

# Leaf-Classification

Use deep learning to classify the species of leaf automatically.

Chia Hao Tang

# Content

## Motivation & Purpose

➤ Motivation

➤ Purpose

Classify the species of leaf  
automatically?

## Data information

➤ Data source

➤ Data file

☐ Train.csv

☐ Test.csv

➤ Data feature

☐ Margin

☐ Shape

☐ Texture

## Setup

➤ Preprocess data

➤ Model structure

☐ Model0

☐ Model1

☐ Model2

☐ Model3

☐ Model4

☐ Model5

## Result

➤ Fitting  
environment(each  
model is same)

➤ Accuracy  
rate([Model0](#),[Model1](#),[Model2](#),[Model3](#),[Model4](#),[Model5](#))

# Motivation & Purpose

Classify the species of leaf automatically?

There are estimated to be nearly half a million species of plant in the world. Classification of species has been historically problematic and often results in duplicate identifications.

If we can create the classifier to classify the species of leaf automatically, it means we can create the model as botanist through the trained model with dataset of leaf.

My purpose is **try building a classifier that uses the provided pre-extracted features.**

---

# Date information

## Data source

### Data description

The data consists approximately 1,584 data of leaf specimens (16 samples each of 99 species) .

## Data feature

### Feature type

Three sets of features are also provided per image: a **shape(shape1~shape 64)** **contiguous descriptor**, an **interior texture(texture 1~texture 64)** **histogram**, and a **fine-scale margin(margin 1~margin 64)** **histogram**. For each feature, a **64-attribute vector** is given per leaf sample.

## Data file

### File description

- **Train.csv**(990 data containing 64 features and corresponding species)
- **Test.csv**(594 data containing 64 features and no species)

# Data file (ex: Train.csv include 990 data)

Features of leaf

id	species	margin1	margin2	margin3	margin4	margin5	margin6	margin7	margin8	margin9	margin10	margin11	margin12	margin13
1	Acer_Opalus	0.007612	0.023438	0.023438	0.003906	0.011719	0.009766	0.027344	0	0.001953	0.033203	0.013672	0.019531	
2	Pterocarya_Stenopt	0.005859	0	0.03125	0.015625	0.025391	0.001953	0.019531	0	0	0.007812	0.003906	0.027344	
3	Quercus_Hartwissian	0.005859	0.009766	0.019531	0.007812	0.003906	0.005859	0.068359	0	0	0.044922	0.007812	0.011719	
5	Villia_Tomentosa	0	0.003906	0.023438	0.005859	0.021484	0.019531	0.023438	0	0.013672	0.017578	0.001953	0.019531	
6	Quercus_Variabilis	0.005859	0.003906	0.048828	0.009766	0.013672	0.015625	0.005859	0	0	0.005859	0.001953	0.044922	
8	Magnolia_Salicifolia	0.070312	0.09375	0.033203	0.001953	0	0.15234	0.007812	0	0.003906	0.027344	0.058594	0	
10	Quercus_Canariensis	0.021484	0.03125	0.017578	0.009766	0.001953	0.042969	0.039062	0	0.003906	0.019531	0.035156	0.015625	
11	Quercus_Rubra	0	0	0.037109	0.050781	0.003906	0	0.003906	0	0.048828	0.003906	0.001953	0.005859	
14	Quercus_Brantii	0.005859	0.001953	0.033203	0.015625	0.001953	0	0.023438	0	0	0.021484	0.007812	0.033203	
15	Salix_Fragilis	0	0	0.009766	0.037109	0.072266	0	0	0	0.007812	0.001953	0	0.029297	
17	Salix_Semata	0.019531	0.03125	0.001953	0.005859	0.003906	0.013672	0.033203	0	0.011719	0.042969	0.015625	0.017578	
18	Betula_Austrosinensi	0.001953	0.001953	0.023438	0.025391	0.076172	0	0.029297	0	0.005859	0.015625	0.001953	0.003906	
20	Quercus_Pontica	0.015625	0.011719	0.041016	0.003906	0.023438	0.015625	0.019531	0	0.009766	0.015625	0.003906	0.046875	
21	Quercus_Alfari	0.011719	0.011719	0.054688	0.017578	0.007812	0.009766	0.011719	0.007812	0.025391	0.015625	0.027344	0.009766	
22	Quercus_Coccifera	0.011719	0.007812	0.11133	0.027344	0.023438	0.039062	0.013672	0	0.001953	0.013672	0.005859	0.009766	
23	Quercus_Sylvatica	0.027344	0.025391	0.066406	0.007812	0.003906	0.052734	0.03125	0	0.003906	0.039062	0.003906	0.001953	
26	Philadelphus	0.009766	0.0625	0.033203	0.029297	0.011719	0.044922	0.005859	0	0.009766	0.017578	0.039062	0.001953	
27	Acer_Palmatum	0	0	0.001953	0.029297	0.11133	0	0	0	0.029297	0	0	0	
28	Quercus_Pubescens	0.001953	0	0.015625	0.03125	0.011719	0	0.021484	0.001953	0.005859	0.013672	0.003906	0.015625	
30	Populus_Adenopoda	0.005859	0.027344	0.017578	0.041016	0.007812	0.017578	0.046875	0.001953	0	0.044922	0.001953	0.001953	
31	Quercus_Trojana	0.019531	0.019531	0.064453	0.025391	0.007812	0.005859	0.023438	0	0.005859	0.003906	0.011719	0.021484	
32	Quercus_Variabilis	0.019531	0.029297	0.080078	0.033203	0.025391	0.023438	0.009766	0.005859	0	0.009766	0.021484	0.011719	
33	Alnus_Sieboldiana	0	0.005859	0.023438	0.001953	0.013672	0.001953	0.015625	0	0.003906	0.007812	0.001953	0.019531	
35	Quercus_Ilex	0.029297	0.033203	0.033203	0.021484	0.001953	0.068359	0.037109	0	0.005859	0.080078	0.029297	0.005859	
37	Arundinaria_Simonii	0.001953	0.023438	0.005859	0.029297	0	0	0	0	0.011719	0	0.10742	0	
38	Acer_Platanoides	0.015625	0.03125	0.10156	0.015625	0.005859	0.017578	0	0	0.041016	0.005859	0.015625	0.007812	
40	Quercus_Phillimorei	0.027344	0.009766	0.021484	0.042969	0.017578	0.009766	0.037109	0.03125	0.005859	0.037109	0.021484	0.003906	
42	Cornus_Chinensis	0.085938	0.095703	0.007812	0.003906	0	0.14844	0.007812	0	0.007812	0.027344	0.023438	0	
43	Quercus_Phillimorei	0.001953	0.003906	0.017578	0.044922	0.041016	0.011719	0.039062	0.013672	0.011719	0.021484	0.011719	0.003906	



Tip

The data source is from Kaggle:  
<https://www.kaggle.com/c/leaf-classification-on-data>

Species of leaf

# Data file (ex:Test.csv include 594 data) Features of leaf

id	margin1	margin2	margin3	margin4	margin5	margin6	margin7	margin8	margin9	margin10	margin11	margin12	margin13	margin14
4	0.019531	0.009766	0.078125	0.011719	0.003906	0.015625	0.005859	0	0.005859	0.023438	0.005859	0.021484	0.076172	
7	0.007812	0.005859	0.064453	0.009766	0.003906	0.013672	0.007812	0	0.033203	0.023438	0.009766	0.019531	0.039062	
9	0	0	0.001953	0.021484	0.041016	0	0.023438	0	0.011719	0.005859	0.001953	0.021484	0.001953	
12	0	0	0.009766	0.011719	0.017578	0	0.003906	0	0.003906	0.001953	0	0.029297	0	
13	0.001953	0	0.015625	0.009766	0.039062	0	0.009766	0	0.005859	0	0.001953	0.033203	0	
16	0.021484	0.033203	0.021484	0.009766	0.015625	0.035156	0.039062	0	0.003906	0.029297	0.013672	0.019531	0.042969	
19	0.015625	0.025391	0.046875	0.009766	0.005859	0.027344	0.042969	0	0	0.027344	0.015625	0.009766	0.044922	
23	0.007812	0.03125	0.011719	0.050781	0	0.11719	0.003906	0	0.011719	0.017578	0.056641	0.001953	0.046875	
24	0.003906	0.007812	0.074219	0.017578	0.015625	0.003906	0.011719	0	0.009766	0.011719	0.023438	0.037109	0.044922	
28	0	0	0.005859	0.021484	0.054688	0	0.015625	0	0.011719	0.005859	0	0.033203	0.001953	
33	0.025391	0.041016	0.033203	0.017578	0.009766	0.056641	0.023438	0	0.005859	0.027344	0.039062	0.001953	0.054688	
36	0.001953	0.009766	0.025391	0.003906	0.015625	0.003906	0.041016	0	0.005859	0.013672	0.007812	0.03125	0.025391	
39	0.013672	0	0.046875	0.019531	0.005859	0	0.041016	0	0.013672	0.013672	0.001953	0.009766	0.017578	
41	0.007812	0.005859	0.060547	0.013672	0.011719	0	0.037109	0	0	0.044922	0.011719	0.005859	0.009766	
44	0.017578	0.039062	0.03125	0.005859	0.005859	0.039062	0.013672	0	0.007812	0.023438	0.017578	0.025391	0.046875	
46	0.011719	0.017578	0.11133	0.009766	0.007812	0.011719	0.027344	0	0	0.005859	0.015625	0.003906	0.033203	
47	0.025391	0.015625	0.13281	0.003906	0.001953	0.009766	0.001953	0	0	0.011719	0.003906	0.009766	0.078125	
51	0.007812	0.007812	0.019531	0.039062	0.03125	0.021484	0.039062	0	0.001953	0.015625	0.013672	0.005859	0.027344	
52	0.001953	0.007812	0.03125	0.005859	0.013672	0.003906	0.015625	0	0	0.005859	0.001953	0.029297	0.025391	
53	0	0	0.082031	0.11133	0.017578	0	0	0	0.013672	0	0	0.009766		
57	0.013672	0.023438	0.007812	0.054688	0.001953	0.083984	0.019531	0	0.001953	0.052734	0.027344	0.005859	0.011719	
59	0.011719	0.011719	0.048828	0.005859	0.007812	0.015625	0.046875	0.005859	0	0.048828	0.015625	0.003906	0.011719	
62	0.037109	0.1582	0.013672	0.009766	0	0.20313	0	0	0.005859	0.001953	0.091797	0.003906	0.134	
65	0.027344	0.056641	0.021484	0.011719	0.005859	0.019531	0.029297	0	0	0.048828	0.064453	0.003906	0.060547	
68	0	0	0.003906	0.021484	0.023438	0	0.003906	0	0.005859	0	0	0.013672	0.001953	
70	0.015625	0.023438	0.025391	0.011719	0.005859	0.005859	0.011719	0	0	0.023438	0.070312	0.001953	0.082031	
74	0.019531	0.064453	0.009766	0.039062	0	0.13867	0.001953	0	0.009766	0.007812	0.041016	0	0.060547	
77	0	0.095703	0	0.017578	0	0	0	0.005859	0	0	0.064453	0	0.418	
79	0.001953	0	0.015625	0.11328	0.023438	0	0	0	0.017578	0.007812	0.005859	0.003906	0.001953	

No species(need to classify through trained model)



Tip

The data source is from Kaggle:  
<https://www.kaggle.com/c/leaf-classification/data>

# Setup

## Processing data

### 1. Processing data(Train data)

I. Encode the species of leaf and Split the train data of encoded species as "label"

II. Split the train data(label) into training data(label) and validation data(label).

III. Take the training and validation data into the array for fitting model's shape and suitably identifying features.

---

# Setup

## Processing data

### 1. Processing data(Train data)

I.Encode the species of leaf and Split the train data of encoded species as "label"

II.Spilt the train data(label) into training data(label) and validation data(label).

III.Take the training and validation data into the array for fitting model's shape and suitably identifying features.

---



# Encode the species of leaf and split the train.csv of encoded species as "label"

Train.csv

id	species	margin1	...	texture62	texture63	texture64
1	Acer_Opalus	0.007812	...	0.004883	0.000000	0.025391
2	Pterocarya_Stenoptera	0.005859	...	0.000977	0.039062	0.022461
3	Quercus_Hartwissiana	0.005859	...	0.000000	0.020508	0.002930
5	Tilia_Tomentosa	0.000000	...	0.017578	0.000000	0.047852
6	Quercus_Variabilis	0.005859	...	0.000000	0.000000	0.031250
...	...	...	...	...	...	...
1575	Magnolia_Salicifolia	0.060547	...	0.000000	0.000000	0.018555
1578	Acer_Pictum	0.001953	...	0.000977	0.000000	0.021484
1581	Alnus_Maximowiczii	0.001953	...	0.027344	0.000000	0.001953
1582	Quercus_Rubra	0.000000	...	0.000000	0.001953	0.002930
1584	Quercus_Afares	0.023438	...	0.023438	0.025391	0.022461

Split

Train data

	margin1	margin2	margin3	...	texture62	texture63	texture64
0	0.007812	0.023438	0.023438	...	0.004883	0.000000	0.025391
1	0.005859	0.000000	0.031250	...	0.000977	0.039062	0.022461
2	0.005859	0.009766	0.019531	...	0.000000	0.020508	0.002930
3	0.000000	0.003906	0.023438	...	0.017578	0.000000	0.047852
4	0.005859	0.003906	0.048828	...	0.000000	0.000000	0.031250
...	...	...	...	...	...	...	...
985	0.060547	0.119140	0.007812	...	0.000000	0.000000	0.018555
986	0.001953	0.003906	0.021484	...	0.000977	0.000000	0.021484
987	0.001953	0.003906	0.000000	...	0.027344	0.000000	0.001953
988	0.000000	0.000000	0.046875	...	0.000000	0.001953	0.002930
989	0.023438	0.019531	0.031250	...	0.023438	0.025391	0.022461

Label

The label of train.csv: [ 3 49 65 94 84 40 54 78 53 89 98 16 74 58 58 31 15 6 73 22 73 31 36 27 94 88 12 28 25 20 60 46 69 69 58 23 76 18 52 54 9 48 47 64 81 83 36 58 21 81 20 62 88 34 92 79 82 20 32 4 84 36 35 72 60 71 72 52 50 54 11 51 18 47 5 8 37 97 20 33 1 59 1 56 1 9 57 20 79 29 16 32 54 93 10 46 59 64 76 15 10 15 0 69 4 51 51 94 36 39 62 2 24 26 35 25 87 0 55 34 38 1 45 7 93 56 38 21 51 75 81 74 33 20 37 9 40 60 31 83 50 71 67 30 66 1 43 61 23 65 84 87 46 57 16 2 28 12 96 44 76 29 75 41 87 67 61 30 5 12 62 3 83 81 6 85 37 57 84 39 71 61 6 76 14 31 98 40 17 51 16 42 63 86 37 69 86 71 80 78 14 35 25 5 39 8 9 26 44 60 13 14 77 13 80 87 18 60 78 92 51 45 78 41 51 30 14 35 46 21 8 6 92 38 40 15 32 17 93 71 92 27 78 15 39 60 21 30 36 49 74 67 95 31 82 45 16 83 63 80 42 22 74 53 15 44 47 57 94 76 17 32 24 15 93 24 80 59 46 12 51 77 79 70 69 16 2 63 83 55 12 53 1 67 0 2 36 42 10 9 52 59 60 66 31 51 37 43 75 90 24 96 45 32 36 60 66 48 73 73 79 56 41 21 25 27 97 18 44 45 40 80 63 20 35 0 8 27 25 35 59 61 21 37 29 6 19 78 50 54 37 93 33 46 79 59 29 43 0 23 17 38 66 38 89 17 25 31 65 10 26 86 58 24 95 93 8 53 32 14 10 34 8 8 64 44 74 30 97 22 11 68 56 90 96 16 43 57 91 24 28 82 90 64 61 92 28 84 70 45 85 34 7 88 89 61 26 88 41 46 8 91 41 14 98 28 26 36 70 74 7 52 70 42 66 22 13 44 91 53 22 16 40 40 28 70 6 60 95 23 16 50 29 49 9 10 55 63 60 18 20 30 31 85 66 60 63 83 64 96 13 34 27 95 36 72 29 91 22 65 71 66 11 32 2 75 39 5 37 67 81 55 61 57 81 82 63 55 54 35 86 25 24 96 10 58 59 28 89 54 52 85 68 69 8 39 95 39 82 48 74 52 74 55 9 47 84 91 12 96 82 64 7 48 73 77 11 36 68 23 28 46 75 43 2 11 47 53 6 62 62 80 56 30 7 86 37 33 73 76 21 5 76 87 68 63 57 47 19 88 96 42 23 44 87 82 49 63 24 94 69 54 5 79 43 12 58 5 52 92 4 84 1 33 49 26 18 44 13 24 73 89 70 67 41 11 46 47 69 0 18 98 44 85 29 53 1 45 3 9 13 2 66 59 79 6 17 43 83 26 1 12 49 71 89 58 93 39 42 15 38 55 15 93 4 90 88 55 40 55 17 34 94 57 92 81 26 60 89 49 89 38 65 58 4 19 4 76 74 71 21 54 13 16 72 68 62 61 25 72 7 12 18 77 98 62 14 3 78 65 37 27 50 95 80 60 72 50 38 87 93 19 7 83 50 3 91 77 7 64 61 69 23 27 65 48 41 92 20 91 18 70 9 29 85 67 0 35 98 91 30 11 53 39 24 85 96 17 7 11 96 39 56 90 79 45 64 97 41 19 74 11 10 95 28 96 18 7 68 7 93 34 42 68 41 14 22 50 12 71 27 98 72 91 3 43 19 61 75 20 81 63 67 56 26 47 11 31 57 62 66 19 75 97 94 13 75 95 32 50 97 52 87 32 3 47 77 48 33 73 64 49 68 43 94 77 68 47 82 2 30 23 33 34 66 33 35 88 68 27 87 54 79 34 67 65 18 42 30 52 86 0 29 80 67 95 39 25 70 58 35 27 17 38 91 13 23 77 79 22 49 98 48 46 48 5 63 97 80 53 20 25 78 10 65 33 41 85 90 98 97 71 95 52 3 29 69 51 70 27 22 34 6 40 72 21 89 17 97 72 80 18 57 64 92 30 15 73 87 43 42 82 33 56 3 42 1 53 55 90 19 6 30 86 64 49 2 8 45 76 92 0 23 69 50 80 32 5 59 85 89 94 45 48 86 81 14 4 77 56 82 2 85 70 88 0 75 14 86 81 97 70 72 28 49 5 11 78 543

# Setup

## Processing data

### 1. Processing data(Train data)

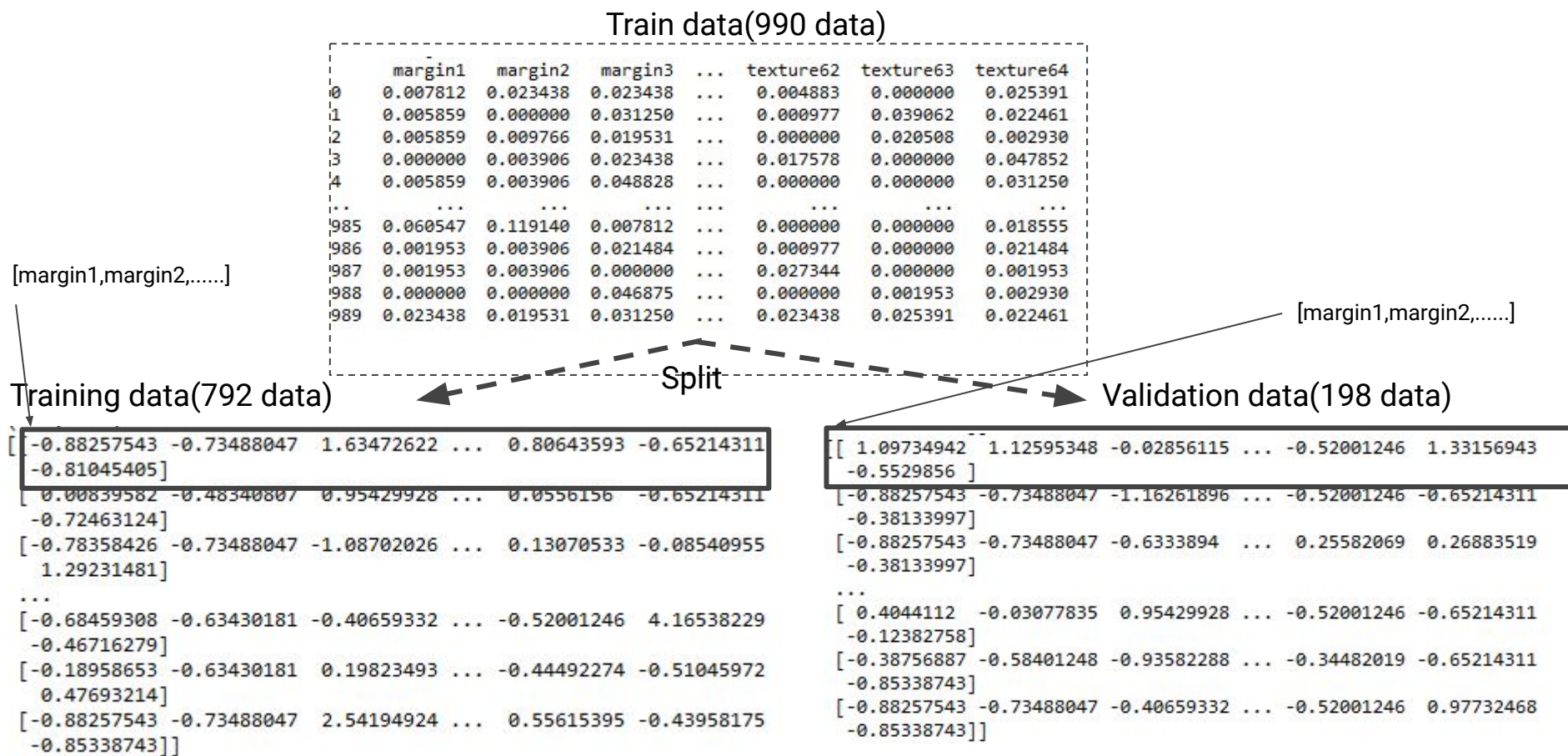
I.Encode the species of leaf and Split the train data of encoded species as "label"

II.Spilt the train data(label) into training data(label) and validation data(label).

III.Take the training and validation data into the array for fitting model's shape and suitably identifying features.

---

Spilt the train data(label) into training data(label) and validation data(label).



# Setup

## Processing data

### 1. Processing data(Train data)

I.Encode the species of leaf and Split the train data of encoded species as "label"

II.Split the train data(label) into training data(label) and validation data(label)

III.Take the training and validation data into the array for fitting model's shape and suitably identifying features.

---

Take the training and validation data into the array for fitting model's shape and suitably identifying features.

Training data(792 data),shape=(792, 192)

```
[[-0.88257543 -0.73488047 1.63472622 ... 0.80643593 -0.65214311
 -0.81045405]
 [ 0.00839582 -0.48340807 0.95429928 ... 0.0556156 -0.65214311
 -0.72463124]
 [-0.78358426 -0.73488047 -1.08702026 ... 0.13070533 -0.08540955
 1.29231481]
 ...
 [-0.68459308 -0.63430181 -0.40659332 ... -0.52001246 4.16538229
 -0.46716279]
 [-0.18958653 -0.63430181 0.19823493 ... -0.44492274 -0.51045972
 0.47693214]
 [-0.88257543 -0.73488047 2.54194924 ... 0.55615395 -0.43958175
 -0.85338743]]
```

reshape

Validation data(198 data),shape=(198, 192)

```
[[ 1.09734942 1.12595348 -0.02856115 ... -0.52001246 1.33156943
 -0.5529856 ]
 [-0.88257543 -0.73488047 -1.16261896 ... -0.52001246 -0.65214311
 -0.38133997]
 [-0.88257543 -0.73488047 -0.6333894 ... 0.25582069 0.26883519
 -0.38133997]
 ...
 [ 0.4044112 -0.03077835 0.95429928 ... -0.52001246 -0.65214311
 -0.12382758]
 [-0.38756887 -0.58401248 -0.93582288 ... -0.34482019 -0.65214311
 -0.85338743]
 [-0.88257543 -0.73488047 -0.40659332 ... -0.52001246 0.97732468
 -0.85338743]]
```

reshape

Training data(792 data),shape=(792, 64,3)

```
[[[-0.88257543 -1.25830954 -0.40640949]
 [ 0.73488047 1.23081218 -0.50940915]
 [ 1.63472622 1.23394044 2.97485715]
 ...
 [-0.48188279 -1.18529523 0.80643593]
 [-0.80952285 -1.18074941 -0.85214311]
 [-0.47299956 -1.22450995 -0.81045405]
 ...
 [ 0.00839582 -0.42467616 -0.18791417]
 [-0.43430181 -0.40659332 -0.52001246]
 [ 0.19823493 -0.44492274 -0.51045972]
 ...
 [ 0.55615395 -0.43958175 -0.85338743]
 [ 0.3404924 -0.40482798 0.5214311]
 [ 0.25170533 -0.54012098 0.74651245]
 ...
 [ 0.78358426 0.45078236 0.12266814]
 [ 0.73488047 0.59451781 -0.34091449]
 [-1.08702026 0.56212516 0.63798744]
 ...
 [ 0.40617395 0.41592081 0.13070533]
 [-1.08505429 0.40365376 -0.08540955]
 [-0.26170533 0.41180656 1.29231481]
 ...
 [ 0.68459308 -1.72817818 -0.4763923]
 [ 0.63430181 -1.8256338 1.65844315]
 [ 0.40659332 -1.82920818 0.93937622]
 ...
 [ 0.00839582 -1.79525744 -0.52001246]
 [ 0.78931521 -1.73186359 4.16538229]
 [ 0.47299956 -1.59550667 -0.46716279]
 ...
 [ 0.18958653 1.2212882 -0.3181936]
 [ 0.63430181 1.24813178 -0.45219055]
 [ 0.1923493 1.84047777 -0.56689179]
 ...
 [-0.48188279 0.82054048 -0.44492274]
 [-0.80952285 0.87350942 -0.51045972]
 [-0.47299956 0.9952082 -0.47652141]
 ...
 [ 0.88257543 -1.47820205 -0.4763923]
 [ 0.73488047 -1.45564021 -0.51232083]
 [ 2.54194924 -1.31263549 -0.7973585]
 ...
 [ 0.4828279 -1.51310413 0.5615395]
 [-0.70987421 -1.62045411 -0.49305175]
 [-0.47299956 -1.64016516 -0.85338743]]]
```

Validation data(198 data),shape=(198, 64,3)

```
[[[ 1.09734942 1.37463544 -0.54130829]
 [ 1.12595348 1.26802844 -0.08547774]
 [ 0.02856115 1.54041844 3.71370649]
 ...
 [-0.41882798 -1.15747514 -0.20812439]
 [ 1.28258914 -1.56743678 -0.13150454]
 [-0.27005044 -1.32840944 -0.52001246]
 ...
 [ 0.25754314 0.44517681 -0.37570886]
 [ 0.4044112 0.33959335 -0.12382758]
 [ 0.95429928 -0.44492274 -0.51045972]
 ...
 [-1.18389744 -0.50916514 -0.5214311]
 [-0.06212098 -1.14432824 -0.81379745]
 [ 0.4044112 -0.03077835 0.95429928]
 ...
 [-0.82575431 -0.40661768 -0.12266814]
 [-0.3404924 -0.38756887 -0.51045972]
 [-0.12382758 -0.58401248 -0.93582288]
 ...
 [ 1.02965384 -0.58477854 -0.2582069]
 [-1.18389744 -0.8728587 -0.26883519]
 [ 0.73488047 1.1668052 -0.81379745]
 ...
 [ 0.40441204 2.28203404 7.43832757]
 [-0.87783156 -0.34011872 -0.40954924]
 [ 0.54092792 -1.14761897 -1.48406814]
 ...
 [-2.93811554 -0.44006434 -0.20812439]
 [ 1.28258914 2.282424 -0.5214311]
 [-0.06212098 -0.80831524 -0.12382758]
 ...
 [-0.87568875 -1.08233674 -0.54130829]
 [-0.38728798 -0.58419514 -0.74763544]
 [-0.41882798 -0.90519078 -0.44820195]
 ...
 [-0.90413544 -1.11974943 -0.5214311]
 [-0.27005044 -1.14747514 -0.51045972]
 ...
 [ 0.82575431 -0.51097714 -0.40640949]
 [ 0.3404924 0.44719134 2.12755382]
 [ 0.95429928 -0.39545614 3.71370649]
 ...
 [ 2.78229404 -1.29141594 -0.20812439]
 [-1.08984364 -0.70847734 0.77324824]
 [-0.81789444 -0.44981794 -0.51045972]]]
```

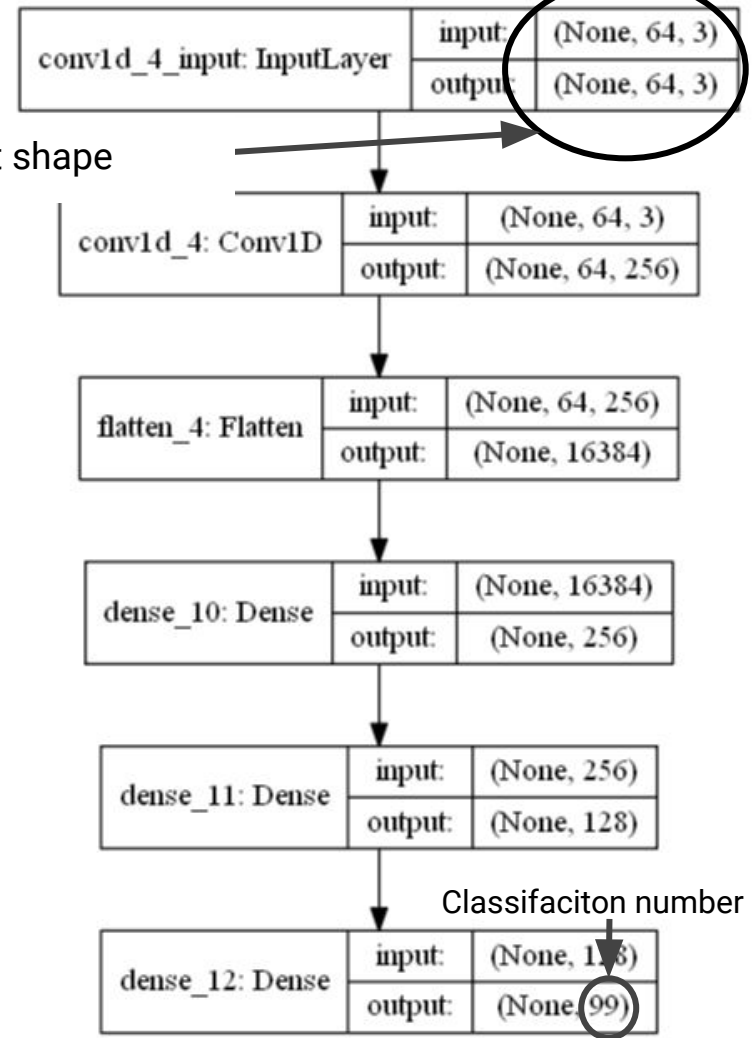
channel=[margin,shape,texture]



# Setup

Model Structure:Model0

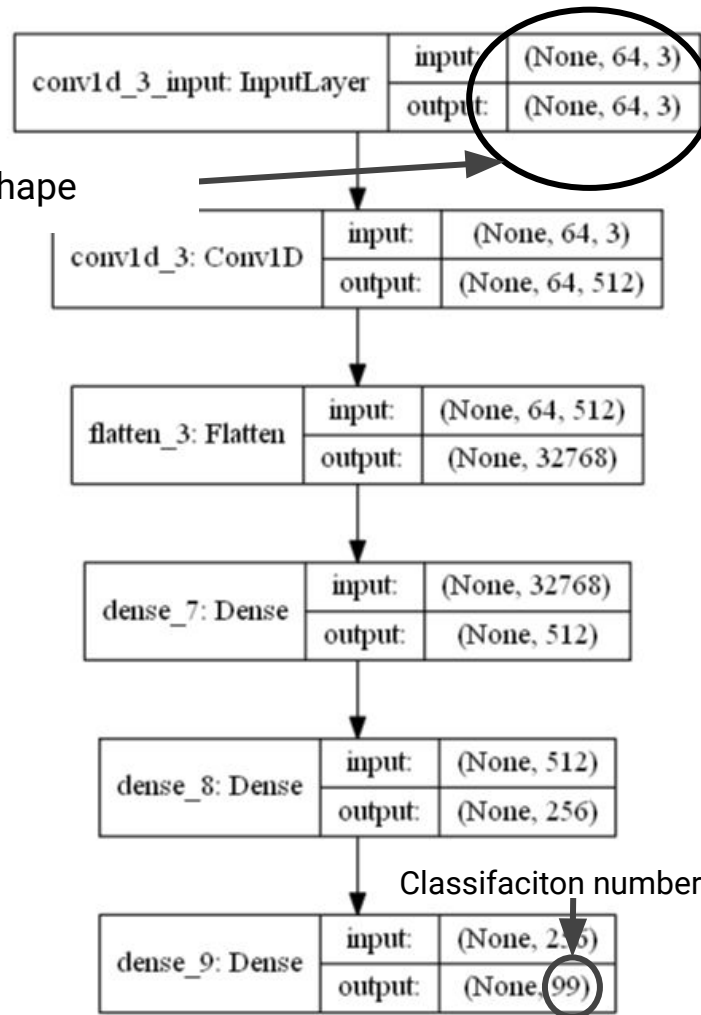
Input shape



# Setup

Model Structure:Model1

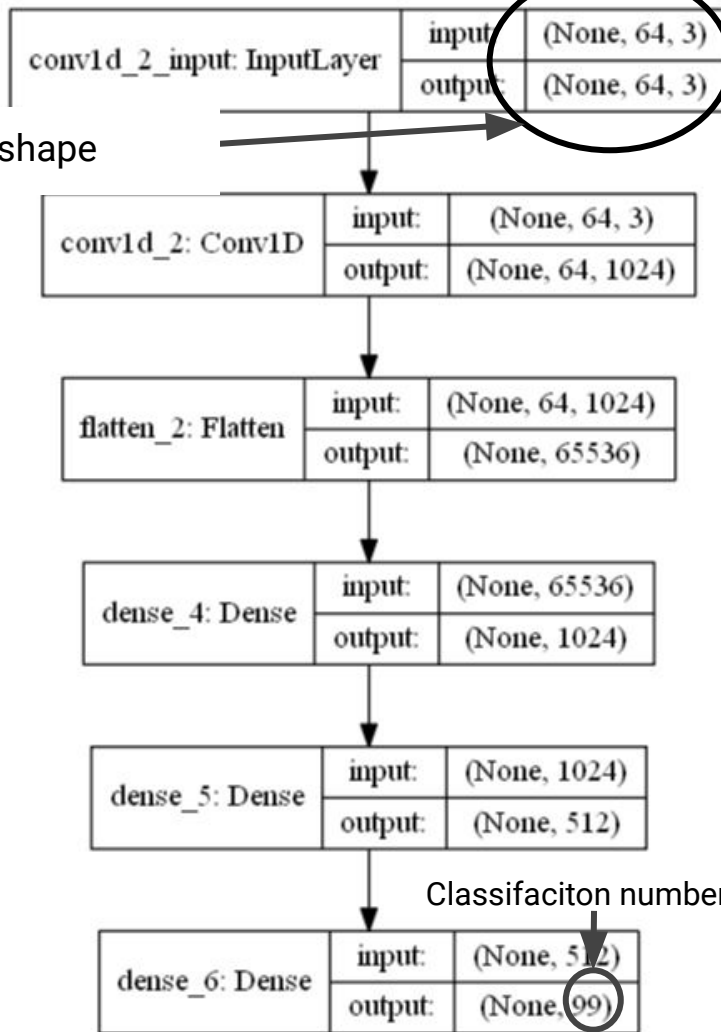
Input shape



# Setup

Model Structure:Model2

Input shape

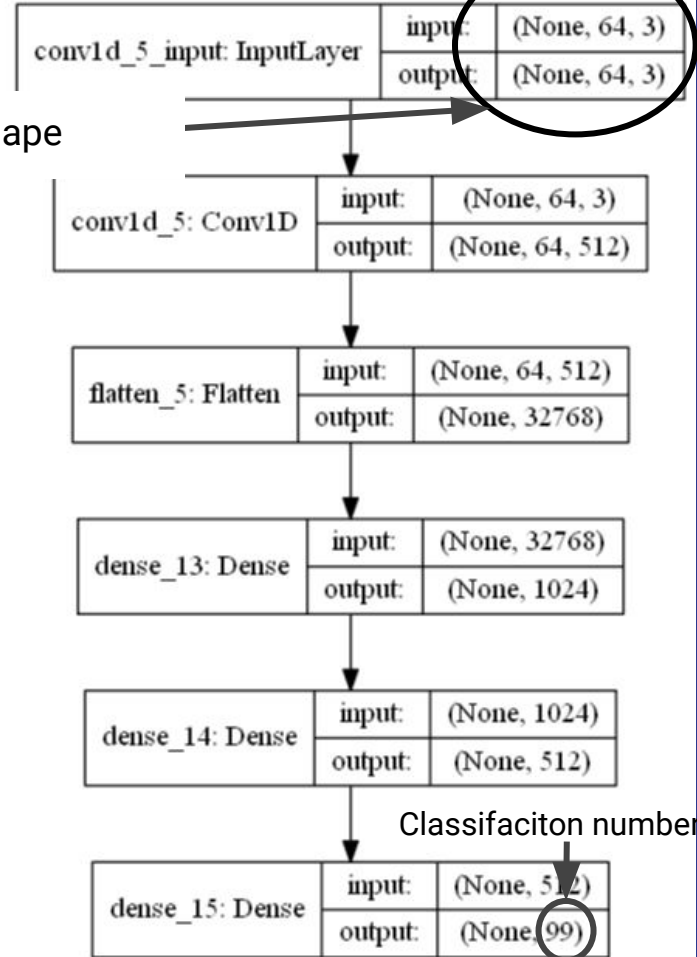




# Setup

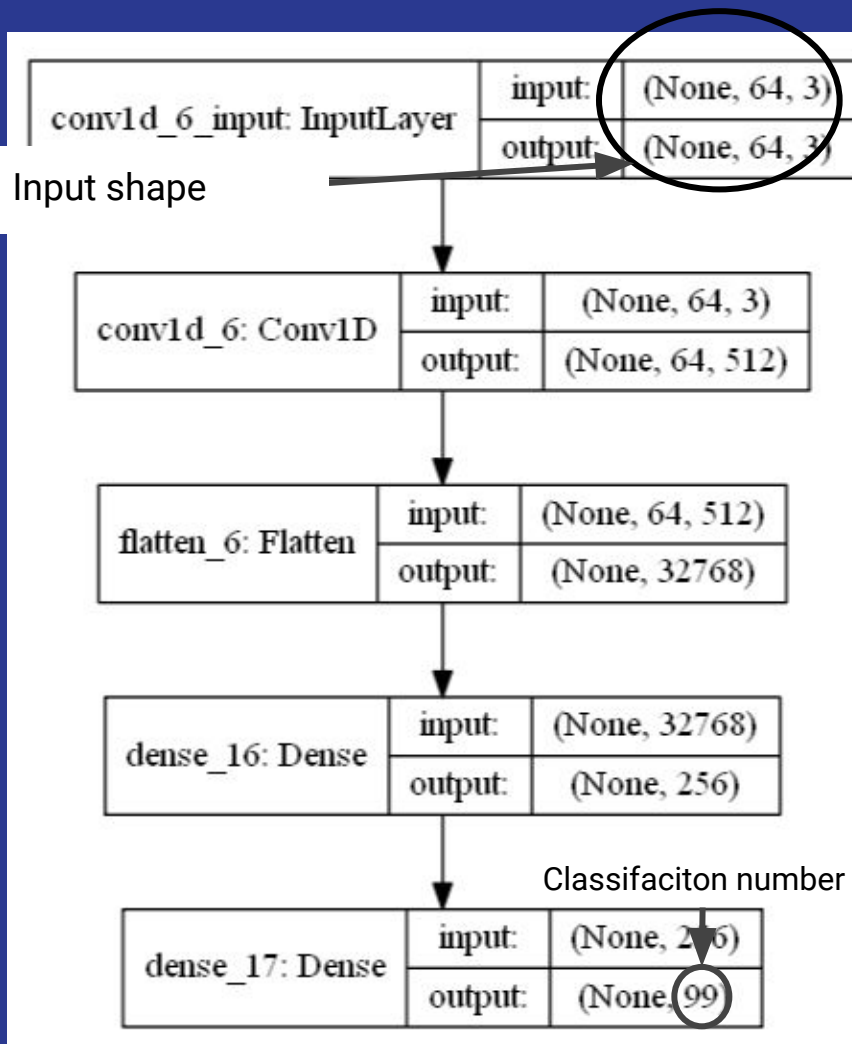
Model Structure:Model3

Input shape



# Setup

Model Structure:Model4



# Setup

Model Structure:Model5

Input shape

conv1d_7_input: InputLayer	input:	(None, 64, 3)
	output:	(None, 64, 3)

conv1d_7: Conv1D	input:	(None, 64, 3)
	output:	(None, 64, 512)

flatten_7: Flatten	input:	(None, 64, 512)
	output:	(None, 32768)

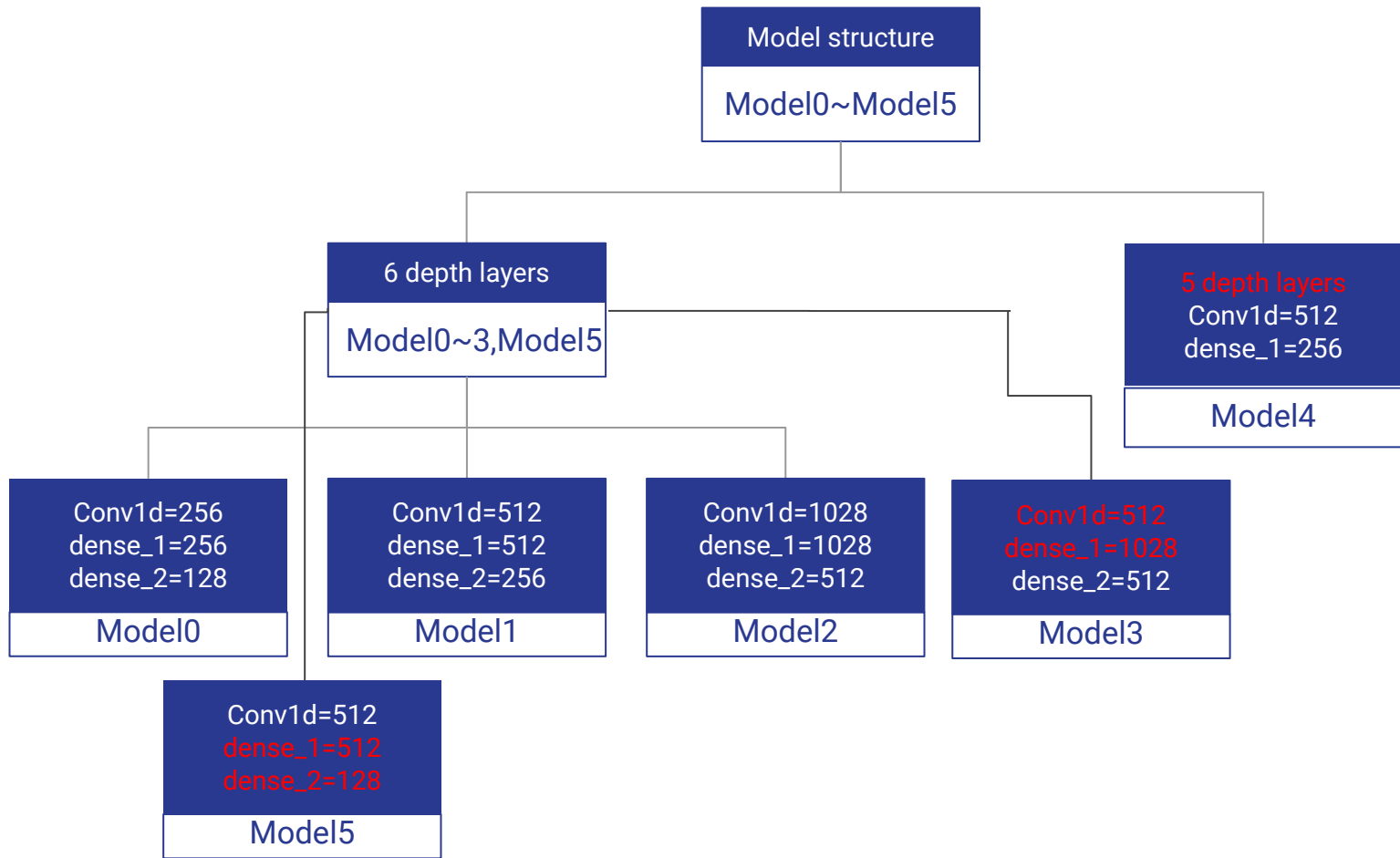
dense_18: Dense	input:	(None, 32768)
	output:	(None, 512)

dense_19: Dense	input:	(None, 512)
	output:	(None, 128)

Classifaciton number

dense_20: Dense	input:	(None, 128)
	output:	(None, 99)

# Model structure



# Result

Fitting environment(**same with  
each model**)

1. The fitting environment is(for each model) :

I.epochs=15

II.batch\_size=16

III.Use the training data and validation data.

---

# Fitting progress: Model0

Overfit happened

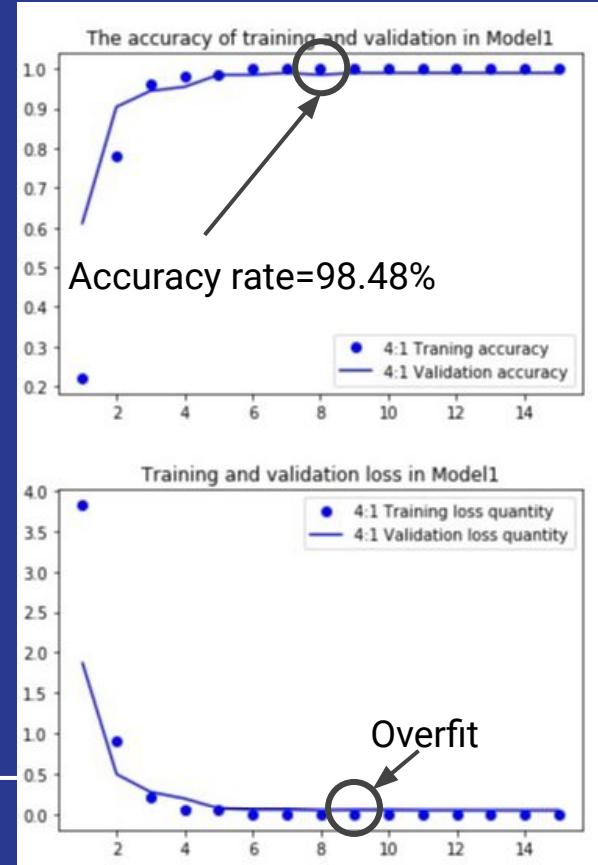
Accuracy rate

Epoch 1/15	792/792 [=====]	- 30s 38ms/step	- loss: 3.8213	- acc: 0.2210	- val_loss: 1.8698	- val_acc: 0.6111
Epoch 2/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.9059	- acc: 0.7816	- val_loss: 0.4979	- val_acc: 0.9040
Epoch 3/15	792/792 [=====]	- 30s 38ms/step	- loss: 0.2068	- acc: 0.9596	- val_loss: 0.2771	- val_acc: 0.9444
Epoch 4/15	792/792 [=====]	- 30s 38ms/step	- loss: 0.0619	- acc: 0.9811	- val_loss: 0.1965	- val_acc: 0.9545
Epoch 5/15	792/792 [=====]	- 31s 39ms/step	- loss: 0.0532	- acc: 0.9861	- val_loss: 0.0739	- val_acc: 0.9848
Epoch 6/15	792/792 [=====]	- 30s 38ms/step	- loss: 0.0081	- acc: 1.0000	- val_loss: 0.0600	- val_acc: 0.9848
Epoch 7/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0046	- acc: 1.0000	- val_loss: 0.0605	- val_acc: 0.9899
Epoch 8/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0033	- acc: 1.0000	- val_loss: 0.0504	- val_acc: 0.9848
Epoch 9/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0026	- acc: 1.0000	- val_loss: 0.0531	- val_acc: 0.9899
Epoch 10/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0022	- acc: 1.0000	- val_loss: 0.0530	- val_acc: 0.9899
Epoch 11/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0019	- acc: 1.0000	- val_loss: 0.0502	- val_acc: 0.9899
Epoch 12/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0017	- acc: 1.0000	- val_loss: 0.0497	- val_acc: 0.9899
Epoch 13/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0015	- acc: 1.0000	- val_loss: 0.0491	- val_acc: 0.9899
Epoch 14/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0014	- acc: 1.0000	- val_loss: 0.0488	- val_acc: 0.9899
Epoch 15/15	792/792 [=====]	- 30s 37ms/step	- loss: 0.0013	- acc: 1.0000	- val_loss: 0.0486	- val_acc: 0.9899

# Result

Model0 result

1. Accuracy rate= 98.48%
2. Overfit happened epochs=9



# Fitting progress: Model1

Epoch 1/15							
792/792 [=====]	- 8s 10ms/step	- loss: 3.9693	- acc: 0.2184	- val_loss: 2.2701	- val_acc: 0.5758		
Epoch 2/15							
792/792 [=====]	- 8s 10ms/step	- loss: 1.0422	- acc: 0.7677	- val_loss: 0.5421	- val_acc: 0.8788		
Epoch 3/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.2041	- acc: 0.9609	- val_loss: 0.1351	- val_acc: 0.9747		
Epoch 4/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.0651	- acc: 0.9874	- val_loss: 0.2105	- val_acc: 0.9646		
Epoch 5/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.0442	- acc: 0.9899	- val_loss: 0.1216	- val_acc: 0.9747		
Epoch 6/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.0282	- acc: 0.9937	- val_loss: 0.0506	- val_acc: 0.9949		
Epoch 7/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.0228	- acc: 0.9962	- val_loss: 0.0428	- val_acc: 0.9949		
Epoch 8/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.0070	- acc: 0.9987	- val_loss: 0.0938	- val_acc: 0.9848		
Epoch 9/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.0102	- acc: 0.9975	- val_loss: 0.0554	- val_acc: 0.9949		
Epoch 10/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.0107	- acc: 0.9987	- val_loss: 0.0573	- val_acc: 0.9949		
Epoch 11/15							
792/792 [=====]	- 7s 9ms/step	- loss: 0.0048	- acc: 0.9987	- val_loss: 0.0492	- val_acc: 0.9949		
Epoch 12/15							
792/792 [=====]	- 8s 10ms/step	- loss: 0.0022	- acc: 1.0000	- val_loss: 0.0464	- val_acc: 0.9949		
Epoch 13/15							
792/792 [=====]	- 7s 9ms/step	- loss: 0.0018	- acc: 1.0000	- val_loss: 0.0451	- val_acc: 0.9949		
Epoch 14/15							
792/792 [=====]	- 7s 9ms/step	- loss: 0.0016	- acc: 1.0000	- val_loss: 0.0454	- val_acc: 0.9949		
Epoch 15/15							
792/792 [=====]	- 7s 9ms/step	- loss: 0.0014	- acc: 1.0000	- val_loss: 0.0445	- val_acc: 0.9949		

Overfit happened

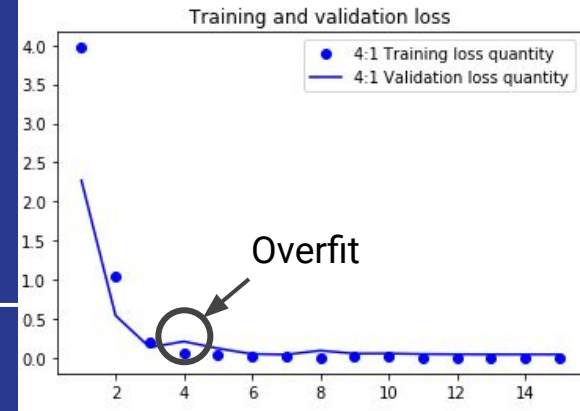
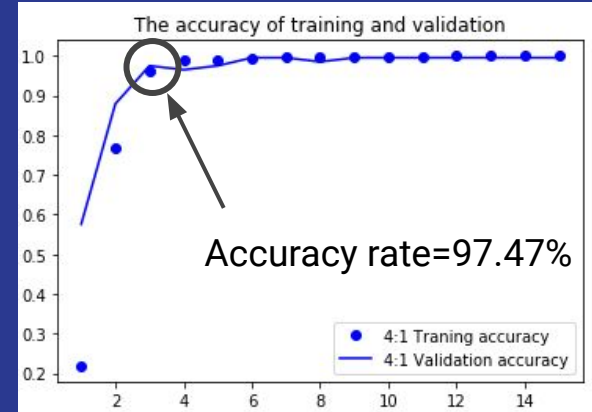
Accuracy rate



# Result

## Model1

1. Accuracy rate= 97.47%
2. Overfit happened epochs=4



# Fitting progress: Model2

Epoch 1/15	792/792 [=====]	- 2s 3ms/step	- loss: 4.1455	- acc: 0.1351	- val_loss: 2.9070	- val_acc: 0.4345
Epoch 2/15	792/792 [=====]	- 2s 2ms/step	- loss: 1.5922	- acc: 0.6465	- val_loss: 0.6796	- val_acc: 0.8586
Epoch 3/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.2797	- acc: 0.9381	- val_loss: 0.2728	- val_acc: 0.9040
Epoch 4/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0999	- acc: 0.9773	- val_loss: 0.1079	- val_acc: 0.9747
Epoch 5/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0478	- acc: 0.9886	- val_loss: 0.1273	- val_acc: 0.9545
Epoch 6/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0352	- acc: 0.9924	- val_loss: 0.0820	- val_acc: 0.9798
Epoch 7/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0170	- acc: 0.9987	- val_loss: 0.1473	- val_acc: 0.9697
Epoch 8/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0435	- acc: 0.9861	- val_loss: 0.1029	- val_acc: 0.9747
Epoch 9/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0091	- acc: 0.9975	- val_loss: 0.0958	- val_acc: 0.9848
Epoch 10/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0102	- acc: 0.9975	- val_loss: 0.1003	- val_acc: 0.9848
Epoch 11/15	792/792 [=====]	- 2s 3ms/step	- loss: 0.0035	- acc: 1.0000	- val_loss: 0.0673	- val_acc: 0.9798
Epoch 12/15	792/792 [=====]	- 2s 3ms/step	- loss: 0.0023	- acc: 1.0000	- val_loss: 0.0663	- val_acc: 0.9848
Epoch 13/15	792/792 [=====]	- 2s 3ms/step	- loss: 0.0019	- acc: 1.0000	- val_loss: 0.0657	- val_acc: 0.9848
Epoch 14/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0017	- acc: 1.0000	- val_loss: 0.0657	- val_acc: 0.9899
Epoch 15/15	792/792 [=====]	- 2s 2ms/step	- loss: 0.0015	- acc: 1.0000	- val_loss: 0.0658	- val_acc: 0.9848

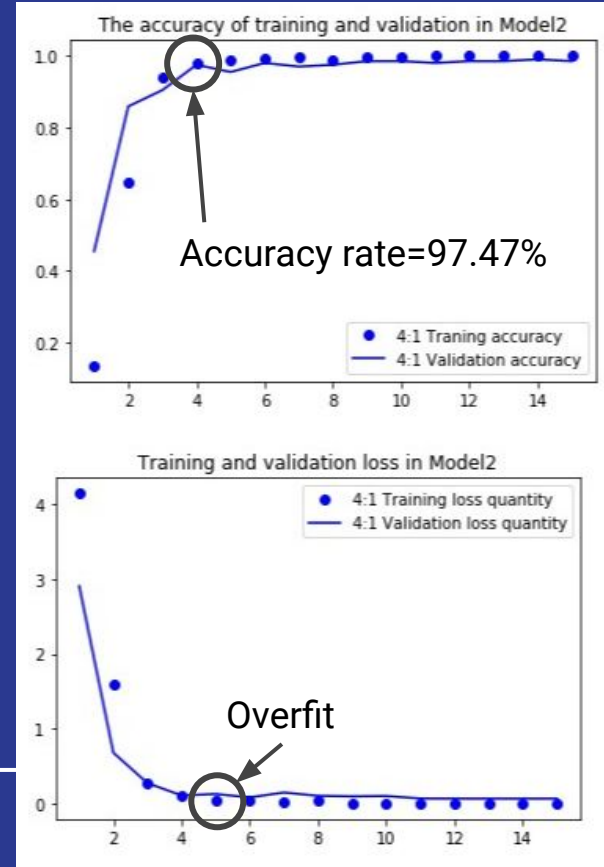
Overfit happened

Accuracy rate

# Result

## Model2 result

1. Accuracy rate= 97.47%
2. Overfit happened epochs=5



# Fitting progress: Model3

```
Epoch 1/15
792/792 [=====] - 16s 20ms/step - loss: 3.8588 - acc: 0.2652 - val_loss: 2.0517 - val_acc: 0.6465
Epoch 2/15
792/792 [=====] - 15s 19ms/step - loss: 0.9014 - acc: 0.8030 - val_loss: 0.3854 - val_acc: 0.9091
Epoch 3/15
792/792 [=====] - 16s 20ms/step - loss: 0.2313 - acc: 0.9571 - val_loss: 0.1691 - val_acc: 0.9495
Epoch 4/15
792/792 [=====] - 16s 21ms/step - loss: 0.0569 - acc: 0.9874 - val_loss: 0.1173 - val_acc: 0.9848
Epoch 5/15
792/792 [=====] - 16s 20ms/step - loss: 0.0306 - acc: 0.9937 - val_loss: 0.0788 - val_acc: 0.9899
Epoch 6/15
792/792 [=====] - 15s 19ms/step - loss: 0.0072 - acc: 1.0000 - val_loss: 0.0670 - val_acc: 0.9899
Epoch 7/15
792/792 [=====] - 16s 20ms/step - loss: 0.0036 - acc: 1.0000 - val_loss: 0.0635 - val_acc: 0.9899
Epoch 8/15
792/792 [=====] - 16s 20ms/step - loss: 0.0027 - acc: 1.0000 - val_loss: 0.0600 - val_acc: 0.9899
Epoch 9/15
792/792 [=====] - 16s 20ms/step - loss: 0.0023 - acc: 1.0000 - val_loss: 0.0589 - val_acc: 0.9899
Epoch 10/15
792/792 [=====] - 16s 20ms/step - loss: 0.0020 - acc: 1.0000 - val_loss: 0.0582 - val_acc: 0.9899
Epoch 11/15
792/792 [=====] - 16s 20ms/step - loss: 0.0017 - acc: 1.0000 - val_loss: 0.0574 - val_acc: 0.9899
Epoch 12/15
792/792 [=====] - 16s 20ms/step - loss: 0.0015 - acc: 1.0000 - val_loss: 0.0555 - val_acc: 0.9899
Epoch 13/15
792/792 [=====] - 16s 20ms/step - loss: 0.0014 - acc: 1.0000 - val_loss: 0.0549 - val_acc: 0.9899
Epoch 14/15
792/792 [=====] - 15s 19ms/step - loss: 0.0013 - acc: 1.0000 - val_loss: 0.0553 - val_acc: 0.9899
Epoch 15/15
792/792 [=====] - 15s 19ms/step - loss: 0.0012 - acc: 1.0000 - val_loss: 0.0545 - val_acc: 0.9899
```

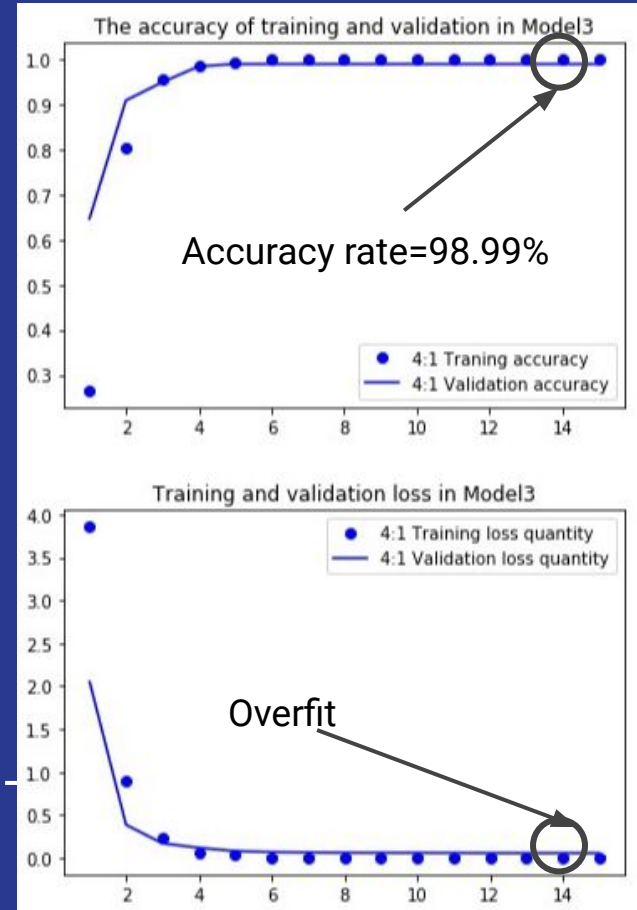
Overfit happened

Accuracy rate

# Result

## Model3 result

1. Accuracy rate= 98.99%
2. Overfit happened epochs=14



# Fitting progress: Model4

Epoch 1/15	792/792 [=====]	- 4s 5ms/step	- loss: 3.6674	- acc: 0.2816	- val_loss: 1.6294	- val_acc: 0.7222
Epoch 2/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.6367	- acc: 0.8699	- val_loss: 0.3461	- val_acc: 0.9242
Epoch 3/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.1247	- acc: 0.9773	- val_loss: 0.1908	- val_acc: 0.9394
Epoch 4/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0523	- acc: 0.9861	- val_loss: 0.2502	- val_acc: 0.9444
Epoch 5/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0410	- acc: 0.9899	- val_loss: 0.1139	- val_acc: 0.9747
Epoch 6/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0109	- acc: 1.0000	- val_loss: 0.0798	- val_acc: 0.9747
Epoch 7/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0110	- acc: 0.9962	- val_loss: 0.0815	- val_acc: 0.9747
Epoch 8/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0160	- acc: 0.9975	- val_loss: 0.1042	- val_acc: 0.9747
Epoch 9/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0063	- acc: 1.0000	- val_loss: 0.0953	- val_acc: 0.9747
Epoch 10/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0120	- acc: 0.9987	- val_loss: 0.0995	- val_acc: 0.9747
Epoch 11/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0048	- acc: 0.9987	- val_loss: 0.0772	- val_acc: 0.9747
Epoch 12/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0082	- acc: 0.9987	- val_loss: 0.1112	- val_acc: 0.9747
Epoch 13/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0035	- acc: 1.0000	- val_loss: 0.0819	- val_acc: 0.9747
Epoch 14/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0028	- acc: 1.0000	- val_loss: 0.0770	- val_acc: 0.9747
Epoch 15/15	792/792 [=====]	- 4s 5ms/step	- loss: 0.0025	- acc: 1.0000	- val_loss: 0.0769	- val_acc: 0.9747

Overfit happened

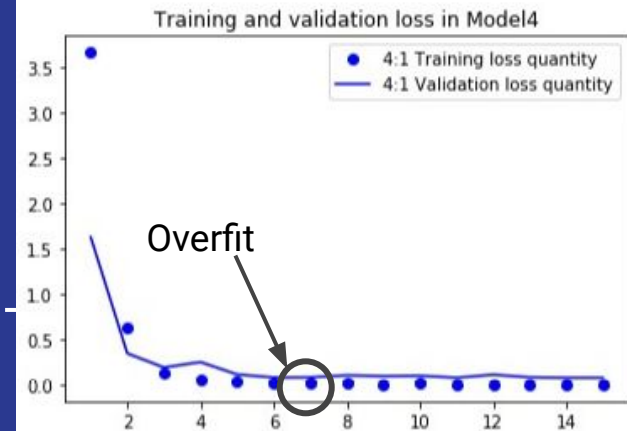
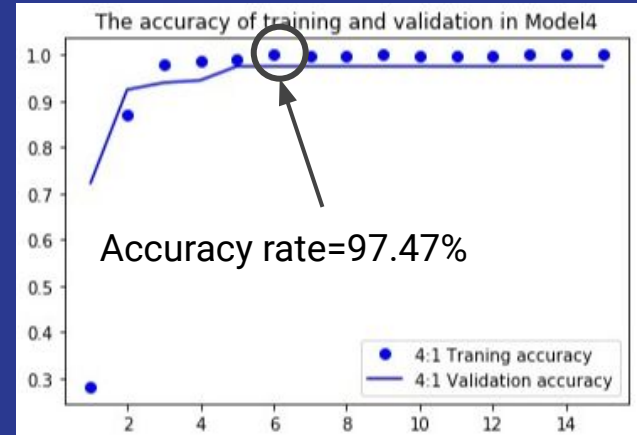
Accuracy rate



# Result

## Model4 result

1. Accuracy rate= 97.47%
2. Overfit happened epochs=7



# Fitting progress: Model5

Accuracy rate

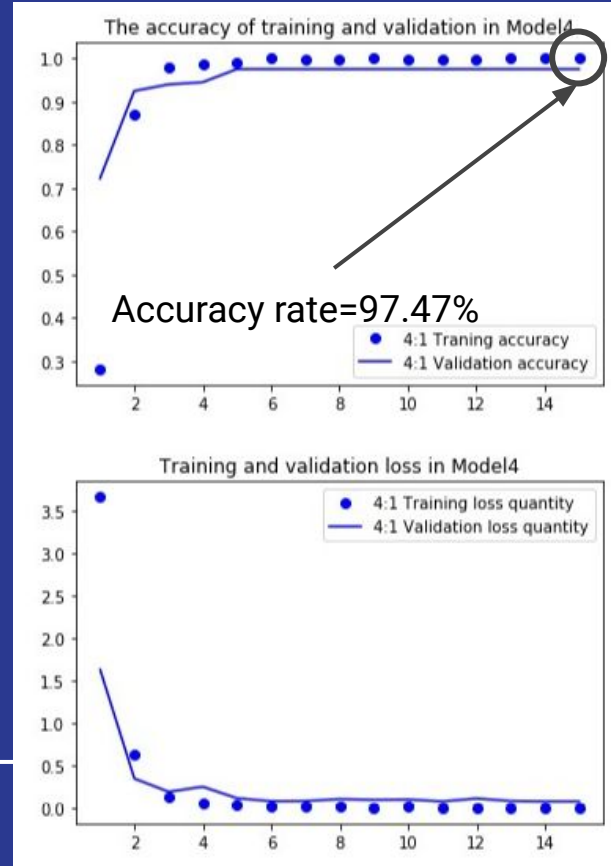
```
Epoch 1/15
792/792 [=====] - 8s 11ms/step - loss: 4.1181 - acc: 0.1528 - val_loss: 2.8541 - val_acc: 0.4848
Epoch 2/15
792/792 [=====] - 8s 11ms/step - loss: 1.3932 - acc: 0.7096 - val_loss: 0.5805 - val_acc: 0.8586
Epoch 3/15
792/792 [=====] - 8s 11ms/step - loss: 0.2547 - acc: 0.9495 - val_loss: 0.2601 - val_acc: 0.9141
Epoch 4/15
792/792 [=====] - 8s 11ms/step - loss: 0.0889 - acc: 0.9773 - val_loss: 0.1478 - val_acc: 0.9697
Epoch 5/15
792/792 [=====] - 8s 11ms/step - loss: 0.0561 - acc: 0.9899 - val_loss: 0.0974 - val_acc: 0.9798
Epoch 6/15
792/792 [=====] - 9s 11ms/step - loss: 0.0302 - acc: 0.9937 - val_loss: 0.0717 - val_acc: 0.9747
Epoch 7/15
792/792 [=====] - 8s 10ms/step - loss: 0.0075 - acc: 0.9987 - val_loss: 0.0632 - val_acc: 0.9848
Epoch 8/15
792/792 [=====] - 8s 10ms/step - loss: 0.0132 - acc: 0.9962 - val_loss: 0.0696 - val_acc: 0.9899
Epoch 9/15
792/792 [=====] - 8s 10ms/step - loss: 0.0035 - acc: 1.0000 - val_loss: 0.0632 - val_acc: 0.9899
Epoch 10/15
792/792 [=====] - 8s 10ms/step - loss: 0.0026 - acc: 1.0000 - val_loss: 0.0596 - val_acc: 0.9899
Epoch 11/15
792/792 [=====] - 8s 10ms/step - loss: 0.0022 - acc: 1.0000 - val_loss: 0.0583 - val_acc: 0.9899
Epoch 12/15
792/792 [=====] - 8s 10ms/step - loss: 0.0019 - acc: 1.0000 - val_loss: 0.0576 - val_acc: 0.9899
Epoch 13/15
792/792 [=====] - 8s 10ms/step - loss: 0.0017 - acc: 1.0000 - val_loss: 0.0571 - val_acc: 0.9899
Epoch 14/15
792/792 [=====] - 8s 10ms/step - loss: 0.0015 - acc: 1.0000 - val_loss: 0.0561 - val_acc: 0.9899
Epoch 15/15
792/792 [=====] - 8s 10ms/step - loss: 0.0014 - acc: 1.0000 - val_loss: 0.0545 - val_acc: 0.9899
```



# Result

Model5 result

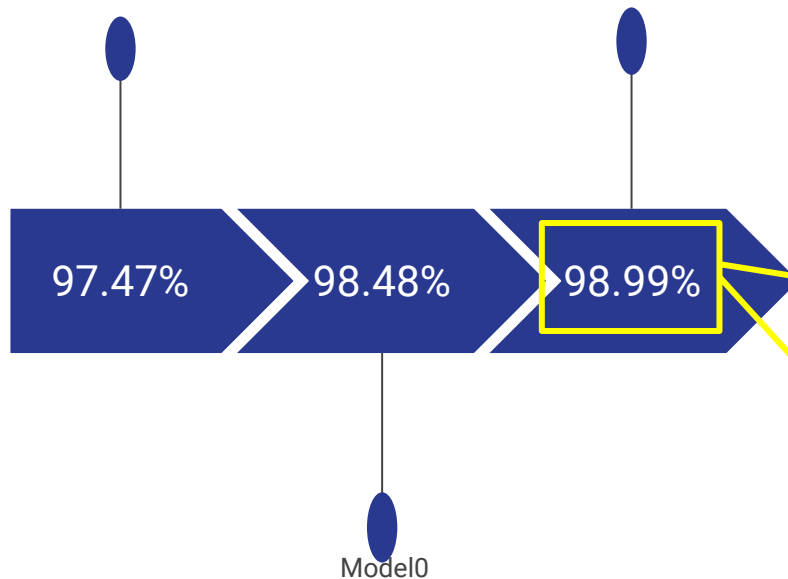
1. Accuracy rate= 98.99%
2. Overfit happened epochs=None



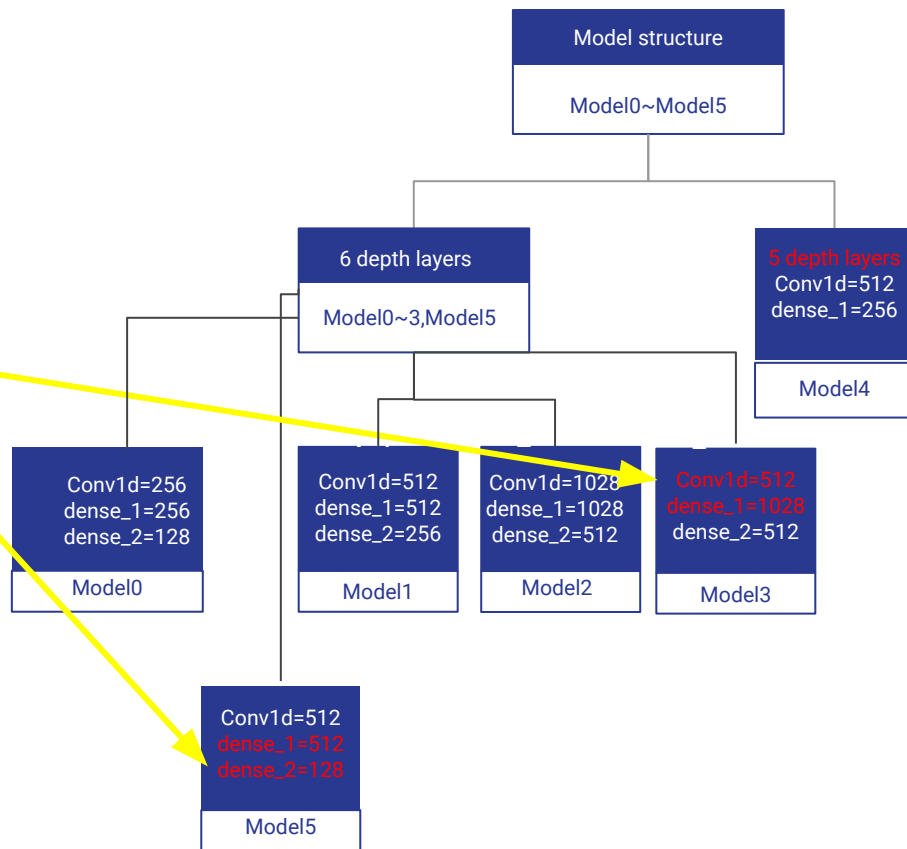
# Accuracy rate

Model1,Model2,Model4

Model3,Model5



# Model structure



# Conclusion

I. In our simulation, the model3 and model5 have highest accuracy rate in 6 different models.

II. In future, we can try more different model to find the more high accuracy rate of model. Regrettably, there is no rule and precise theory to build the model which has absolute highest accuracy rate.

III. We used the CNN layer as our first layer to achieve to classify the species of leaf, and the model we build has approximately 97.47%~98.99% accuracy rate.