



## **Deep Learning and Neural Network**

### Leaf Classification

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## **Project description:**

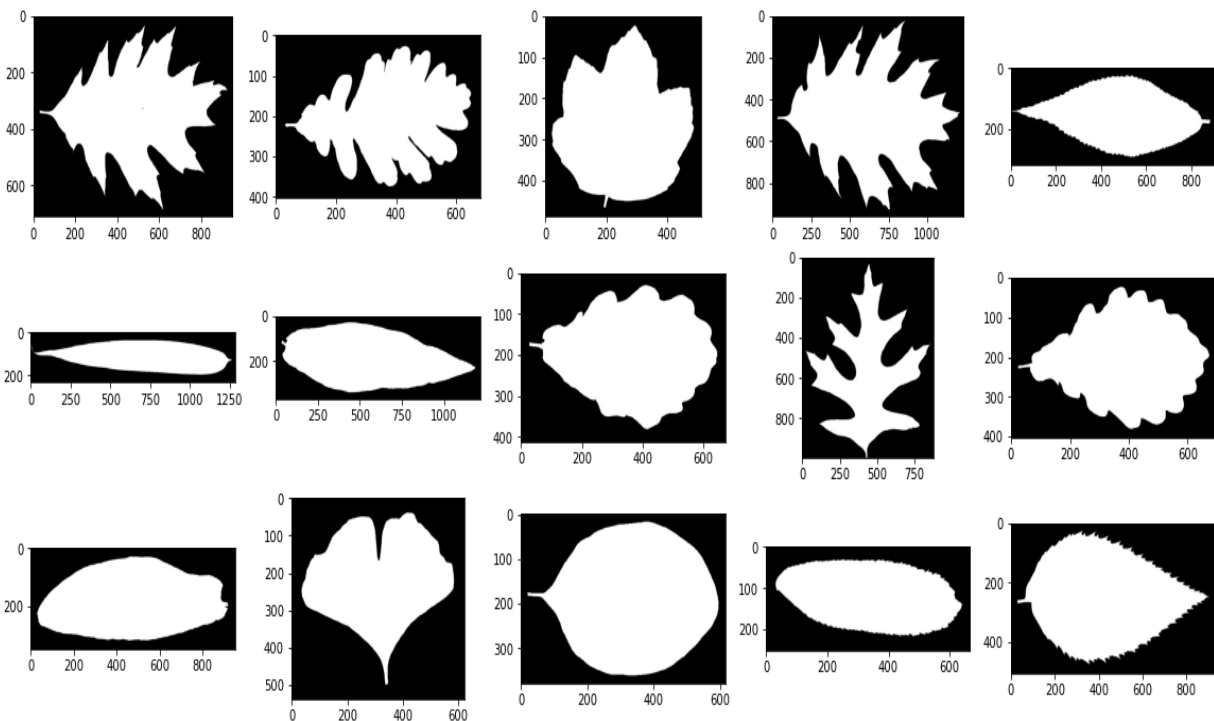
The objective of this project is to use extracted features, including shape, margin & texture, to accurately identify 99 species of plants. Leaves, due to their volume, prevalence, and unique characteristics, are an effective means of differentiating plant species.

In this project, 3-layer MLP model is implemented which consists of one input layer, one hidden layer with tanh activation and one output layer with SoftMax as activation function. This neural network will be used to classify the data in our dataset using TensorFlow and the built-in modules in keras to build the model.

The project includes many trials with different hyper parameters—, optimizers, learning rate and number of neurons in each layer to be able to reach the optimal solution that will best classify our data.

## **Dataset:**

The dataset consists approximately 1,584 images of leaf specimens (16 samples each of 99 species) which have been converted to binary black leaves against white backgrounds. Three sets of features are also provided per image: a shape contiguous descriptor, an interior texture histogram, and a fine-scale margin histogram. For each feature, a 64-attribute vector is given per leaf sample.



## **Data fields:**

1. id - an anonymous id unique to an image.
2. margin\_1, margin\_2, margin\_3, ..., margin\_64 - each of the 64 attribute vectors for the margin feature.
3. shape\_1, shape\_2, shape\_3, ..., shape\_64 - each of the 64 attribute vectors for the shape feature.
4. texture\_1, texture\_2, texture\_3, ..., texture\_64 - each of the 64 attribute vectors for the texture feature.

## **Methods:**

Firstly, we check if there are missing values, duplicate values then we calculate z-score to check if we need to make standard scaler. Based on correlation between columns we drop useless columns.

After that, we made function contains the whole model with all hyperparameters and the evaluation of the model. This function contains the following hyperparameters:

1. Batch size
2. Hidden nodes
3. Learning rate
4. Epochs
5. L2-regularization
6. Dropout

We set the default values of hyperparameters on each optimizer then we set different values of hyperparameters. Also, we used a learning rate scheduler to change the learning rate for each epoch. Then we plot a graph for each model to represent the difference between training loss and validation loss, training accuracy, and validation accuracy.

## **Optimizers:**

1. SGD
2. Adam
3. RMSProp

## Discussion:

1. -Learning rate scheduler that adjusts the learning rate between epochs or iterations as the training progresses.
2. -There are three cases in learning rate:
  - If the learning rate is too high that run faster and not reaches to minimum point cause divergent.
  - The optimal learning rate reaches the min point.
  - If the learning rate is too small requires more than one update and it takes time to reach the min point.
3. -L2-regularization doesn't sparse weights are used to prevent the overfitting (when L2-regularization has a small value the overfitting will be decreased).
4. -Dropout is a technique where randomly selected neurons to be ignored during training. It uses to prevent the overfitting.

### • SGD:

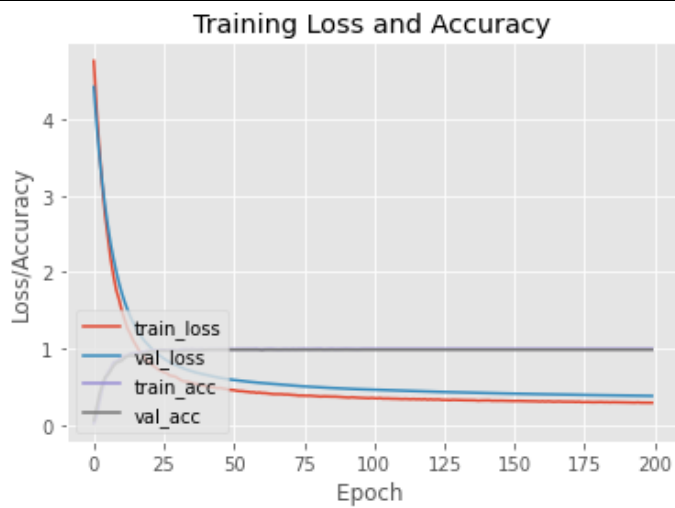
Stochastic gradient descent is considered an iterative method for optimizing an objective function with suitable smoothness properties. It can be regarded as a stochastic approximation of gradient descent optimization, since it replaces the actual gradient that is calculated from the entire data set by an estimate thereof calculated from a randomly selected subset of the data. This reduces the computational complexity especially in high-dimensional optimization problems which help in achieving faster iterations in trade for a lower convergence rate. SGD was able to solve the Gradient Descent problem by using only single records to updates parameters. But still SGD is slow to converge as it needs forward and backward propagation for each record and therefore the path to reach global minima becomes very noisy.

Optimizer (SGD)	Hidden nodes	L2-regularization	Learning rate	Dropout	epochs	Accuracy
First Trial	800	0.01	0.001	0.4	100	0.66
Second Trial	1070	0.001	0.01	0.4	200	0.98
Third Trial	400	0.01	0.1	0.6	20	0.97



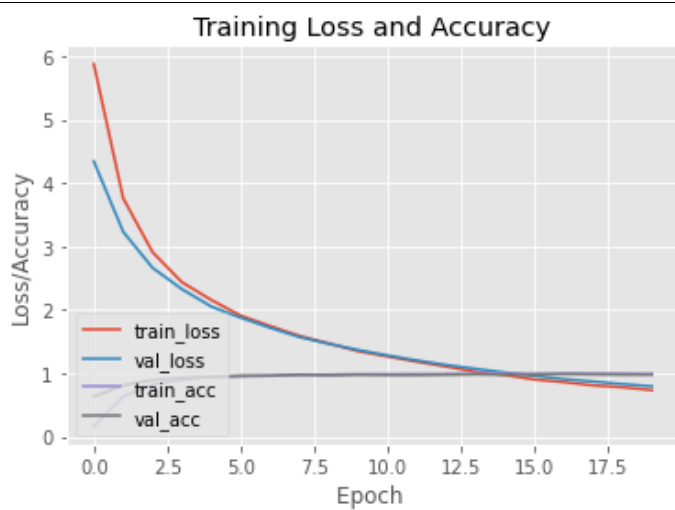
### First Trial

loss: 4.9 - accuracy: 0.66



### Second Trial

loss: 0.38- accuracy: 0.98



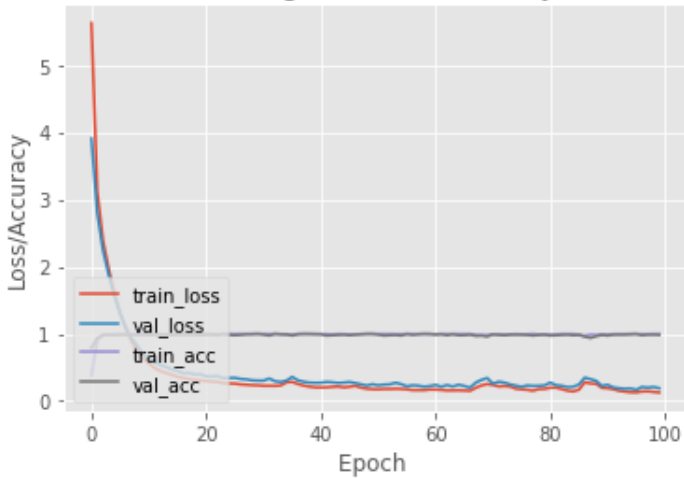
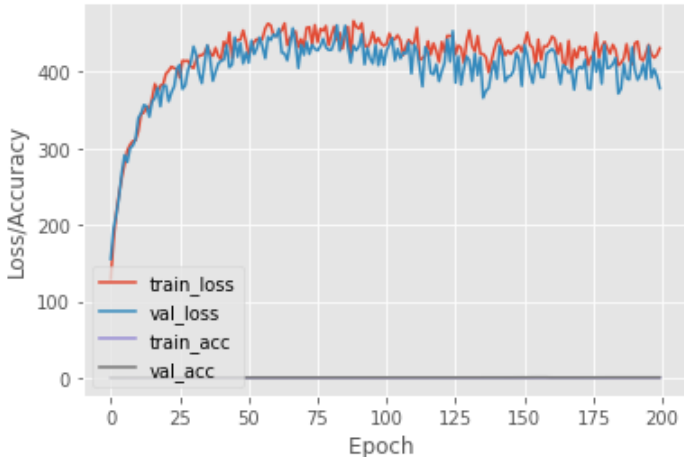
### Third Trial

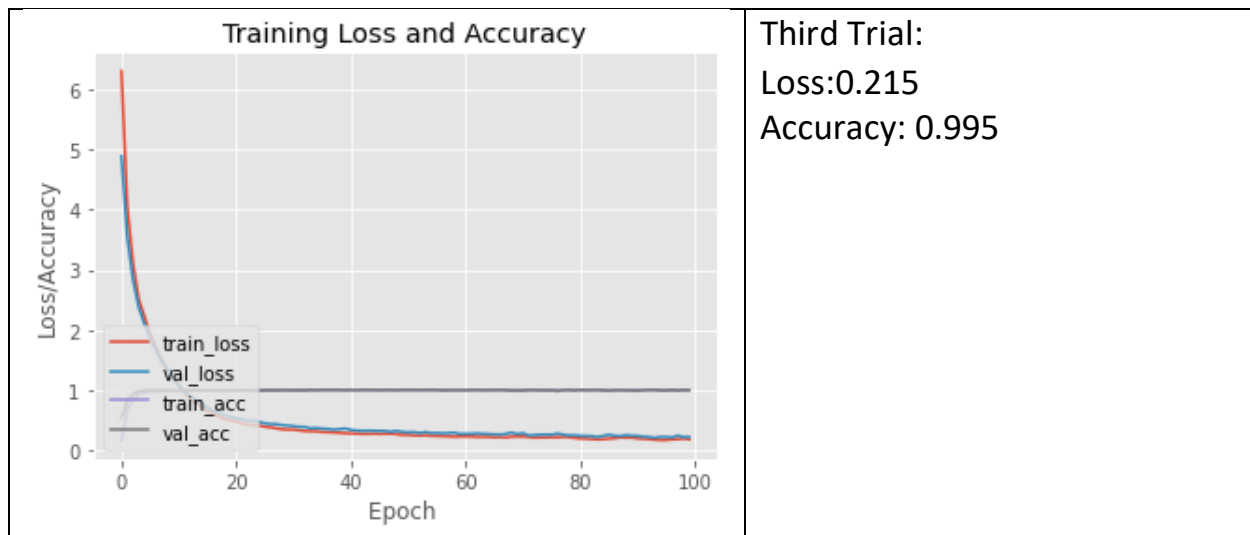
loss: 0.8 - accuracy: 0.97

- **Adam:**

Adam optimization extends on stochastic gradient descent to solve non-convex problems faster that is based on adaptive estimation of first order and second-order moments. The method is efficient with working on large problem involving a lot of data or parameters. It requires less memory and efficient.

Optimizer (Adam)	Hidden nodes	L2- regularization	Learning rate	Dropout	epochs	Accuracy
First Trial	1092	0.01	0.001	0.4	100	0.98
Second Trial	800	0.1	0.1	0.4	200	0.626
Third Trial	600	0.01	0.001	0.6	100	0.995


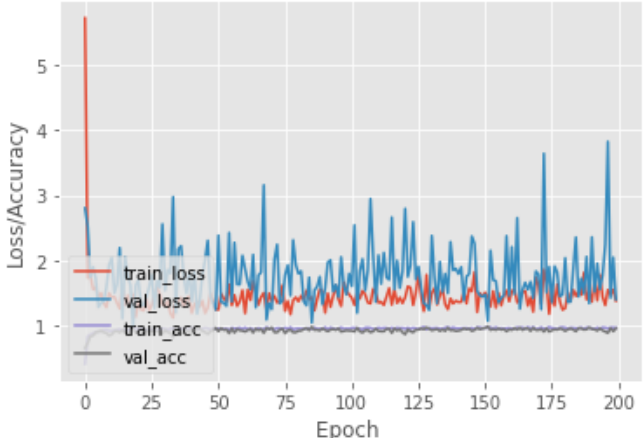

Graph	Accuracy
<p>Training Loss and Accuracy</p> 	<p>First Trial: Loss:0.19 Accuracy: 0.98</p>
<p>Training Loss and Accuracy</p> 	<p>Second Trial: Loss:378.3 Accuracy: 0.626</p>



- **RMSProp:**

The RMSprop optimizer is like the gradient descent algorithm with momentum. The RMSprop optimizer restricts the oscillations in the vertical direction. As a result, we can increase our learning rate and our algorithm could take larger steps converging faster. The difference between RMSprop and gradient descent is on how the gradients are calculated.

Optimizer (RMSProp)	Hidden nodes	L2-regularization	Learning rate	Dropout	epochs	Accuracy
First Trial	1092	0.01	0.1	0.6	100	0.79
Second Trial	1070	0.001	0.01	0.4	200	0.98989
Third Trial	1000	0.01	0.1	0.6	100	0.9596

Graph	Accuracy
<p data-bbox="402 155 732 184">Training Loss and Accuracy</p> 	<p data-bbox="894 155 1045 184">First Trial:</p> <p data-bbox="894 201 1317 231">Loss:215.41    Accuracy:0.79</p>
<p data-bbox="391 672 743 701">Training Loss and Accuracy</p> 	<p data-bbox="894 672 1089 701">Second Trial:</p> <p data-bbox="894 718 1300 747">Loss:1.4    Accuracy:0.9545</p>
<p data-bbox="402 1163 732 1192">Training Loss and Accuracy</p> 	<p data-bbox="894 1163 1057 1192">Third Trial:</p> <p data-bbox="894 1209 1312 1239">Loss:233.66 -Accuracy: 0.68</p>



### **Now we will display results with Learning Rate Schedule**

Optimizers	Hidden nodes	L2-regularization	Dropout	Epochs	Loss-Accuracy
Adam	1092	0.01	0.4	100	0.0876 - 0.9899
RMSProp	900	0.01	0.4	100	0.2836-0.989
SGD	1092	0.001	0.4	20	1.26-0.919

### **Note:**

RMSProp gives us the same accuracy as Adam but Adam gives us the least loss with high accuracy

### **Conclusion**

To prevent the overfitting, we use dropout and L2-regularization. According to the above outputs, the Adam & and RMSProp optimizers are close in accuracy. However, Adam is the optimization to choose the least loss function with highest accuracy.