

Long Short-Term Memory Recurrent Neural Networks for Plant disease Identification

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Abstract: Farming profitability is something on which economy profoundly depends. This is the one reason that sickness recognition in plants assumes a critical job in farming field, as having infection in plants are very common. In the event that legitimate consideration isn't taken here, it causes genuine consequences for plants and because of which particular item quality, amount or profitability is influenced. This paper displays an algorithm for image segmentation technique which is utilized for automatic identification and classification plant leaf infections. It additionally covers review on various classification techniques that can be utilized for plant leaf ailment discovery. As the infected regions vary in length it is difficult to develop a feature vector of identical finite length representing all the sequences. A simple method to go around this issue is given by Recurrent Neural Networks (RNN). In this work we separate a feature vector through the use of Long Short-Term Memory (LSTM) recurrent neural networks. The LSTM network recursively repeats and concentrates two limited vectors whose link yields finite length vector portrayal.

Keywords: Recurrent Neural Networks, Long Short-Term Memory, Feature Extraction, Classification.

Introduction

Plant disease is a big threat to the agriculture industry across the world because even through horticulture when new hybrid variants of plants were made using Israel technology, if the plant disease is not identified well in advance it may result in total spoil of the entire harvest. A study says that there are around 4 hundred thousand plant species all over the globe and more than 50,000 the varieties of diseases found in plants.

Plant pathology also called as phytopathology is a study of diseases in plants. Plant diseases are caused by infectious organisms (pathogens) and by also environmental conditions (physiological factors). Organisms that because infectious disease include fungi, oomycetes, bacteria, viruses, viroids, virus-like organisms, phytoplasmas, protozoa, nematodes and parasitic plants. Most common plant diseases are Canker, Leaf gall, Leaf curl, Leaf Spot, Powdery Mildew, Root Rot, Wilt, Stunting etc. A symptom of plant disease is a visible effect of disease on the plant. Symptoms may include a detectable change in color, shape or function of the plant as it responds to the pathogen. Leaf wilting is a typical symptom of verticillium wilt, caused by the fungal plant pathogens *Verticillium albo-atrum* and *V. dahliae*. Common bacterial blight symptoms include brown, necrotic lesions surrounded by a bright yellow halo at the leaf margin or interior of the leaf on bean plants.

To treat these plant diseases there are various methods available but to identify the plant disease the only expert method is human intervention to inspect the plant manually and find out the type of disease. The challenging issue is that the success of findings will entirely depend on the expertness of the expert which will differ from person to person. Also, on the other hand there are more similarities from one plant disease and the other where human inspection may result in false identification. One solution to the above problem is to automate the process of identification using image processing techniques. Several machine learning techniques like Support vector machine (SVM), Artificial Neural networks (ANN), K-Nearest neighbour and other AI techniques could be used to recognise or detect disease pattern in plants. But the challenge in doing so is the data set. Though we tend to collect all species all possible disease data set the problem is that every disease may every plan in different fashions. Hence to face all these high challenges we have proposed a Deep learning automated model to develop its own data set and detect the disease with much intelligence, aiming at high success ratio.

Deep learning is one of the subfields of artificial Intelligence (AI) and a growing research area which is employed in almost all areas like medical field, computer vision, biology, speech recognition. Deep learning also employs supervised learning framework in addition. The greater efficiency of deep learning is the mapping of output vectors to the corresponding input vectors even for very large dataset. Deep learning architecture is a widely emerging areas where deep belief network, convolutional neural network and many more efficient architectures are developed day by day. Hence our research work has employed on deep learning approach to develop an automated system for plant disease identification. In narrowed sense the research work has implemented LSTM-RN to extract the features.

Another point to be considered while addressing the plant disease is that, the plant disease can be seen in leaves or flowers or in stems or in fruits among which few of them like flowers and fruits are seasonal. This research work focusses only on leaves which is seen throughout a year. The consequences of disease are seen as brown spots, yellow spots, early scorch and late scorch in leaves.

Literature Survey

Dhaygude Sanjay B et al., in their work have proposed a detection algorithm which is vision based. In their work they have masked green pixels and have used color co-occurrence method to address the goal. In their conclusion they have also suggested that use of Neural network can increase the recognition rate or classification rate [1].

S. Arivazhagan et al., have also worked in the same area of identifying plant diseases using texture features. As like Prof. Sanjay et al., they have also tried color co-occurrence method using Support vector machine as classifier. In their findings they have suggested that by increasing the training samples along with the optimal features, the disease identification can yield better results [2].

Kulkarni Anand. H et al., have used Gabor filter for feature identification and Artificial neural network classifier for classification. The authors have got a reasonable success rate of 78.82% [3]. Piyush Chaudhary et al., have worked on color transform based disease approach to detect disease spot on a leaf. The authors have used median filter for image smoothing and used Otsu used to automatically perform clustering-based image thresholding. In the results they were able to achieve 68.89% success rate [4].

Yan cheng Zang et al., in their research has proposed fuzzy surface and Fuzzy curves for selecting the features of cotton leaves disease [5]. To be more specific they have used a two-step model. The first step is to isolate small set of significant features from original features. Second step is to eliminate the spurious features from the isolated features. The result is the faster execution speed and higher classification success rate as this method does not suffer from local minima problems. Ajay A Gurjar et al., have used eigen feature regularization and extraction technique to detect the plant disease [6]. In their research they are able to detect almost their disease with 90% success ratio.

Dheeb Al Bashish et al., have proposed neural network classifier for detection of plant disease and their work gives out a precision of 93% [7]. A. Meunkaewjinda et al have used back propagation neural network with self-organising map to recognise colors of leaf and further used MSOFM and GA for segmentation and finally SVM for classification [8]. The system demonstrates a promising result. Libo Liu et al., have used BP neural network as classifier [9]. They have confined the problem to identification of brown spot on Paddy crop leaves. But in the conclusion, they have also found that this method is suitable for identifying other disease too.

Tushar H Jaware et al., have used K-means clustering technique for segmentation and after many intermediate processes they have used a pre-trained neural network [10]. Their results gives a precision ranging from 83% to 94%. P. Revathi et al., have used homogeneous segmentation Edge detection techniques. They have used almost spotted eight cotton leaf diseases using neural network [11]. Finally, they suggest that this research can be taken to a level

of implementing the same in mobile phone by developing an application so that the farmers can detect the disease by just a click in their mobile phones.

H. Muhammad Asraf et al., have used support vector machines (SVM) classifier with three kernels and also, they have targeted palm leaves diseases [12]. The polynomial kernel with soft margin has given an accuracy of 95% in successful classification. Satish Madhogaria et al., have worked on detection of unhealthy regions in leaves [13]. They have proposed a three folded algorithm where they have used SVM and neighbourhood-check to identify the unhealthy spots. Their results show that their proposed method excels the existing methods in success rate. Yuan Tian et al., have used three SVM based classifiers [14]. The three features are color, shape and texture respectively. Using the three features the MCS (multiple classifier system) have given higher accuracy.

T. Rumpf et al, have targeted beet leaves disease identification [15]. In their work they have used spectral vegetation indices and support vector machines (SVM). They have expressed that their aim is to identify the disease before the symptom becomes visible to naked eye. The experimental results show that they have achieved an accuracy of 97% in disease identification. S. Phadikar et al., in their research work have targeted paddy plant's morphological change caused by brown spots of the plant [16]. The technique they have used is that the radial distribution of hue from the centre of the boundary of the spot image is obtained and it serves as an important feature for identification. Technically they have used Support vector machine (SVM) and Bayes classifier to do the purpose.

Sannakki S.S et al., have proposed a fast and robust technique for classification and detection of diseases in pomegranate plant [17]. Apart from identification the system also categorises the stage in which the disease is in. They have made use of four folded methodology of implementing artificial neural network, decision tree learning, fuzzy logics and Bayesian networks. Pranjali Vinayak Keskar et al., have also developed a leaf detection and diagnosis system for detection and identification of various plant diseases [18]. For identification of spots they have used component labelling algorithm and for classification they have used artificial neural network.

Classification Methodologies

Before discussing the proposed method, it is necessary to have a brief idea about the methodologies normally used to classify leaf disease by various researchers widely around the globe. Some well-known classification techniques are K-Nearest neighbour, support vector machine, artificial neural network, self-organising map, Probabilistic Neural Networks, Fuzzy Logic etc.

Support vector machine

SVM is also called support vector network, it also one of the supervised learning models. SVM is basically a nonlinear classifier. It is widely used in texture classification and for pattern

recognitions [19-21]. SVM aims in increasing the marginal distance between two classes. Unlike other methods support vector machine has only two classes. The two classes were divided by different kernels. The samples chosen to determine the hyper plane is called support vectors. It is also possible to do multiclass classification by extending the concept to two class SVM (i.e. one-verses-one and one-verses-all).

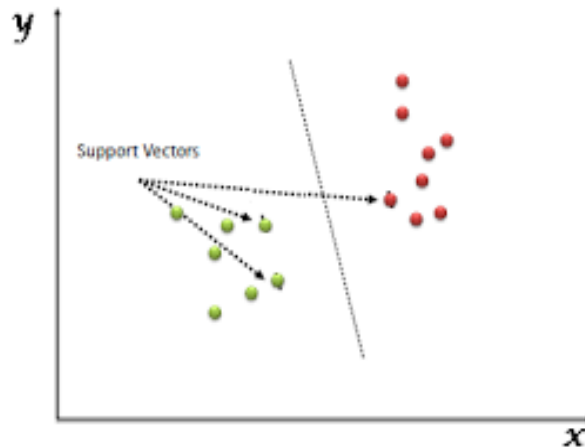


Figure1. Support Vector Machine

Generally, SVM model represents of the examples as points in space. These are mapped in such a way that the examples of the separate categories are divided by a clear wide gap. Also, the New examples are then mapped into that same space predicting a category which is based on the side of gap they fall.

Artificial Neural Network

ANN is also called as connectionist systems. Connectionism is an approach in the fields of cognitive science, that hopes to explain mental phenomena using artificial neural networks (ANN). It is basically an engineering approach depicting the function of neuron. Neural networks are organised as layers by layers. In neural network every hidden layer neuron receives signal from other neurons in input layer. The strength and biases are represented by weights and constants. The weights and constants are calculated during training phase. Once the weights are added the result is then transformed by a transfer function into the output.

The initial artificial neural network that was proposed had only input and output neurons which are capable to solve only linear problems. But later Multi-layer perceptron (MLP) was developed which had one or more feed-forward networks in between input and output layer.

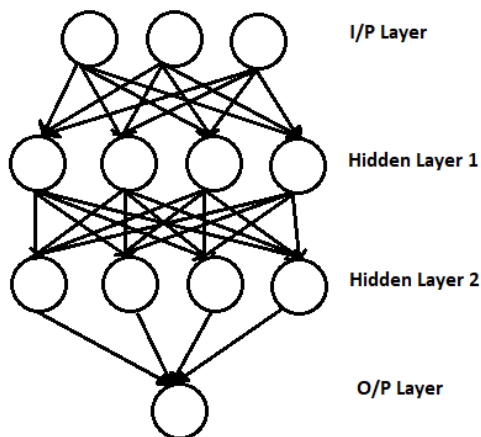


Figure 2. Artificial Neural network

Proposed Methodology

A step by step approach for the proposed image recognition and segmentation system is given as follows:

- (1) Image acquisition is the first step that involves in capturing an image using a digital camera.
- (2) Pre-processing of input image is done to improve the image quality and to remove the unwanted distortions from the image. If needed Clipping of the leaf image is done to get the interested region and then image smoothing is done using the smoothing filter. To increase the contrast Image enhancement is also done.
- (3) Then using the Long Short-Term Memory Recurrent Neural Network the features are extracted in recursive way after many iterations
- (4) The obtained useful segments are used classify the leaf diseases

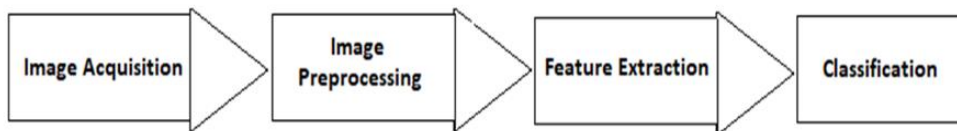


Figure 3. Image Pre-processing

A) Image Pre-processing

Crude images will not fit for image processing and should be changed over into the handled format, for example, jpeg, jpg and tiff for further analysis purpose (Figure 3). In this work, the acquired images were put away in a format of Nikon camera, named Nikon Electronic File (NEF). Adobe Photoshop was utilized to change over these crude images into Tagged Image File Format (TIFF). Likewise, the texture noises of the images were diminished by utilizing Adobe Photoshop and MATLAB R2016a was utilized for resizing and image conversion.

B) Feature Extraction and Classification

For feature extraction and classification long short term memory units is used as it LSTMs help preserve the error that can be back propagated through layers and time. The detailed implementation is discussed in the following sections.

Algorithms and Implementations

Long Short-Term Memory units [LSTMs] are basically an improved version of recurrent neural networks. LSTMs help save the mistake that can be backpropagated through time and layers. By maintaining a progressively consistent mistake, they enable intermittent nets to keep on learning over many time ventures (more than 1000), in this manner opening a channel to interface circumstances and end results remotely. This is one of the focal difficulties to machine learning and AI, since calculations are much of the time stood up to by situations where compensate signals are inadequate and deferred. LSTMs contain data outside the typical stream of the intermittent system in a gated cell. Data can be put away in, written to, or read from a cell, much like information in a PC's memory. The cell settles on choices about what to store, and when to permit peruses, composes and deletions, by means of doors that open and close. In contrast to the computerized stockpiling on PCs, be that as it may, these entryways are simple, executed with component insightful duplication by sigmoids, which are all in the scope of 0-1. Simple has the preferred standpoint over computerized of being differentiable, and thusly reasonable for back-propagation (Figure 4).

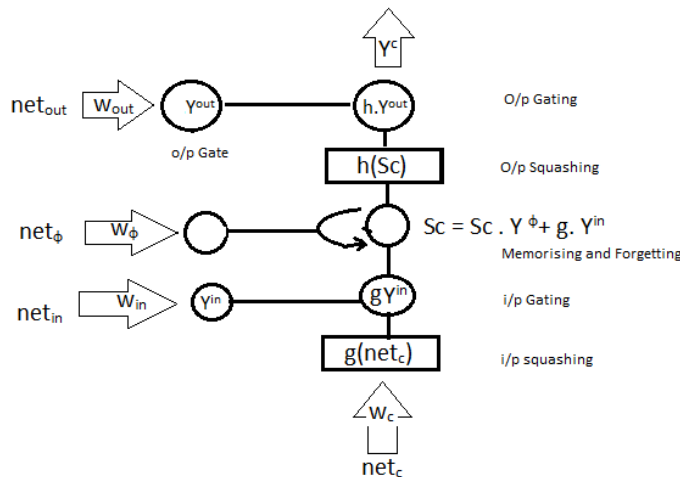


Figure 4. Algorithms and Implementation

Those entryways follow up on the signs they get, and like the neural system's hubs, they square or pass on data dependent on its quality and import, which they channel with their very own arrangements of loads. Those loads, similar to the loads that tweak input and shrouded states, are balanced by means of the repetitive systems learning process. That is, the cells realize when to enable information to enter, leave or be erased through the iterative procedure of

making surmises, back-propagating blunder, and modifying loads by means of angle plummet. The diagram beneath outlines how data moves through a memory cell and is controlled by its Gates.

Starting from the base, the Block arrow show where information flows into the cell at different points. That combination of present input and past cell state is sustained not exclusively to the cell itself, yet additionally to each of its three gates, which will decide how the input will be dealt with.

The gates determine respectively whether to give new input access, erase the present cell state, and additionally given that state a chance to impact the system's yield at the present time step. S_c is the current state of the memory cell, and g_{y_in} is the current input to it. Keep in mind that each gate can be open or shut, and they will recombine their open and shut states at each step. The cell can forget its state, or not; be composed to, or not; and be perused from, or not, at each time step, and those flows are also represented.

In this work, we prepared three distinctive AI calculations on an indistinguishable dataset portrayed in the following sections. The dataset contains 2641 samples of infected leaves and 4489 likely non-infected leaves with 7130 all in total samples. Because of the marginally lopsided nature of the dataset, we utilized defined parts to make a held out test set comprising of 20% of the information just as to part the rest of the preparation occurrences to decide hyper parameters during 5-fold cross validation.

Results of LSTM

The LSTM repetitive neural system applied to the sample grouping highlight portrayal of the leaves was bidirectional. This means the neural network recurred over each sequence of amino acids from both the N-terminus to C-terminus direction and the C-terminus to N-terminus direction. For each sample composing the sequence an input of 86 features was provided. The hidden layer consisted of 512 LSTM hidden units for each direction so the bidirectional hidden layer representation was a 1024 length vector after concatenation. The first and last outputs from the bidirectional hidden layer representation were then concatenated to generate a 2048 length vector, and passed through a feed-forward dense layer into a 2 element softmax layer for classification.

Hyperparameters for the LSTM arrange were tuned physically utilizing a similar 5-Fold cross approval as different methods analyzed. The Adam, adaptive momentum, optimizer was utilized with default parameters including a learning pace of $1.0e4$. A batch size of 128 was picked, and the last system was prepared for 55 epochs. The system likewise didn't utilize peepholes, the default setting in Tensorflow. This implies the terms containing the image p in (2), (3) and (5) are basically focused out and can be disregarded.

As mentioned over, the 86 example highlights filled in as the info grouping to the LSTM. The highlights were focused and scaled with the goal that the mean contribution for each element

over all arrangement components in the preparation set has mean zero and unitvariance aside from the NNAAIndex factors which were just mean focused and the one-hot vectors which were neither focused nor scaled.

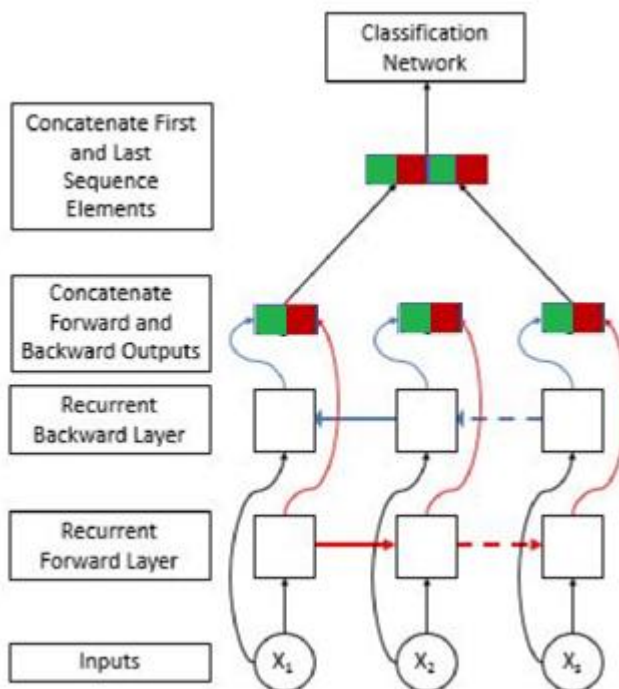


Figure 5. Bidirectional Long Short Term Memory recurrent neural network Topology

The accuracy of 95.79% and Matthew’s Correlation Coefficient (MCC) of .9096 shown in Table I was achieved by LSTM. This result suggested that the peptide representation derived by LSTM at the concatenation layer efficiently summarized the sequence of amino acid feature vectors in a way that was relevant to the classification task.

Table 1. Algorithm Performance

Algorithm	Accuracy	MCC
LSTM	95.79%	.9096
RF	94.95%	.8915
KNN	93.19%	.8538

Results of Random Forests

The RF algorithm performed almost just as the LSTM. As can be found in Table I, the RF algorithm achieved 94.95% accuracy and a MCC of .8915. The optimal performing RF

during cross validation utilized: Gini impurity for measuring the quality of splits in the decision trees, and the square root of the total number of features during each split [22-27]. Additionally, each tree could grow in depth until there were less than 3 samples at an internal node and there were at least 3 samples at each leaf node. The forest was composed of 512 decision trees.

Conclusion

The best performing kNN algorithm on validation data used 4 neighbors and the distance between the query point and its neighbors calculated as $1/(1+\text{bit-score})$, where bit-score is the similarity between the pairs. The bit-score is essentially a normalized version of a raw score. The raw score is the summed cost of matches and mismatches of residues in the alignment while the bit score takes into account the query sequence length and the database size during the normalization process. This makes the bit-score largely independent of the number of peptides in the database and query inputs to proteinprotein BLAST+. The kNN test set classification accuracy was 93.19% and its MCC was .8538, which indicate it underperformed both random forests and the LSTM. The final test set scores shown under the three algorithms in Table I show the LSTM outperforms the RF and kNN methods in terms of accuracy but the difference in performance between the LSTM and RF is likely insignificant with a difference of approximately 1% on an identical test set. A potential reason for the underperformance of the kNN algorithm is its total reliance on sequence similarity alone.

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Conflict of interest

The Authors have no conflicts of interest to declare that they are relevant to the content of this article

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