Application for Plant's Leaf Disease Detection using Deep Learning Techniques

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Abstract - *In developing countries agriculture/farming is main source of income to the farmers and for them yield estimation is the central challenge. This can be achieved by monitoring the plant or crop i.e. agricultural monitoring to predict the disease of the particular type of the plant which can help to prevent famine and support our Indian farmers before harvesting any plant. So, we are introducing accurate and generic methods to predict the plant disease using deep learning techniques. First, we will address the diseases to that particular plant and their yield estimation by remotes sensing community and we will propose an approach to tackle the problem based on some of the modern representation learning techniques. We will use the dataset of the country level graph leaf with their respective diseases which allows us to build a model to a train using convolutional neural network and conditional random field techniques which will be incorporated with image processing. This preferred problem in our country show that our approach will perform some competitive techniques.*

Key Words: CNN, agriculture, optimizers, RNN, neural networks, Feature extraction.

1. INTRODUCTION

The relevance of the problem is economical, technological and societal because the detection of plant leaf is very important factor which prevents the serious outbreak within in our national and it also helps our economy's growth. Where we see that automatic detection of plant leaf disease is a challenging essential research topic in India. The most plant diseases have or caused by bacteria, fungi and many deadly harmful viruses which we cannot detect with our naked eye for this we need technological aspects , some experts in observing and identifying the plant diseases by use of some computational approaches such as computer vision, Artificial Intelligence etc. These diseases will destroy the live plants effecting the scarcity of the production to us and keeping the farmers life at stake which is the societal problem too. This challenging problem make developing countries experts expensive and time consuming.

2. LITERATURE SURVEY

Outspread premise work systems [13] called as radial basis function networks (RBFN) and bit neural systems (KNN), for example, a particular probabilistic neural system (PNN), and studies their similitudes and contrasts. So as to [29] keep away from the gigantic measure of concealed units of the KNNs (or PNNs) and lessen the preparation time for the RBFNs, this paper proposes another feedforward neural system model alluded to as outspread premise probabilistic neural system (RBPNN).

This new system model acquires the benefits of the two old models, as it were, and maintains a strategic distance from their imperfections here and there. At last, [34] we apply this new RBPNN to the acknowledgment of one-dimensional cross-pictures of radar targets (five sorts of an airplane).

This computerized [14] strategy classifies maladies on potato plants from 'Plant Village', which is a freely accessible plant picture database. The division approach and usage of an SVM exhibited illness classification in more than 300 pictures and acquired a normal precision of 95%.

The ReliefF [36] technique was first used to separate a sum of 129 highlights, and afterward, an SVM model was prepared with the most significant highlights. The outcomes showed that picture acknowledgment of the four hay leaf maladies can be actualized and acquired a normal exactness of 94.74%.

Different sorts of calculations [15] are incorporated into application programming. Picture examination is one significant technique that assists fragment with imaging into articles and foundation. One of the key strides in picture investigation is an element discovery. The outcomes show that the adequacy of [35] highlights chose by the FC and FS strategy is far superior to that chosen by human haphazardly or different strategies.

Likewise, another methodology is utilized to finding the grape leaf illness recognizable proof or determination, for example, paper clarifying the grape leaf ailment [37] recognition from shading fanciful utilizing crossbreed keen framework, in that programmed plant sickness determination utilizing different fake astute methods.

Customary [39] methodologies for picture classification errands had been founded available built highlights, whose exhibition affected vigorously the general outcomes. FE is an intricate, tedious procedure that should be modified [16] at whatever point the issue or the dataset changes. In this way, FE establishes a costly effort that relies upon specialists' information and doesn't sum up well.

Then again, DL doesn't require FE, [38] finding the significant highlights itself through preparing. A portion of the CNN approaches joined their model with a classifier at the yield layer, for example, [28] calculated relapse, Scalable Vector Machines (SVM), straight relapse, Large Margin Classifiers (LCM) and naturally visible cell automata.

The extricated estimations of the highlights are less for k-implies grouping. The lucidity of k-implies grouping is more exact than another strategy. [17] The RGB picture is utilized for the recognizable proof of sickness. In the wake of applying k-implies bunching systems, the green pixels is recognized and afterward utilizing Otsu's [40] strategy, changing limit esteem is acquired. For the component extraction, shading co-occurrence strategy is utilized.

Significant picture preparing [18] utilized for the recognizable proof of leaf sicknesses is k-implies grouping, SVM. This methodology can fundamentally bolster an exact location of leaf sickness. There are [31] five stages for the leaf sickness ID which are said to be picture obtaining, picture pre-preparing, division, include extraction, grouping.

CNN is a [41] significant example acknowledgment technique both in principle and in the application. The imaginative system which upgrades the profound [19] learning capacity of CNN's which is contrasted with preferable technique over ZCA - Whitening strategy to evacuate the connection of information.

Utilizing histogram handling for enhancement [20] of influenced tissue and concealment of non-influenced tissue. Fluffy C-mean bunching calculation is then utilized with part naming to extricate striking ailment highlights. Shading, [42] shape and size data are taken care of to back-engendering neural system in the phase of malady characterization.

Highlights, for example, shading histogram, surface or edge-based strategies [21] are utilized for finding homogeneous locales in a picture. Picture division strategies are classified as managed or solo. The regulated [43] division approach predefines the qualities of various locales in a picture though in solo division there is no such earlier data. Unaided calculations incorporate parting blending technique.

Cotton Diseases Control has been created in a BP neural system as a dynamic framework. Cotton foliar ailments introduced [22] a strategy for programmed grouping of cotton maladies utilized Wavelet change vitality has been utilized for include extraction while Support Vector Machine has been utilized for order. Prior [44] paper the fluffy element choice methodology fluffy bends (FC) and surfaces (FS) - is proposed to choose highlights of cotton illness leaf the picture.

The proposed frameworks mean at [23] preparing the pictures caught in common conditions from shifting separations. This makes the framework increasingly powerful under various climatic conditions and frameworks [33] proposed for the recognizable proof of Alternaria, Bacterial leaf curse and Myrothecium ailments on cotton leaf.

The [46] pictures are procured utilizing an advanced camera and picture pre-processing systems are utilized to smooth the pictures. At that point picture division strategies are applied to pictures to separate the sickness spot from the foundation. The [45] highlights are separated from these portioned parts and the critical highlights are used to prepare the system that completes the characterization.

The methodology given right now set extraction is the Color Co-event Method. For programmed identification of sicknesses in leaves, neural systems are utilized [24]. The methodology proposed can essentially bolster an exact discovery of the leaf, and is by all accounts a significant methodology, if [47] there should be an occurrence of steam, and root illnesses, investing less amounts of energy in calculation.

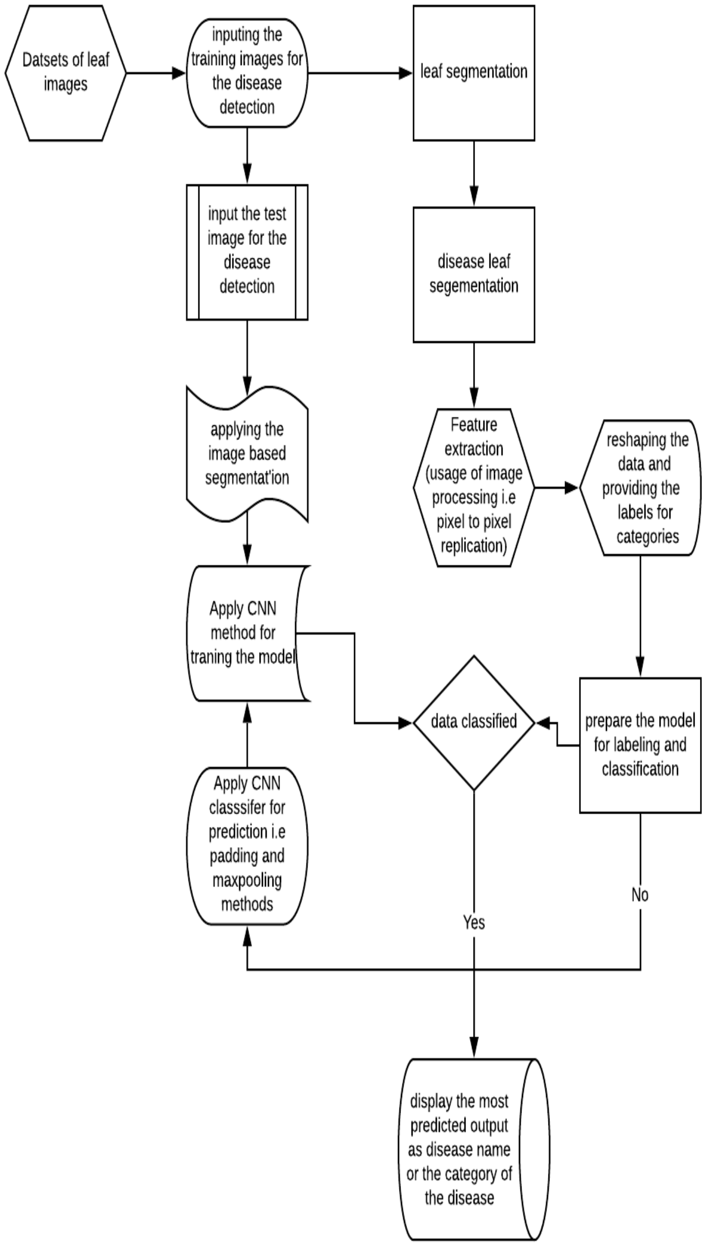
In picture division, [48]an improved histogram division technique that can ascertain limit naturally and precisely is proposed. In the meantime, the territorial development technique and real nature picture preparing are joined with this [25] framework to improve the exactness and insight edge division strategies are presented.

What's more,[49] there are four sections portraying this framework in detail: improved histogram division technique, Disease Recognition System Based on Multiple Linear Regression, multi-selection intelligent picture division strategies.

The unaided eye perception technique is commonly used to choose malady seriousness in the creation practice, yet results are emotional [26] and it is absurd to expect to gauge the infection degree decisively. Matrix tallying technique can be utilized to improve the exactness, yet this strategy has an unwieldy activity procedure and tedious. Picture handling innovation in rural research has made critical advancement. [50] To perceive and characterize sugarcane growths infection a robotized framework has been actualized utilizing a calculation, for example, chain code strategy, bouncing box technique, and minute investigation. The developed processing scheme consists of four main steps, first a color transformation structure for the input RGB image [1] is crated, this RGB is converted to HSI because RGB is for color generation and his for-color descriptor. Than green pixels are masked and removed using specific threshold value, then the image is segmented and the useful segments are extracted, finally the texture statistics is computed. from SGDM matrices. Finally, the presence of diseases on the plant loaf is valuated. Machine vision techniques are [2] used in this system to solve problems of features extraction and analysis of tobacco leaves, which include features of color, size, shape and surface texture. The experimental results show that this system is a viable way for the features extraction of tobacco leaves and can [32] by used for the automatic classification of tobacco leaves. The pixels with zeroes red, green, [3] blue components as well as pixels on the boundaries of infected cluster are completely removed. This is helpful as it gives more accurate disease classification and significantly reduces the processing time. Infected cluster is converted from RGB to HSI color format. The Classification of the presence of diseases on the plant leaf will by identified. In the initial step, RGB images of leaf samples were picked up [4]. The step-by-step procedure as shown blow: RGB image acquisition; convert the input image into color space; Segment the components; obtain the useful segments; [27] Computing the texture features; Configuring the neural networks for recognition. The raw images are divided into training dataset and test dataset. 360 Symptom and 120 healthy images are selected for training [5] and the rest images are used for testing. To prevent over-fitting, the training dataset is further split into training (80%) and validation data (20%). Thus, the training dataset is 960 samples in total, validation dataset is 240 samples in total and test dataset is 419 samples in total.

In this paper, we considered detectors namely Faster Region-Based Convolutional Neural Network (Faster R-CNN), Region-based [6] Fully Convolutional Networks (R-FCN) and Single Shot Multibox Detector (SSD). Each of the architecture should be able to be merged with any feature extractor depending on the application or need. The first part of the model (features extraction), [7] which was the same for full-color approach and gray-scale approach, it consist of 4 Convolutional layers with Relu activation function, each followed by Max Pooling layer. Appropriate datasets are required at all stages of object recognition research, starting from training phase to evaluating the performance [8] of recognition algorithms. Images downloaded from the Internet were in various formats along with different resolutions and quality. In order to get better [47] feature extraction, final images intended to be used as dataset for deep neural network classifier were preprocessed in order to gain consistency. Initially Edge detection based Image segmentation is done, and finally image analysis and classification of diseases is [9] performed using our proposed Homogenous Pixel Counting Technique for Cotton Diseases Detection (HPCCDD) Algorithm. The goal of this research work is identify the disease affected part of cotton leaf sport by using the image analysis technique. It is enhanced by five iterations of Anisotropic Diffusion to preserve the information of affected portion. Anisotropic diffusion is a [10] generalization of this diffusion process; it produces a family of parametrized images, but each resulting image is a combination between the original image and a filter that depends on the local content of the original image. For image recognition applications, [11] several bassline architectures of CNNs have been developed, which have been successfully applied to complicated tasks of visual imagery. The RGB images of citrus leaf are converted [12] into color space representation. The principle of color space is to facilitate the specification of colors in some standard, generally accepted way

3. ARCHITECTURE



Step 1: Identifying the data analytics problems that offer the greatest opportunities to the organization
Step 2: Determining the correct data sets and variables
Step 3: Collecting large sets of structured and unstructured data from disparate sources
Step 4: Cleaning and validating the data to ensure accuracy, completeness, and Uniformity
Step 5: Devising and applying models and algorithms to mine the stores of big Data
Step 6: Analyzing the data to identify patterns and trends
Step 7: Interpreting the data to discover solution s and opportunities
Step 8: Communicating findings to stakeholders using visualization and other means
Step 9: First the images from the dataset are read and converted to arrays and stored with label.

Step 10: Resizing the images.
Step 11: Creating the pickle files for future use.
Step 12: Reshaping the data for model compatibility.
Converting the labels to categories for model compatibility.
Constructing the neural network using convolution, carpooling and dense layers.
Step 13: Fitting the model with 15% shuffling validation data.
Step 14: Saving the model into the pipeline.
Evaluating the model on test data.
Sending the trained model and deploying the model into the server.
Step 15: Now inserting the test data into the website server will send the data to the trained neural network and model will be Predicting a sample image.
Step 16: The front end will deliver the name of the disease to the client

4. ALGORITHM CORRESPONDING TO TRAINING PHASE

Step 1: Convolution is the first layer to extract features from an input image.

Step 2: Stride were the number of pixels shifts over the input matrix. When the stride is 1 then we move the filters to 1 pixel at a time.

Step 3: Padding: Sometimes filter does not fit perfectly fit the input image. We have two options: • Pad the picture with zeros (zero-padding) so that it fits • Drop the part of the image where the filter did not fit. This is called valid padding which keeps only valid part of the image.

Step 4: Non-Linearity Rectified Linear Unit for a non-linear operation. The output is $f(x) = max(0,x)$.

Step 5: Pooling Layer: In this section would reduce the number of parameters when the images are too large. Spatial pooling also called subsampling or down sampling which reduces the dimensionality of each map but retains the important information.

Step 6: Fully Connected Layer we call as FC layer, we flattened our matrix into vector and feed it into a fully connected layer like neural network

5. TECHNICAL SUSTAINABILITY

Grape (Vitis vinifera) cultivation-Viticulture is one of the most remunerative farming enterprises in India. Grapes originated in Western Asia and Europe. Fruit is eaten fresh or made into juice, fermented to wines and brandy and dried into raisins. Grapes also have medicinal properties to cure many diseases. Grapes generally require a hot and dry climate during its growth and fruiting periods. It is successfully grown in areas where the temperature range is from 150-400C. High temperatures above 400C during the fruit growth and development reduce fruit set and consequently the berry size. Low temperatures below 15 C followed by forward pruning impair the budbreak leading to crop failure. Grapes can be cultivated in variety of soils including sandy loams, red sandy soils, sandy clay loams, shallow to medium black soils and red loams. Grape suffers from huge crop losses on account of downy mildew, powdery mildew and anthracnose.

In case of downy mildew, the losses are very high when the clusters are attacked before fruit set. Entire clusters decay, dry and drop down [16]. Plant disease is one of the crucial causes of reduction in quantity and degrades quality of the product. The naked eye observation of experts is the main approach adopted in practice for detection and identification of plant diseases. This approach is prohibitively expensive and time consuming in large farms. Further, in some developing countries, farmers may need to go long distances to contact experts. Diseases are managed by adjusting the pruning time and using various fungicides. Observations during research at NRCG, Pune show that precision farming i.e. using information technology for decision making has improved the yield and quality of crops. This is why our project would be a transformational technology. It would eliminate the need for farmers to travel long distances to contact experts as their phone would be all that is required. This would also explain the sustainability of our model. Being lucrative businesspeople would be continuing to use our system for long periods of time and therefore it is highly economical and sustainable.

6. Comparison with existing models in terms of Technology, cost and feasibility

There are a couple of existing use case models where in grape farmers can check their leaves for diseases. The most standard one involves calling a farming consultant or an expert physically to your form to inspect the leaves in person and deliver a judgement. This method is highly costly, time intense, resource intensive and error prone. Generally using any technology and asking experts will lead to high amount of money put by either farmer or government because to build the prototype itself it costs so much amount of money like governments plan to give farmers for irrigation , pesticides, seeds and then using all these data they will predict whether the usage of this variety of seeds or pesticides will a good resistance or not to the plants. But our model is purely on the data which we collect and provide the strategic prediction which clearly give benefit to the farmers. Another use case model is for the farmer to send samples to the experts and wait for feedback from the expert. Again, this process is cost intensive, time intensive and even more prone to error. Furthermore, there are existing technological platforms which provide similar services, but their drawbacks outweigh their benefits. Namely, they are compute intensive which doesn't suit the rural farmer, they are not specific to grape plants which makes them error prone and they charge high subscription fees. Yet in another case how it can be helpful if there is any destruction caused by locusts (we can see in India from past few days)and how the plant yield can be effected by the millions of locust(swarms) this model can also predict the yield too with zero redundancy.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 254, 254, 32)      896
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 252, 252, 32)      9248
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 31, 31, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 29, 29, 32)        9248
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 27, 27, 32)        9248
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 3, 3, 32)          0
_________________________________________________________________
activation (Activation)      (None, 3, 3, 32)          0
_________________________________________________________________
flatten (Flatten)            (None, 288)               0
_________________________________________________________________
dense (Dense)                (None, 256)               73984
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 1028
=================================================================
Total params: 103,652
Trainable params: 103,652
Non-trainable params: 0
```

Chart -1: Model Summary

7. CONCLUSION

The verification and testing aspects of the project is done by using some of the evaluation metrics accuracy, loss, precision and recall – we are proudly saying that we have achieved 97.36 percent of accuracy in evaluating our neural network model. We have used test data to check the optimal verification to achieve this milestone and this resembles that our dataset what we have preprocessed perfectly was beneficial for testing/ verification aspects. Since we are trying to get firm results if we change the image pixel ratio whether will it give the substantial validation to our model or not, for this we need some time to implement. Fine parameter tuning will be done in order to make our model completely error free and still we our working on pipeline network for the model.

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