



FINAL CAPSTONE PROJECT

CIFAR10 Dataset

Image Recognition using Convolutional Neural networks

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PROJECT DESCRIPTION AND PURPOSE



Description

- Dataset: https://www.cs.toronto.edu/~kriz/cifar.html
- CIFAR-10 is a subset of the 80 million tiny images dataset created by Canadian Institute for Advanced Research (CIFAR).
- The CIFAR-10 dataset consists of 60000 32x32x3 color images in 10 equal classes, (6000 images per class).
- Each class of images corresponds to a physical object (automobile, cat, dog, airplane, etc.)
- In total there are 10 classes including airplane, automobile, bird, cat, deer, dog, frog, horse, ship and a truck.

Problem Summary

- The purpose of this project is to develop a multi class classification model successfully predicting different classes.
- Our goal is to train and test different machine learning models as per our requirement and then come up with one specific model which provides us with the best possible and consistent results in a timely fashion.
- For this purpose we will be building eleven different machine learning models, two each for the Random Forest, Logistic Regression and Gradient Boost followed by 6 separate models of Convolutional Neural Networks.

RANDOM FOREST



Without PCA

Variables: 3,072

Estimators: 500

Max depth: 10

R² Train Data: 0.64

R² Test Data: 0.43

Mean Absolute Error: 2.03

Mean Squared Error: 10.67

Root Mean Squared Error: 3.26

Time: 00:08:16.12

With PCA

Components = 56

Estimators: 500

Max depth: 10

R² Train Data: 0.60

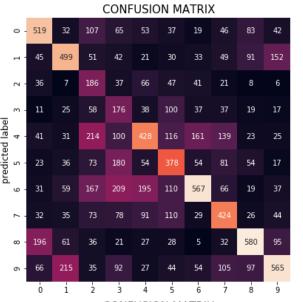
R² Test Data: 0.43

Mean Absolute Error: 2.05

Mean Squared Error: 10.66

Root Mean Squared Error: 3.26

Time: 00:01:53.35



- 500

400

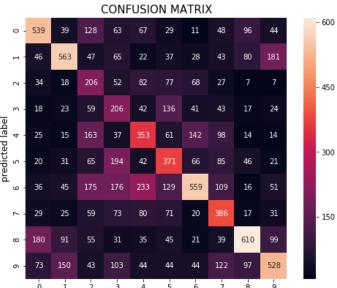
300

- 200

- 100

300

150



true label

Classifica	tion	Report Testi	ng Set		
		precision	recall	f1-score	support
	0	0.52	0.52	0.52	1000
	1	0.49	0.50	0.50	1000
	2	0.41	0.19	0.26	1000
	3	0.34	0.18	0.23	1000
	4	0.33	0.43	0.38	1000
	5	0.40	0.38	0.39	1000
	6	0.39	0.57	0.46	1000
	7	0.45	0.42	0.44	1000
	8	0.54	0.58	0.56	1000
	9	0.43	0.56	0.49	1000
micro a	vg	0.43	0.43	0.43	10000
macro a	vg	0.43	0.43	0.42	10000
weighted a	vg	0.43	0.43	0.42	10000

Classification Report Testing Set				
	precision	_	f1-score	support
_				
0	0.51	0.54	0.52	1000
1	0.51	0.56	0.53	1000
2	0.36	0.21	0.26	1000
3	0.34	0.21	0.26	1000
4	0.38	0.35	0.37	1000
5	0.39	0.37	0.38	1000
6	0.37	0.56	0.44	1000
7	0.49	0.39	0.43	1000
8	0.51	0.61	0.55	1000
9	0.42	0.53	0.47	1000
micro avg	0.43	0.43	0.43	10000
macro avg	0.43	0.43	0.42	10000
weighted avg	0.43	0.43	0.42	10000

LOGISTIC REGRESSION

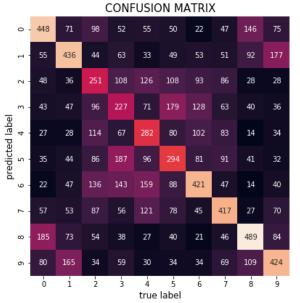


Without PCA

- Variables: 3,072
- R² Train Data: 0.52
- R² Test Data: 0.36
- Mean Absolute Error: 2.31
- Mean Squared Error: 12.20
- Root Mean Squared Error: 3.49
- Time: 01:49:33.14

With PCA

- Components = 56
- R² Train Data: 0.3832
- R² Test Data: 0.38
- Mean Absolute Error: 2.25
- Mean Squared Error: 11.86
- Root Mean Squared Error: 3.44
- Time: 00:00:16.38



- 480

- 400

320

- 240

160

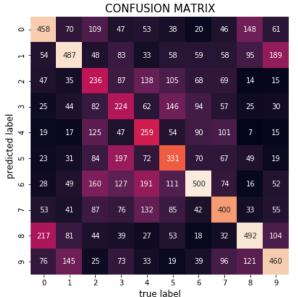
- 500

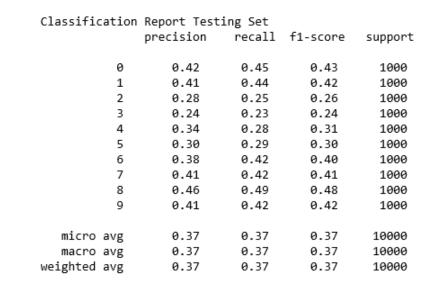
400

300

200

- 100





Classification Report Testing Set				
	precision	recall	f1-score	support
0	0.44	0.46	0.45	1000
1	0.42	0.49	0.45	1000
2	0.29	0.24	0.26	1000
3	0.28	0.22	0.25	1000
4	0.35	0.26	0.30	1000
5	0.35	0.33	0.34	1000
6	0.38	0.50	0.43	1000
7	0.40	0.40	0.40	1000
8	0.44	0.49	0.47	1000
9	0.42	0.46	0.44	1000
micro avg macro avg	0.38 0.38	0.38 0.38	0.38 0.38	10000 10000
weighted avg	0.38	0.38	0.38	10000

GRADIENT BOOST



Without PCA

Variables: 3,072

R² Train Data: 0.94

R² Test Data: 0.44

• Mean Absolute Error: 1.98

Mean Squared Error: 10.21

Root Mean Squared Error: 3.19

Subsample = 0.3

• Estimators = 50

Max depth =10

• Time: 09:24:40.93

With PCA

• Components = 56

• R² Train Data: 0.92

R² Test Data: 0.44

Mean Absolute Error: 2.01

Mean Squared Error: 10.35

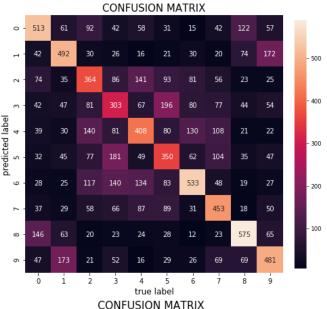
• Root Mean Squared Error: 3.21

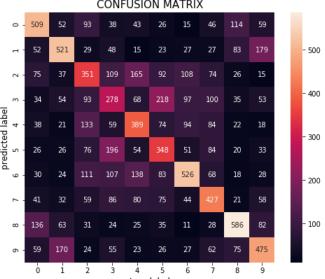
• Subsample = 0.3

• Estimators = 50

Max depth =10

Time: 00:14:35.99





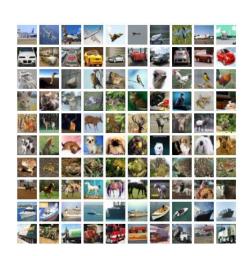
Classifica	ation	Report Test:	ing Set		
		precision	recall	f1-score	support
	0	0.51	0.51	0.51	1000
	1	0.52	0.52	0.52	1000
	2	0.33	0.35	0.34	1000
	3	0.27	0.28	0.27	1000
	4	0.42	0.39	0.40	1000
	5	0.38	0.35	0.36	1000
	6	0.46	0.53	0.49	1000
	7	0.46	0.43	0.44	1000
	8	0.57	0.59	0.58	1000
	9	0.48	0.47	0.48	1000
micro a	avg	0.44	0.44	0.44	10000
macro a	avg	0.44	0.44	0.44	10000
weighted a	avg	0.44	0.44	0.44	10000

MODEL COMPARISON



	Random Forest	Logistic Regression	Gradient boost	
Without PCA	R² Train Data: 0.64 R² Test Data: 0.43	R² Train Data: 0.52 R² Test Data: 0.36	R ² Train Data: 0.94 R ² Test Data: 0.44	(X)
Time	00:08:16.12	01:49:33.14	09:24:40.93	
With PCA	R ² Train Data: 0.60 R ² Test Data: 0.43	R ² Train Data: 0.38 R ² Test Data: 0.38	R ² Train Data: 0.92 R ² Test Data: 0.44	\odot
Time	00:01:53.35	00:00:16.38	00:09:43.77	_

- For comparison model parameters are kept same for both instances.
- It shows that we are better off using Principle Component Analysis (PCA).
- Processing times can be considerably reduced without compromising accuracy.
- Models still require further tuning and fail to produce desired results.





MODEL 1 (4 Layers)

Name: model1

Variables: 3,072

• Convolutional layers: 4

• Max pooling layers: 2

Dense Layers: 2

• Dropout layers: 3 (0.25 – 0.5)

• Activation Functions used

• Rectified Linear Unit (RELU)

Soft max

Optimizer: SGD

Loss = sparse categorical cross entropy

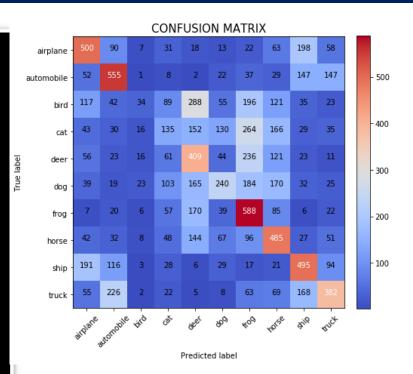
Learning rate = 0.0001

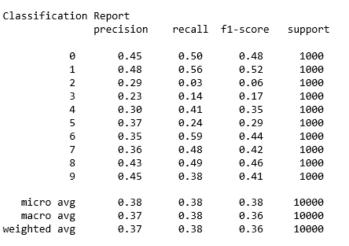
Batch size = 32

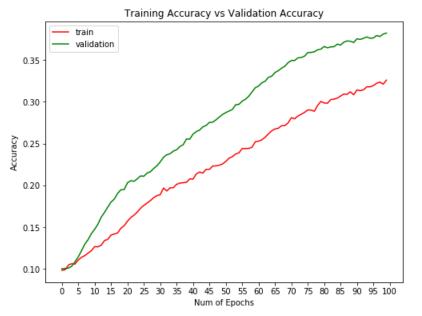
Epochs = 100

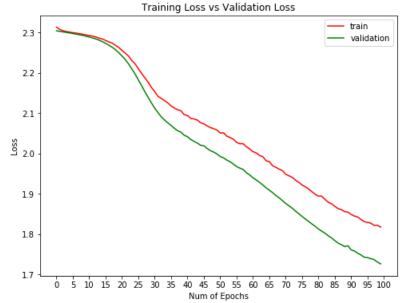
Total time: 02:29:19.31

Test loss: 1.72











MODEL 2 (4 Layers)

Name: model1b

• Variables: 3,072

• Convolutional layers: 4

• Max pooling layers: 2

Dense Layers: 2

• Dropout layers: 3 (0.25 – 0.5)

Activation Functions used

Rectified Linear Unit (RELU)

Soft max

Optimizer: SGD

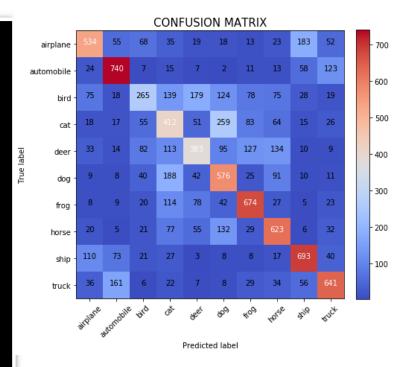
Loss = sparse categorical cross entropy

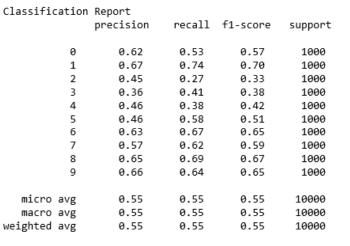
Learning rate = 0.001 +

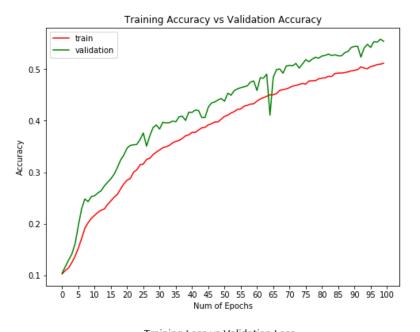
Batch size = 64 +

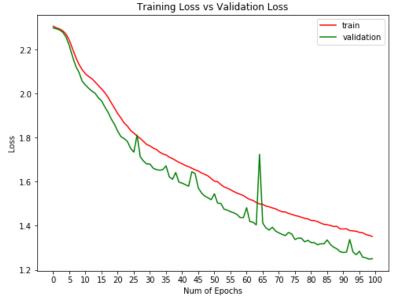
• Epochs = 100

Total time: 02:18:07.45









Test loss: 1.25



MODEL 3 (6 Layers)

Name: model2b

• Variables: 3,072

• Convolutional layers: 6 +

Max pooling layers: 3 +

Dense Layers: 2

Dropout layers: 4 (0.25 – 0.5) +

Activation Functions used

• Rectified Linear Unit (RELU)

Soft max

Optimizer: SGD

Loss = sparse categorical cross entropy

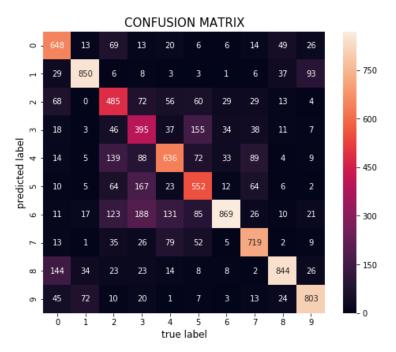
Learning rate = 0.001

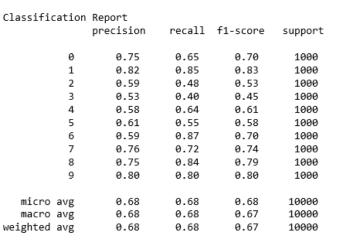
Batch size = 32

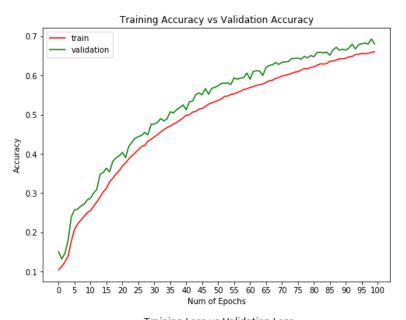
Epochs = 100 +

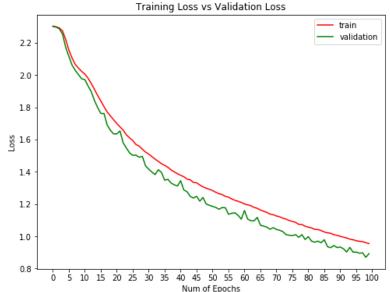
• Total time: 04:27:32.18

Test loss: 0.89











MODEL 4 (8 Layers)

Name: model3

• Variables: 3,072

• Convolutional layers: 8 +

Max pooling layers: 4

Dense Layers: 2

Dropout layers: 5 (0.25 – 0.5) +

Activation Functions used

Rectified Linear Unit (RELU)

Soft max

Optimizer: SGD

Loss = sparse categorical cross entropy

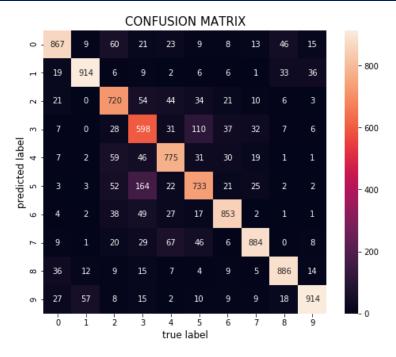
Learning rate = 0.0001 -

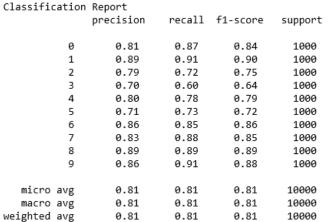
Batch size = 64 +

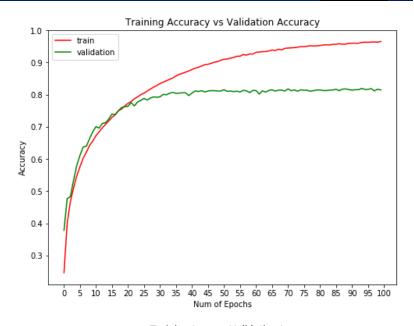
Epochs = 100

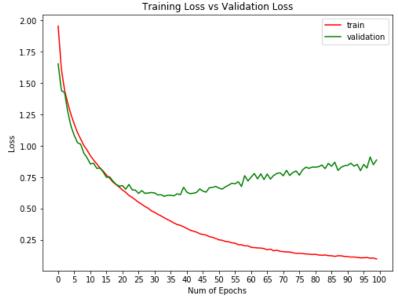
• Total time: 05:28:11.04

Test loss: 0.886











MODEL 5 (10 Layers)

Name: model4

• Variables: 3,072

Convolutional layers: 10 +

Max pooling layers: 4

• Dense Layers: 2

Dropout layers: 5 (0.25 – 0.5) +

Activation Functions used

Rectified Linear Unit (RELU)

Soft max

Optimizer: SGD

Loss = sparse categorical cross entropy

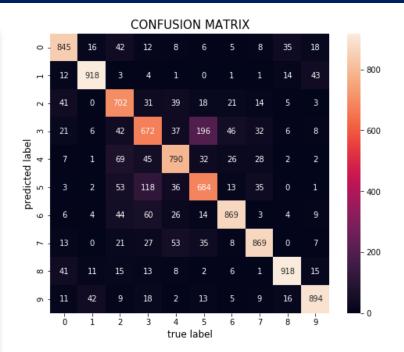
Learning rate = 0.0001

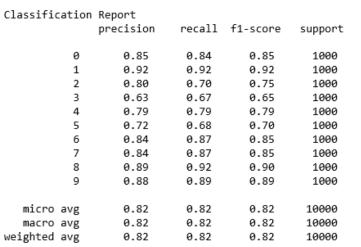
Batch size = 64

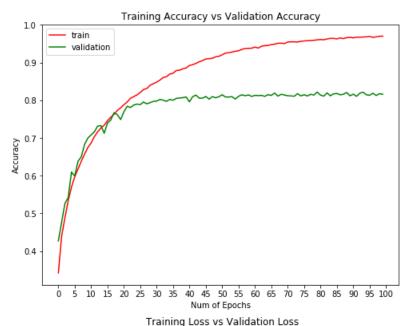
Epochs = 100

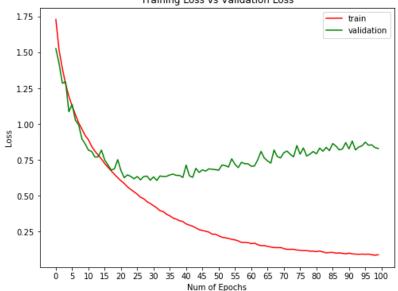
• Total time: 10:30:20.44

Test loss: 0.830









MODEL COMPARISON



Traditional Models

	Random Forest	Logistic Regression	Gradient boost	
Without PCA R² Train Data: 0.64 R² Test Data: 0.43		R² Train Data: 0.52 R² Test Data: 0.36	R ² Train Data: 0.94 R ² Test Data: 0.44	
Time	00:08:16.12	01:49:33.14	09:24:40.93	
With PCA	R ² Train Data: 0.60 R ² Test Data: 0.43	R ² Train Data: 0.38 R ² Test Data: 0.38	R ² Train Data: 0.92 R ² Test Data: 0.44	
Time	00:01:53.35	00:00:16.38	00:09:43.77	

Convolutional Neural Networks

	Model1	Model1b	Model2b	Model3	Model4
Loss	1.72	1.25	0.89	0.886	0.830
Accuracy	0.38	0.55	0.68	0.814	0.816
Time	02:29:19.31	02:18:07.45	00:09:43.77	05:28:11.04	10:30:20.44

CONCLUSION



- Using Principle Component Analysis (PCA) was found effective for reducing dimensionality. It appeared to provide more time efficient results without compromising accuracy. In some instances results that were achieved using regular modeling techniques and which took extra long time to process were obtained in fraction of the time using PCA.
- Nevertheless traditional learning models such as Random Forest, Logistic Regression and Gradient boosting were time efficient however were unable to provide a higher accuracy in order for the model to be successful.
- For Convolutional Neural Networks adding more layers put heavy penalties on processing times. However at the same time CNN models displayed consistent results showing gradual fall in loss and increase in accuracy.
- In conclusion the models that serve the purpose well for image recognition include Convolutional Neural Networks and Random Forest. CNN although can be time consuming, however it offers far better accuracy than any other traditional machine learning models. Random Forest performed fairly well among traditional models however does not match up in delivering performance as that of Convolutional Neural Networks.
- For this project CNN (Model3) provides best possible results with 81% accuracy and a processing time of 5 hours and 30 minutes. This is followed by another CNN (Model4) which takes in additional layers and provides same level of accuracy within twice the amount of time taken by Model3 which is 10 hours 30 minutes.