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A Deep Learning Based Model for the Classification of Cotton Crop Disease

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Abstract- Plant disease is major factor on the subject of crop yield. Plant health needs daily basis update. Agriculture yield increases with good results if healthy and timely disease diagnosis performed. Artificial intelligence revolution in smart agriculture arise many challenges and opportunities for researchers. Deep learning methods considered smart disease detection and classification technology in Modern agricultural field. The sub-field of Artificial intelligence (Deep Learning) can structure algorithms in layer for development of ANN that can learn and make intelligent decision termed as Deep learning. Deep transfer learning attempts to solve problem of learned model that perform task, modify experimental model for solution of another task. Agricultural crop disease diagnosis becomes easy with several soil, weather text data and plant parts images. In computing the terms, “Smart agriculture or Smart Agro-industry or industry 4.0” termed interchangeably used in scientific community. This study is about detailed deep learning, smart agriculture and related research. Study covers Deep learning applications in agriculture, architecture model and some important model depiction. EfficientNet Model proposed for single label image patches. The data set obtained from different cotton crop in the region. Total no. of leaves images 20000 included for the experimentation. EfficientNet model used for disease classification, the common evaluation matrices such as precision, recall and F1-score used. The results shows recall, precision and F1-score of 0.88%, 0.89% and 0.89%, respectively.

Keyword- Disease classification, Deep learning, Smart agriculture and Agro-industry

I. INTRODUCTION DEEP LEARNING

The sub-field of Artificial intelligence (Deep Learning) can structure algorithms in layer for the development of artificial neural network that can learn and make intelligent decision-making termed as Deep learning. Further the deep transfer learning that attempts to solve problem of learned model that perform task, modify experimental model for solution of another task [1]. The DL models can classify and provide accurate problem solving for prediction from the image dataset. The challenges in agriculture plant diseases from root to leaves can solve by providing efficient neural network based model, which entails the complexities of plant images. Computer technology has been imparting in almost all fields of life. In computing agriculture study with the computer based models and methods terms as “Smart – agriculture”. Smart agriculture provide solutions for serious issues such as disease classification & disease control [2], soil monitoring [4] and weather update [6] was never possible by traditional methods ever before. It is impressive to control water irrigation [5] and soil update with smart IoT based [3] devices to improve water pouring and soil status. Deep learning provide depth of study by implementing several algorithms in different fields of agriculture. The images and video obtained from sensors, further investigated by applying DL learning based models.

1.1 Machine Learning Techniques:

Table-1: ML Techniques and Learning Types

Classification	Supervised	Unsupervised	Reinforcement
Data processing	Regression Classification Estimation/prediction	Prediction Clustering	Decision Making
Training algorithms	Neural Network Bayesian Network Naïve Bayes Hidden Markov Model Support Vector machine	K-Means X- means Gaussain Mixture Model Dirichlet Process Mixture model	TD – Learning Sarsa Learning Q - Learning R – Learning

Data analysis is important phase for model training and testing. In supervised learning usually labeled data is train and tested. Whereas unsupervised learning uses raw data (unlabeled data). Reinforcement learning [8] often used for decision-making problem with smart solution. ML learning [7] focuses on optimizing the performance of the problem. In which optimization of problem optimization is focused for classification of disease.

1.2 Machine Learning Techniques Used in Agriculture:

Table 2: ML Models in Smart Agriculture

Technique	Yield Prediction	Weed detection	Disease Detection	Live stock	Crop Quality	Soil Management	Species recognition	Water Management	Animal Welfare
SVM [9][10]	Yes	Yes	Yes	Yes	Yes	Yes	-	-	-
DT [19]	-	-	-	-	-	-	-	-	Yes
Clustering [11] [12]	Yes	-	Yes	-	-	-	-	-	-
Regression [12]	-	-	-	-	-	Yes	-	Yes	-
Instant based model	-	-	-	-	-	Yes	-	-	-
Artificial & Deep Neural Network [13][14][15]	Yes	Yes	Yes	Yes	-	Yes	Yes	Yes	-
Ensemble Learning [16][17]	-	-	-	-	Yes	-	-	-	Yes
Bayesian Models [18]	Yes	-	-	-	-	-	-	-	Yes

1.3 Problem Statement:

Cotton crop disease [20] are very critical for yield production [21-23]. Whenever any crop faces disease, it damage flower, root, and stem and leafs of plant. In cotton crop disease like viral, fungal and bacterial [24] spreads often due to late recognition symptoms, unfamiliar to detect disease type, pesticides spray and guess of crop disease. These lads very critical results for crop yield and provide low yield rate with economic loss. Deep learning [25-26] is one of advance field which can learn from images data and provide comprehensive classification of disease. It is important to provide computer based latest trend methods for crop yield improvement by disease classification and quick remedy from the disease.

1.4 Objective of Study

This study entails detailed model for image classification. These images captured from cotton crop field to classify the images mainly three types of disease highlighted. Second objective is to preprocess the data and apply data preprocessing techniques. Finally, Apply EfficienetNet Model training and testing performed classification of cotton crop diseases.

1.5 Structure of Paper:

This paper consists of four section. Section I is about introduction of deep learning in perspective of smart agriculture. Section II is about Background study, trends and smart agriculture models using deep learning and section III is about experimentation & results of proposed EfficientNet Model and finally section IV is conclusion and Future recommendations.

II. BACKGROUND

This section provide introduction and few detailed application of Smart agriculture. The discussion provide comprehensive technical detail of IoT, WSN, CloudIoT, Machine learning and Deep learning with emerging role in Smart agriculture.

2.1 Smart Agriculture:

Agricultural science with emerging technology is grew up high in last decade. Advancement is always welcomed for reforms in agriculture cultivation to yield production. IoT, WSN, automated machinery; ML & DL are major fields in modern agriculture methods. The agricultural industry with automation and smart monitoring have much new application with several challenges. Agricultural crop disease diagnosis with monitoring techniques, weather effect monitoring, plant anatomy, and soil science are easy to deal. In computing the terms, “Smart agriculture or Smart Agro-industry or industry 4.0” interchangeably used in many research papers

IoT technology [27] with the integration of WSN can monitor and update without any delay. Although, there are many challenges which IoT and WSN face like energy efficient, Battery power and remote object monitoring and detection. Soil monitoring [28-29] is crucial part of soil constrains by deploying WSN and IoT sensors network. The quality of soil and improve crop production. Smart irrigation [30-31] with implementation of technology base monitoring is useful. Water is a major issue and quality, quantity and timing for water is important before pouring into the field. Water control, water salinity, water pollution and water drift are also important factors for smart irrigation. Water quality monitoring sensors deployment in field and data uploaded over the cloud. Cloud computing [32] and IoT are core part of data extraction and storage over cloud. The combined technology of IoT and cloud computing can provide vast data collection and future predictions. The farmer should aware of new trends and automation techniques. The text data collected via the sensors and image data capture by camera for sample collection from the field [33]. Environmental factors [34] like temperature, humidity, smoke, and dust particles are important to investigate for plant growth. Number of parameters surveyed for comparative crop cultivation conditions and seasonal changes.

2.2 Smart Agriculture Architecture with Deep learning:

Smart agriculture [35-36] provides automated methods of including IoT and WSN architectures. The data warehouse management and auto-monitoring of the warehouse is now a crucial part of the data obtaining process. The important parameters for a crop within premises of can easily be imparted. Deep learning, machine learning, and IoT-based smart systems are major focus of researchers.

Figure.1 depicts general architecture of smart Agriculture using Deep learning Methods.
The Architecture covers application of smart agriculture includes Soil, weather, irrigation and plant images data collection process. IoT

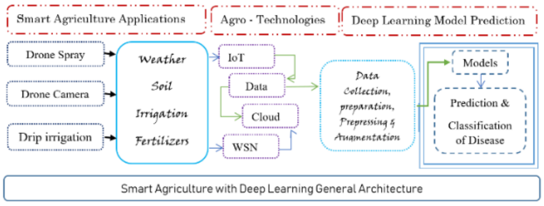

Figure 1: Architecture for Smart Agriculture with deep learning

Network implementation is for data collection from agricultural field. However, after Data collection, data preprocessing and training model depicted. The data acquisition form IoT & WSN [37] network can upload data over cloud, which termed as CloudIoT. Finally, deep learning model prediction based on data obtained.

2.3 Smart Agriculture with IoT Technologies:

Smart IoT-based model that can be able to any interruption in the field. Smart irrigation control with several parameters such as turbidity, water pH level, water poison, water electrical conductivity (EC), Sodium absorption rate (SAR), and content of SO42 can measured by using DHT11, Soil moisture sensors, Hanna SAR sensor Kit, etc. [38-40]. Pakistan agriculture systems lack IoT technology implementation with modern machine learning and deep learning-based approaches. The challenges in smart irrigation system can easily be achieve good results by deploying IoT with cloud IoT. The Deep learning models provide quick and timely update for critical issues identification. The hybridization [43] of models can give optimal results in agricultural applications [41]. Data analytics for providing potential solutions by implementing AI based models is now very crucial and easy way to focus critical factors in plant anatomy. Machine learning methods using obtained statistical data can provide a deep understanding of seasonal changes with future impact. The cloud IoT used for efficient management of data collected from different sensors. This data uploaded over cloud for remote use. Cloud IoT network [47] and with implementation of cyber - physical system in agriculture field [48] can improve field monitoring. The water parameters data can provide track record of the irrigation need and water control in agricultural field.

2.4 Deep learning Models and Data sets for Crops:

Deep leaning models trained and tested on different types of data. The agricultural crop image data further for data preprocessing and data training is used. The DL model can entail the data deep understating with accurate prediction. The following table shows few studies conducted based on Crop data sets by applying deep learning models. These models are being used for different datasets with crucial parameters as focused by studies. The below table 1 shows deep learning models and their parameters for different datasets.

Table-3: Deep Learning Models and Parameters for Different Datasets

Deep Learning Model	**Crop Data Set**	**No. of Image Patches**	**Hyper - Parameters**
CNN/DCNN [50]	Mixed crop image Data	54305	Training epoch – 30 -50 Batch size – 32 - 180 Dropout: 0.2 to 0.8 Learning Rate: 0.01 – 0.0001
VGG16 [49]	Aubergine	2815	Training Mininbatch size: 16 Maximum Epoch: 10 Inintal learn rate: 0.0001 L2 regularisation: 0.0001 Weight l2 factor: 1
ResNet [51]	Multiple fruits Apple, banana, Grape, Peach, Guava, Tomato, Blueberry, Citrus, raspberry	1000 images for each category	Epoch: 20, 40, 60 Shuffle: True batch size: 16, 32 Learning rate: 0.01 Optimizer: Momentum Activation function: ReLU
EfficientNet [52]	14 plant species	54305 images dataset	Epochs: 30, 35, 18, 43, 32, 35, 24

2.5 Data Description

Cotton crop is a major economic zone in south Asia. The bacterial disease in plants can cause greater damage to plant tissue. The symptoms of bacterial diseases can cause vascular wilt, necrosis, soft rot, and tumors. The bacterial invasion of the plant's vascular system can cause vascular wilt results (Ahmed, M. R. 2021). The subsequent multiplication and blockage prevent moments of water and also damage the nutrients via the xylem of the host plant. Fungi can cause a greater part of plant disease by white and true rusts, smuts, needle casts, leaf curls, sooty molds, mildew, and anthracnose. An estimated two-thirds of infectious plant diseases are caused by fungi. They also include most leaf fruits, lights, scabs, root, stem, fruits and wood rots, wilts, leaf, shoot, and bud galls. Different types of fungi may cause disease in one plant specifies (Sain , 2021). The viruses are the major cause of the diseases that can damage the crops resulting in a decrease in the economy of the country (Yogindran, 2021). The viruses disease in plants are Tobacco mosaic virus (TMV), cucumber mosaic virus (CMV), cauliflower mosaic virus (CaMV), Brome

mosaic virus (BMV), and potato virus X (PVX) (Kimathi , 2020).
In order to identify the cotton diseases at an early stage, it is important to develop an efficient smart agriculture system and train it on the data of different disease types. In this paper, a dataset related to the smart agriculture (Agronomics, 2021) is proposed, which can be used to detect and classify different types of cotton crop diseases. The type of data is based on images, text, tables, and figures. This data has been obtained using DSLR camera and a mobile camera. The raw data format is used to collect the data from the cotton crop field. The important parameters are used for the data analysis. The collected images exhibit health and disease-affected leaves of the cotton plant (Li , 2021). Data is collected from different cotton crop areas in the district Shaheed Banzirabad, Sindh, Pakistan. Initially, three locations of different regions of district Shaheed Benazirabad are selected to find out the common diseases in cotton crops. The cotton crop images have been collected in different weather conditions such as cloudy and sunny. Moreover, data variability with the effect of time in the agricultural field is important where plant diseases increase with plant growth. Therefore, different factors such as time, plant growth rate, plant soil status, leaf area affected by viral, bacterial and fungal diseases etc. have been considered for the data collection. The data collected in this research is based on images in which different levels of measures have been considered. Three different areas of agricultural land on the basis of soil type have been selected. The total area considered for data collection is 10 Acres that is a total of 435600Sq ft.

Data Visualization:
Data is visualized before experimentation in Jupiter Notebook using python language. The visualization ensures the dataset is read and correctly shown the figures of classes.

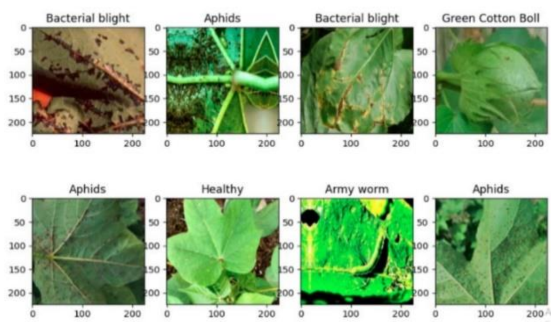

Figure 2 Data exploration and visualization

Figure 2 illustrates some sample images of the dataset captured from the cotton crop fields. The images are collection of different diseases which affect the cotton plants and reduce the production quantity. These diseases also affect the quality of the cotton crops. These disease are caused by different bacterial, viral and fungal effects (Sain , 2021). The images are captured only of leaves because cotton crop disease mostly spread from leaves and are easy target for the cotton insects or other species. More important parts of cotton plants are root, thorn and leaves which are mostly needed to be focused. In this dataset the focus is only given to the cotton plant leaves. A total of 20000 images of cotton crop leaves affected with different type of diseases have been captured. Each leaf may have been affected either with one or more than one diseases.

III. Experimentation and Results

To evaluate the proposed cotton crop disease dataset, an EfficientNet a deep learning-based architecture. The scaling method scales dimensions of depth/width/resolution. The scaling method uniformly scales depth using a compound coefficient [44]. The EfficientNet performs scaling uniformly network width, depth, and resolution with scaling coefficients. The compound scaling used where input of image is higher than the network needs and network require higher neural layers to increase the accessible field capability. The architecture of the EfficientNet model proposed for disease prediction.
The Efficient Net model developed to classify cotton crop diseases from the image patches. Deep learning models vastly used for the segmentation, classification, and diagnosis of plant leaf diseases. EfficientNet used not only for improving accuracy but model accuracy for better and improved classification of plant leaf diseases [45].

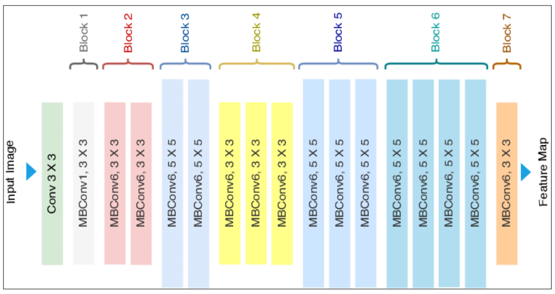

Figure 3 Efficient Net Model Layered Architecture

The figure 3 shows group of the models of efficeintNet consists of 8 models i-e B0 to b7. As the number of the model grows the number of parameters. The Efficient Net model uses a new activation function called Swish instead of traditional CNN models that uses the rectifier linear unit (ReLU) activation function. The inverted bottleneck MBConv is main part of Efficient Net introduced in MobileNetV2 [46]. In MBConv the consecutive layers organized in such a manner, first expands and then compresses the channels, so that bottleneck connections can be directly used with fewer channels than expansion layers. Efficient Net

Architecture has in-depth separable convolutions that reduce calculation by k2 factor as compared to the CNN traditional layers where K shows the kernel size. The traditional CNN layers denote kernel size by k, which used for the width and height of the 2D convolution window. In this paper, Efficient Net B0 used to perform disease classification. Due to the small number of data samples, the B0 model used as it has less number of parameters than other models. The figure 4 shows input model data of Efficient Net B7 for disease classification:

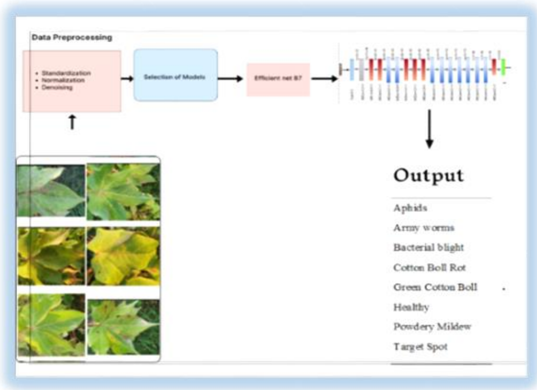

Figure 4 EfficienetNet B7 Input model steps

The dataset divided into two sub-sets i.e. training and testing set using the Scikit-learn's train_test_split method. The training performed on 80% of data samples, while testing performed on the remaining 20% data samples. All the images normalized before passing as input to the network.

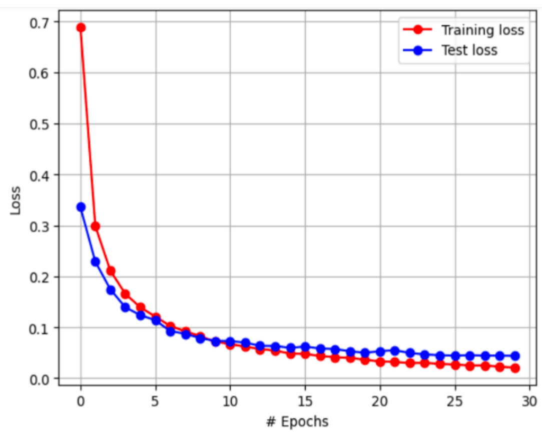

Figure 5 Efficient Net B7 Training Vs Testing Loss

Figure 5 shows the lowest training loss up to 0.7 and the testing loss is 0.38. The model trained with Adam optimizer, sparse categorical cross - entropy, loss function, learning rate of 0.001 and a batch size of 64. The training of the model performed up to 30 epochs.

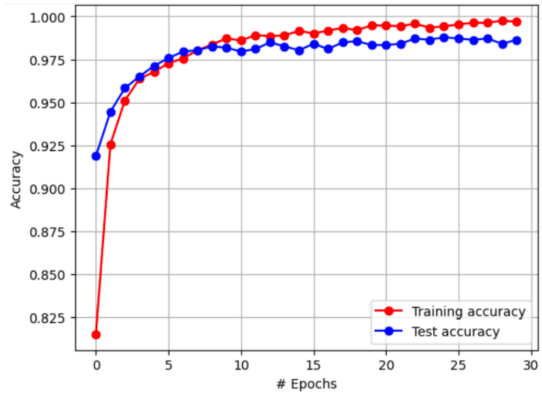

Figure 6 Efficient Net B7 Training Vs Testing Loss

Figure 6 shows training and testing accuracy of Efficient Net Model results. Efficient Net model training accuracy of 0.999 and a testing ac-curacy of 0.990.

To measure the performance of the proposed Efficient Net model disease dataset, the common evaluation matrices such as precision, recall and F1-score used. The proposed method obtained a precision, recall and F1-score of 0.88%, 0.89% and 0.89%, respectively as shown in Table 4.

Table-4. Precision, Recall and F1-Score achieved disease prediction dataset

Method	Precision	Recall	F1-Score	Accuracy
Efficient Net	0.88%	0.89%	0.89%	0.999

Confusion Matrix:

Confusion matrix also known as error matrix is a specific table layout used to visualize the performance of machine learning algorithms. It uses partially in classification problem. It provide summary of how well a model comparing its predictions to the actual outcomes. The rows shows instances from an actual class. Whereas each columns represents instances from a predicted class. In this study confusion matrix is find to evaluate efficient Net B7 model classification performance. The figure below shows model correct predictions vs false predictions.

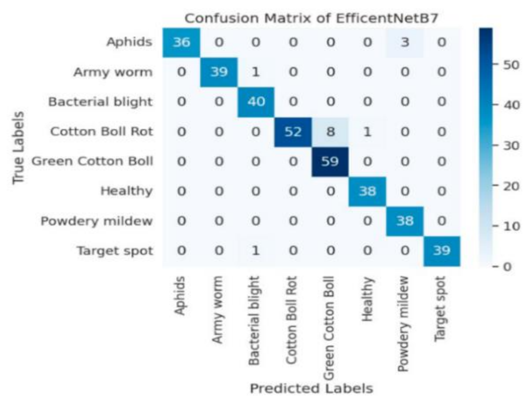

Figure 7 Confusion Matrix Efficient Net B7 for disease classification

The figure 7 shows eight diseases classes' prediction. The blue square numbers shows the correction prediction of efficient Net B7 Model. Whereas the columns shows true labels and rows shows predicted labels of diseases classification. The blue cells counts the instances that falls disease category specifically based on actual and predicted class.

IV. CONCLUSION & RECOMMENDATION

The study conducted few of important aspects of Smart agriculture and Deep learning. Further a detailed discussion with deep learning models training and testing review presented on different crop data sets. This study will provide a comprehensive detail for researchers to improve the cotton crop disease detection and controlled by applying deep learning Models on image data. First collected the data set from different agricultural field of cotton crop. Secondly, data preprocessing phase, labeling of patches constructed with single label. Finally, EfficientNet deep learning network is constructed and tested with training parameters including accuracy, recall and F1-score. Experimentation results shows that EfficientNet Model gives 0.88% accuracy, 0.89 recall and 0.89 F1-score.

4.1 Recommendations:

This study can extend by adding different crop datasets including Soil images and plant roots, stem and color. The video data would more effective in perspective computer vision and advanced deep learning methods.

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