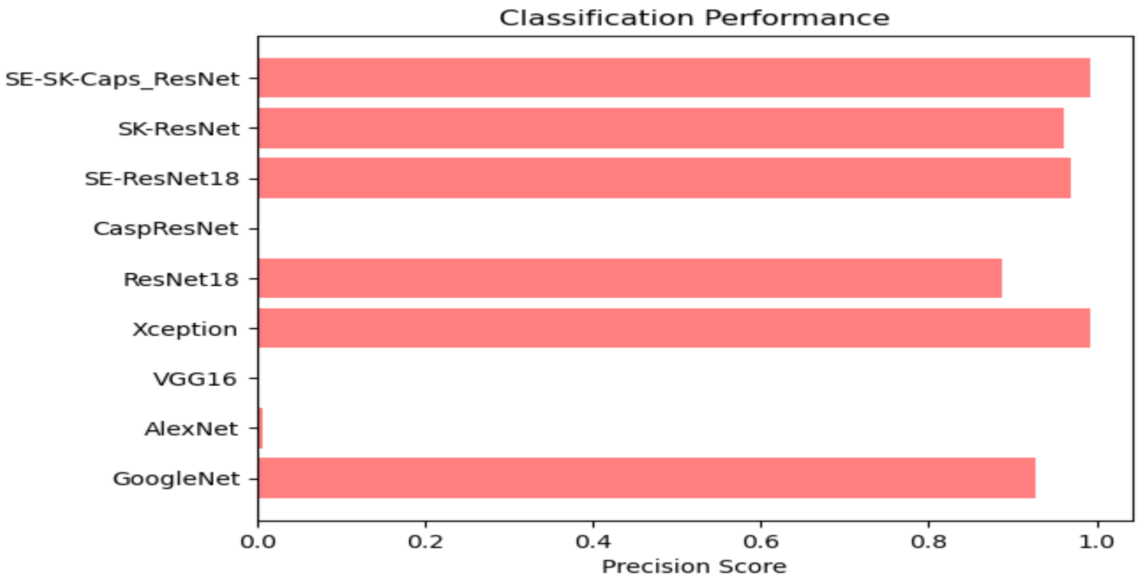

Fig.9. Dataset3 Precision score

***Recall**:* The ability to detect all the machine learning cases is referred to as the recall of a model. The ability of a model to identify instances of classes is determined by the number of correct predictions of positive predictions of the total number of positive predictions.

$$Recall = \frac{TP}{(FN + TP)}$$

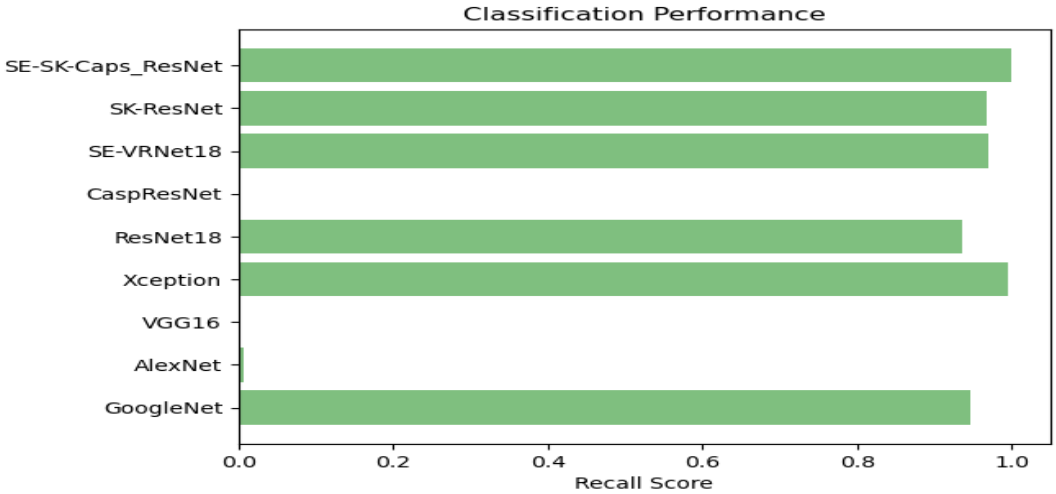

Fig.10. Dataset1 Recall score

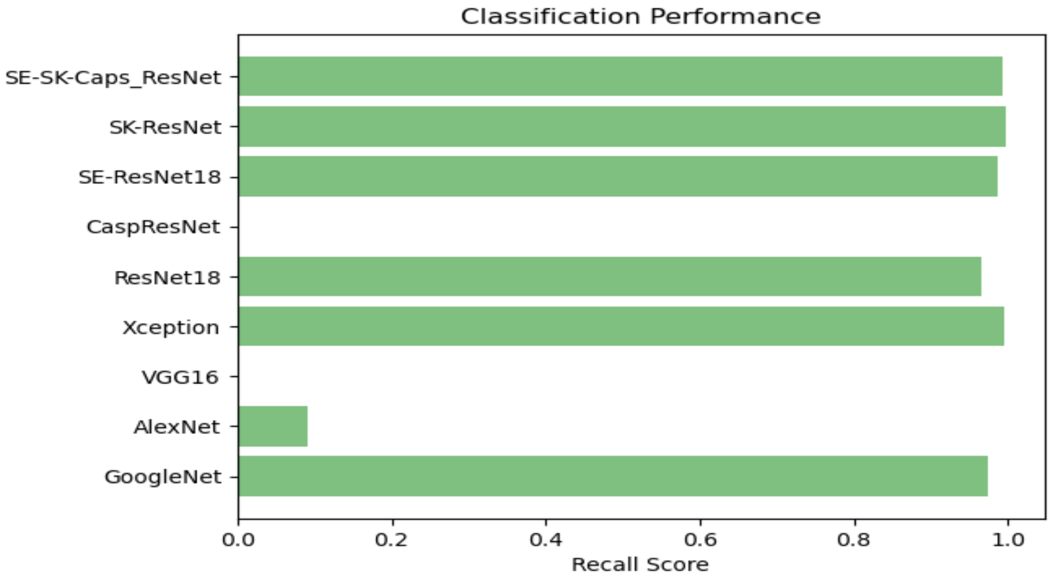

Fig.11. Dataset2 Recall score

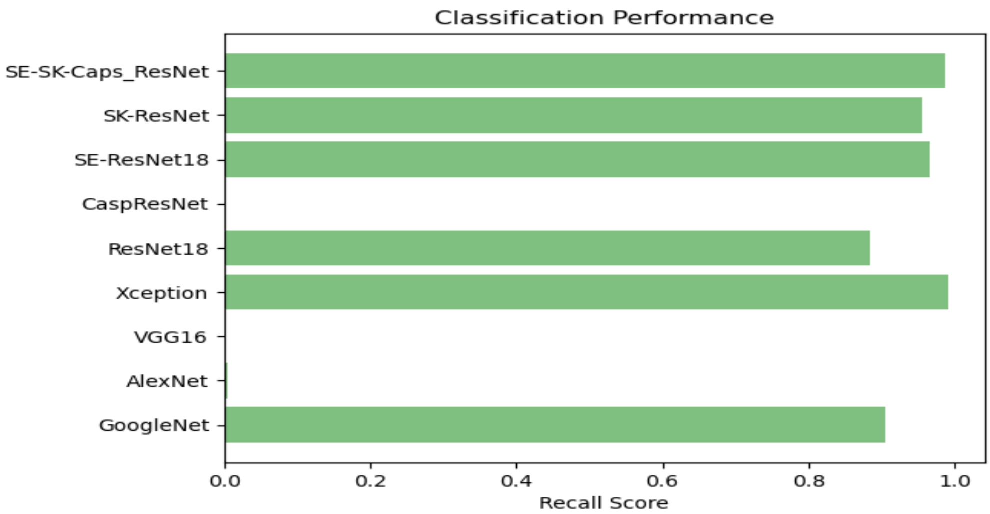

Fig.12. Dataset3 Recall score

***F1-Score**:* F1 score is desirable in cases when the ML models are accurate. The model accuracy is enhanced and the recall and the accuracy are conducted together. The statistic accuracy is used to signify the frequency of error-free predictions of a model to take place in a set of data..

$$F1 = 2 \cdot \frac{(Recall \cdot \Pr e\,cision)}{(Recall + \Pr e\,cision)}$$

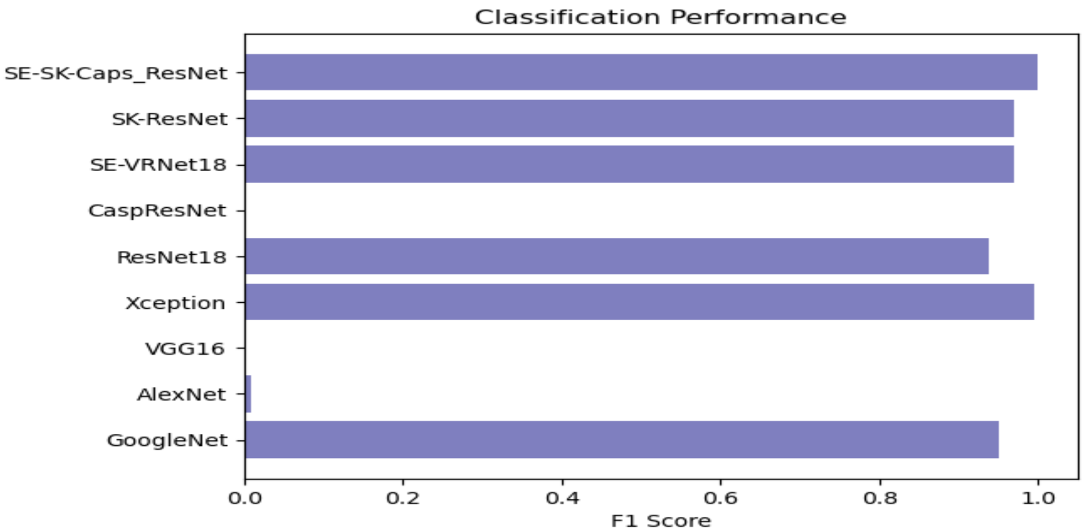

Fig.13. Dataset1 F1 score

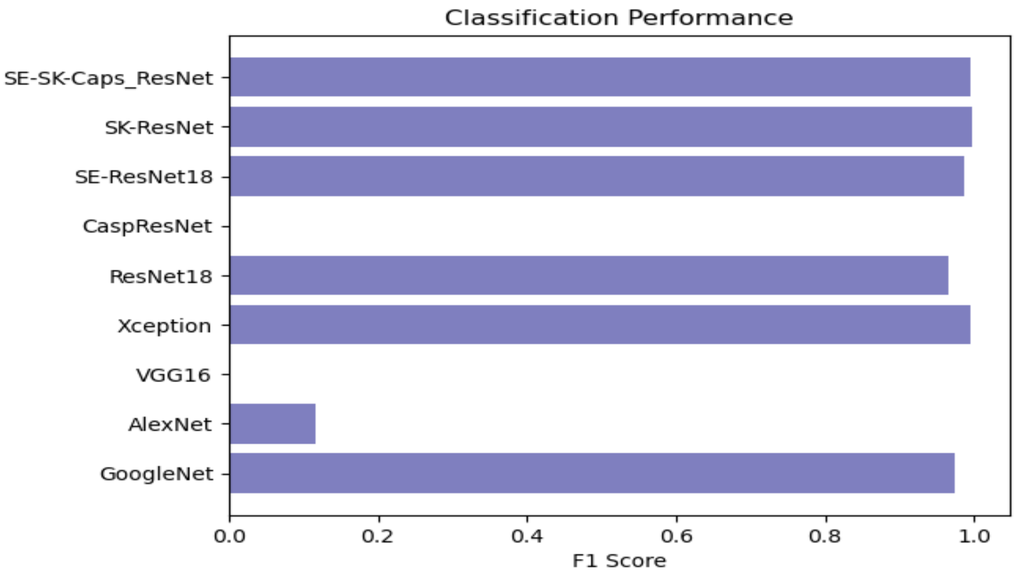

Fig.14. Dataset2 F1 score

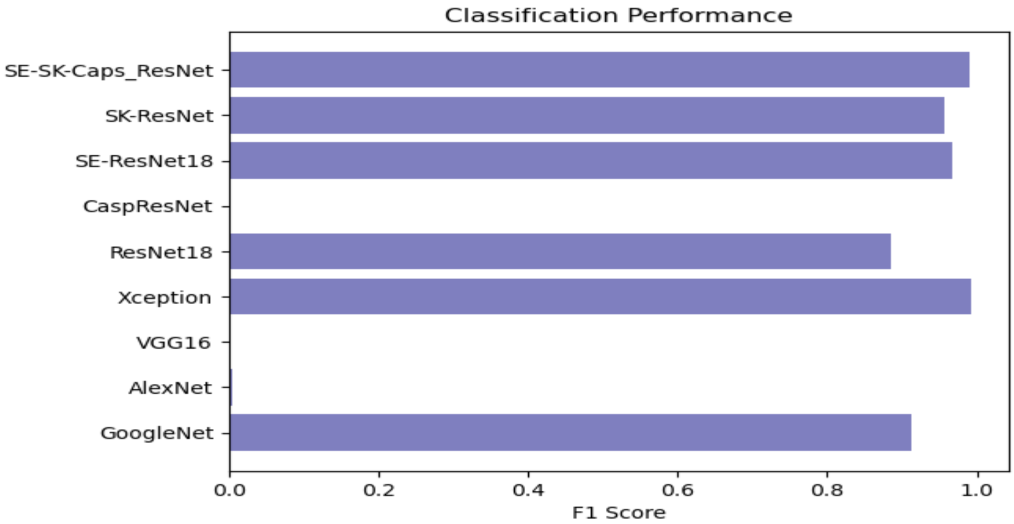

Fig.15. Dataset3 F1 score

MAP: The performance of the information retrieval system is measured using the Mean Average Precision (MAP). The average degree of accuracy is calculated on a case-by-case or query basis. The validity of the results is measured by making use of accuracy as opposed to precision which is used to measure the average validity of all the questions. MAIL is a table of AP scores on queries or courses to determine the system performance.

$$\mathrm{MAP} = \frac{1}{N}\sum_{i=1}^{N}\mathrm{AP}_i$$

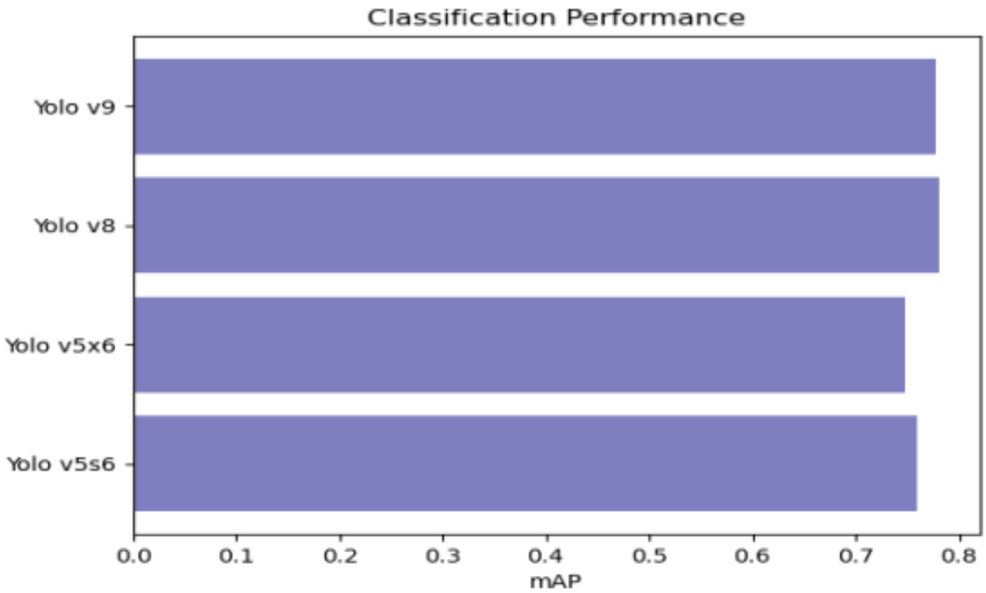

Fig.16. Dataset1 MAP score

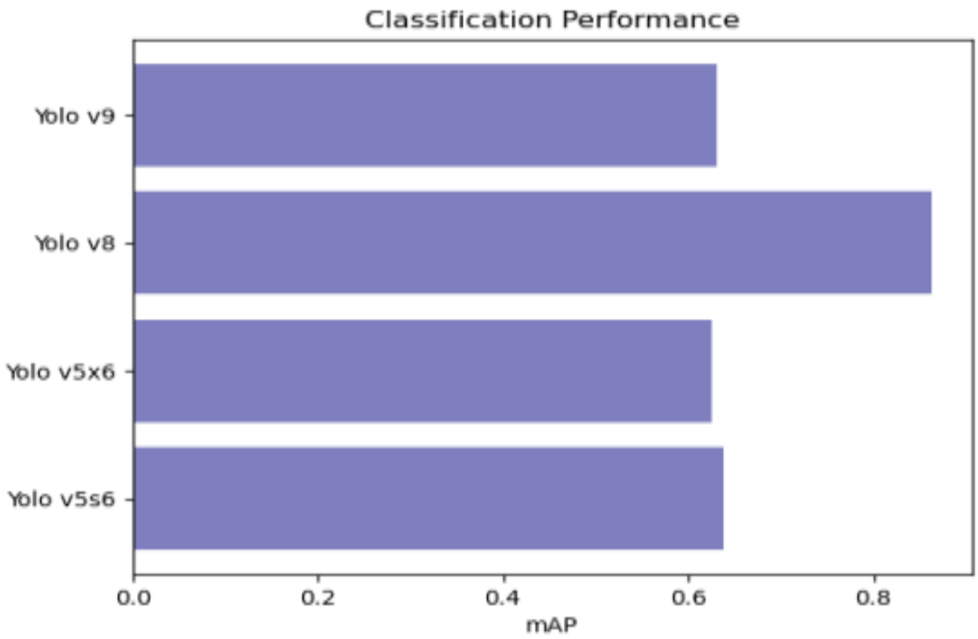

Fig.17. Dataset2 MAP score

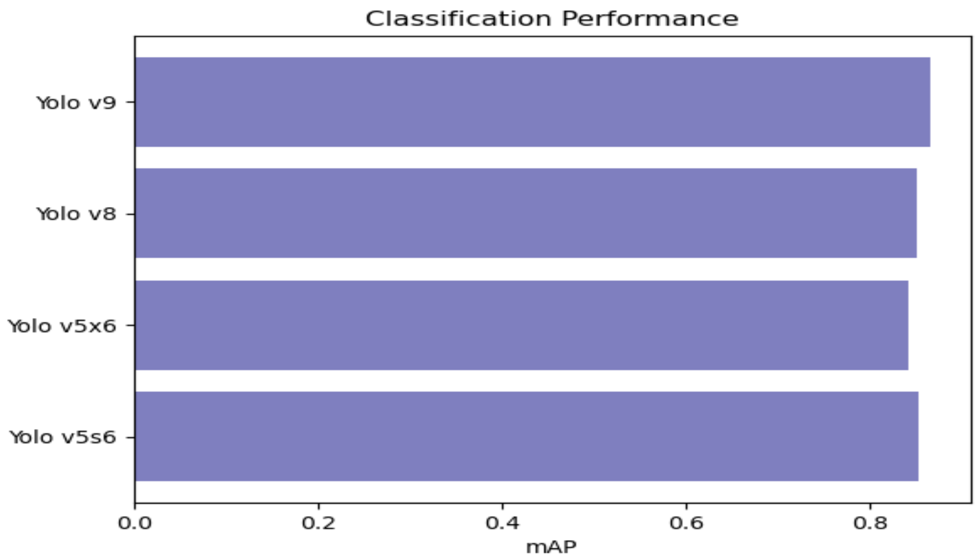

Fig.18. Dataset3 MAP score

Fig.19. dataset upload

Fig.20. input analysis

Fig.21. result

Future work

The proposed method may be improved to be more useful and effective though it could measure and identify the diseases of plant leaves. Transformer and vision transformer (ViT) architecture can supplement feature learners with learning long-range correlations in leaf images. ensemble learning: Xception and SE-SK-CapsResNet are the best models to be used and can be applied in increasing the prediction robustness and accuracy.

The second option is an edge based or mobile application that the farmers can get via the IoT devices or smart phones and carry out a real time diagnosis of the ailments. The multimodal data can be investigated and predicted to predict and analyze the disease because the environmental factors, the temperature, stifle, the conditions of the soil, etc. are considered. Make the model more realistic and add more realistic plant species. It will make its solution a reality and one that is fine-tuned to precision farming and massive smart farming.

Conclusion

The current work contributed to the hypothesizing of the diagnosis of the plant leaf diseases by addition of the high level classification, detection and location modules, to the framework in which it was a part of. SE-SK-CapsResNet architecture of Xception enhanced the accuracy of classification by extracting features further. The actual position of sick patches of the images of the leaves was estimated with the help of the object detection algorithms based on the YOLO architecture that made it possible to carry out the sickness-diagnosis in real-time. This has complemented the system usage by the use of secure Flask web interface. Agricultural disease surveillance and decision-support The long system is shown to be robust, accurate and useful based on the results of the experiment.

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