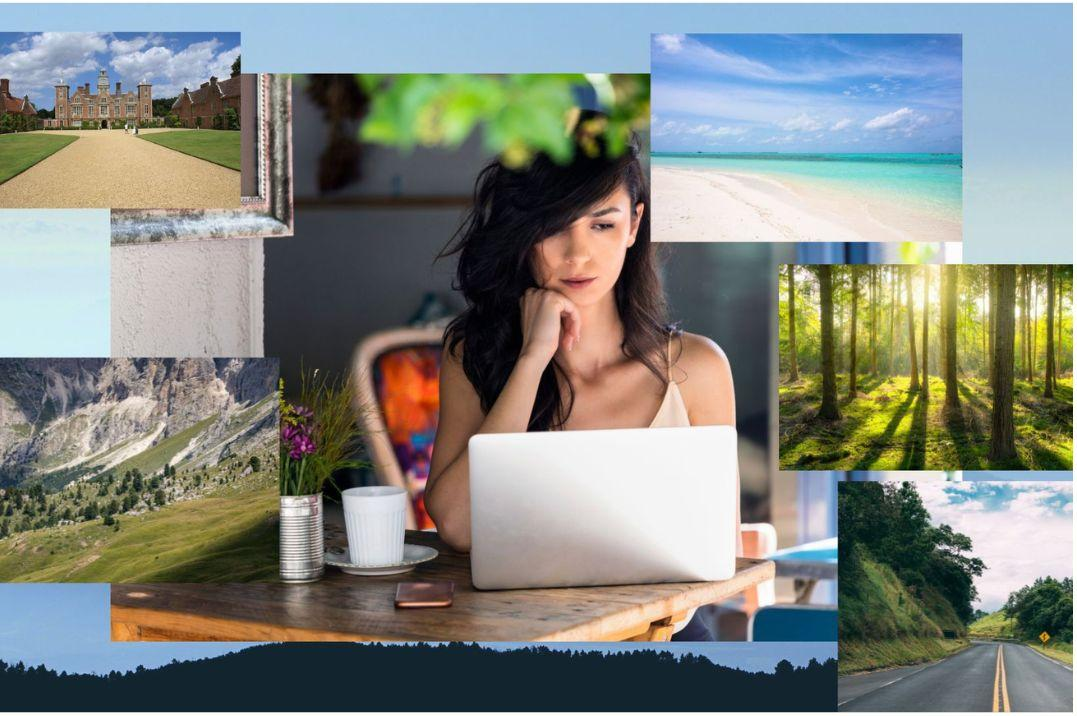
SCENE CLASSIFICATION

DATASCI 207 FINAL PROJECT OF TEAM : KT NORTON, YURI KINAKIN & JUDD GALLARES
PROF. NEDELINA TENEVA, PHD

DECEMBER 6, 2022



Problem Motivation

We work for a photography travel blog website that allows its users to share, view and interact with other users' content and photography.

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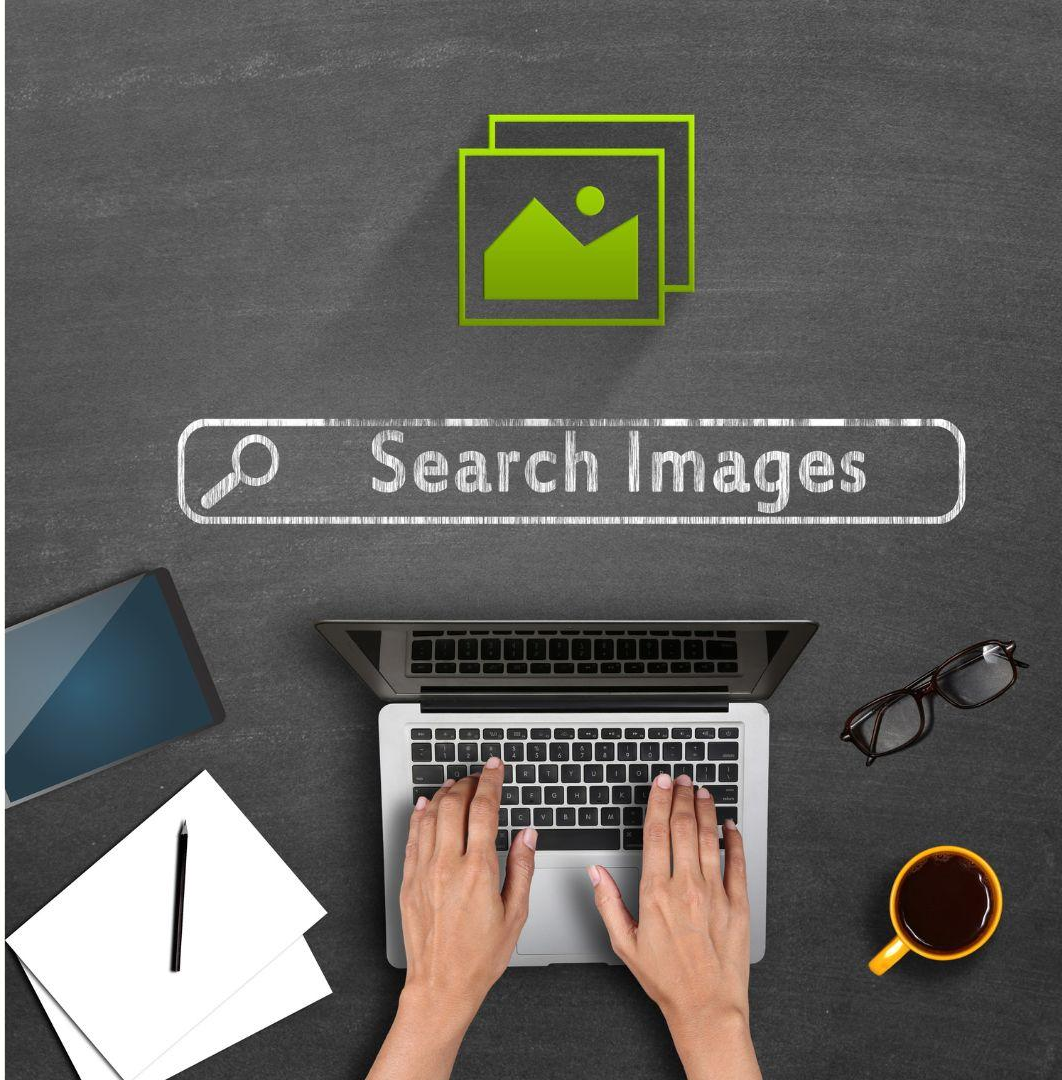
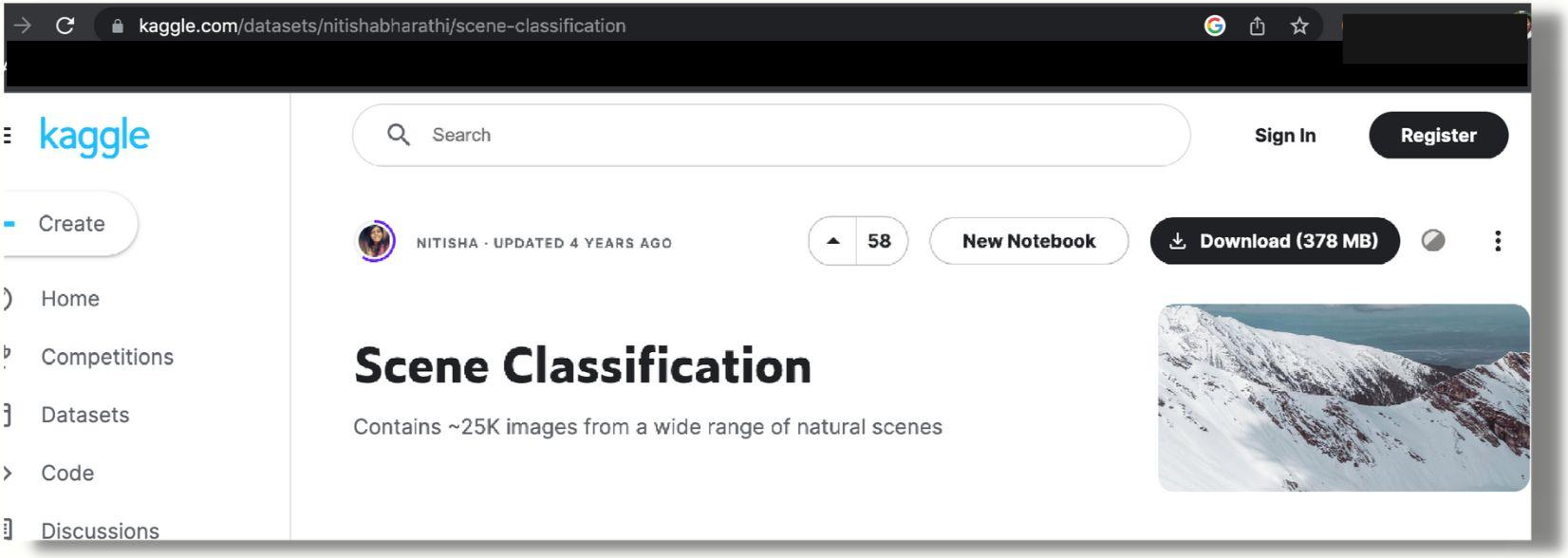
Problem Motivation

We want to recommend blog articles to our users based on photos that they have liked, interacted with, or posted





Data source: Kaggle.com

Problem Statement

We will explore various techniques to classify images based on their natural scene or setting.

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Dataset Description

The data contains ~25k images from around the world of natural outdoor scenes, classified in one of 6 classes.

1. FORESTS
2. MOUNTAINS
3. STREETS
4. SEA
5. BUILDINGS
6. GLACIERS

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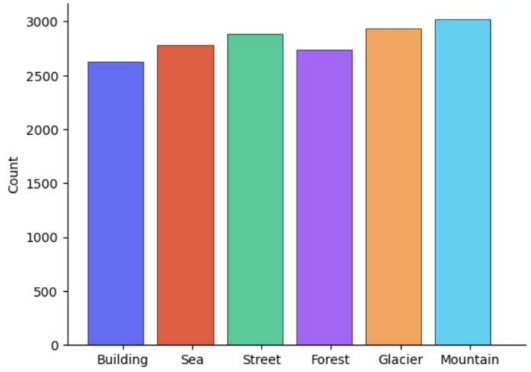
Dataset Description

train	A folder containing 24,335 of mostly 150x150px colored (rgb) jpegs	 - 1.jpg - 12.jpg - 123.jpg ...
train.csv	A csv file with 17,034 rows of labels each describing an image in **train**	 - Buildings - Forests - Mountains - Glaciers - Street - Sea
test_WyRytb0.csv	A csv file containing 7,301 rows of image names (strings) corresponding to a jpeg in **train**. The **train** and **test** csvs should have no duplicates.	 - “3.jpg” - “10.jpg” - “168.jpg” ...

Exploratory Data Analysis



Dataset Summary

A total of 16,979 labelled images (150px x 150px x 3rgb channels) are available for training.

They are split into 6 different categories of approximately equal size.

Our baseline accuracy for each class is therefore **~17%.**

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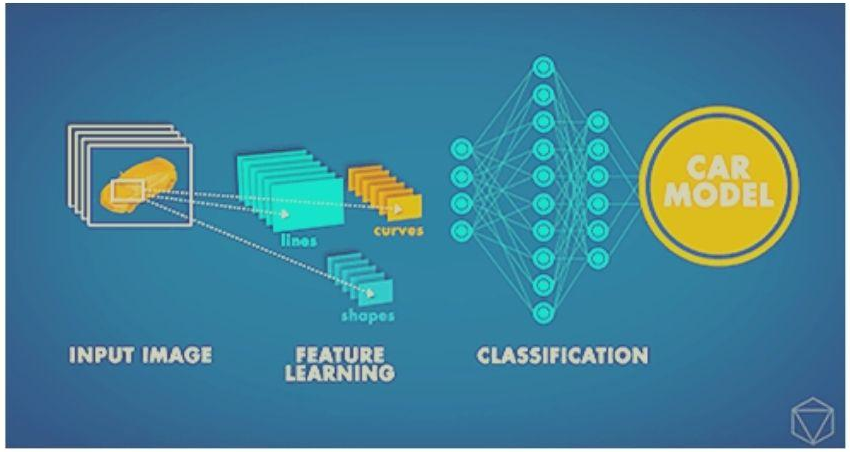
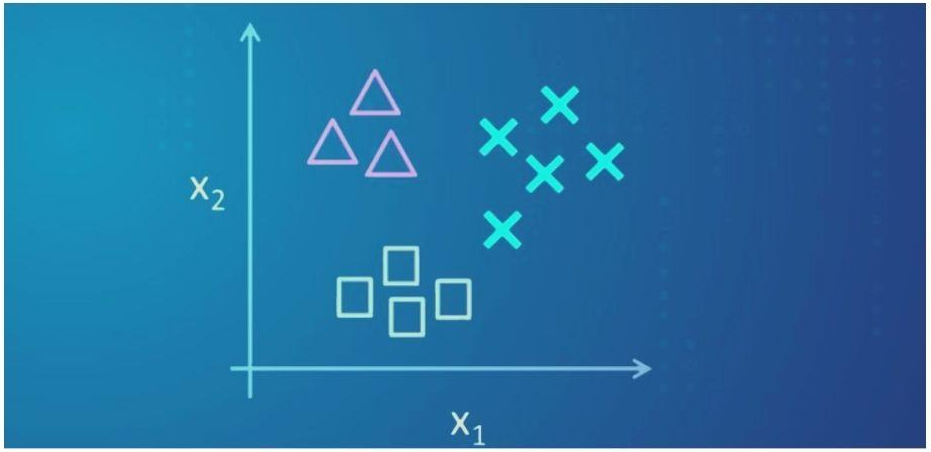
Solution/Approach Description

Our initial analysis utilizing classical machine learning techniques result in a relatively low and imbalance classification accuracy. Our team then tested the approaches below to see which one produced the best results.

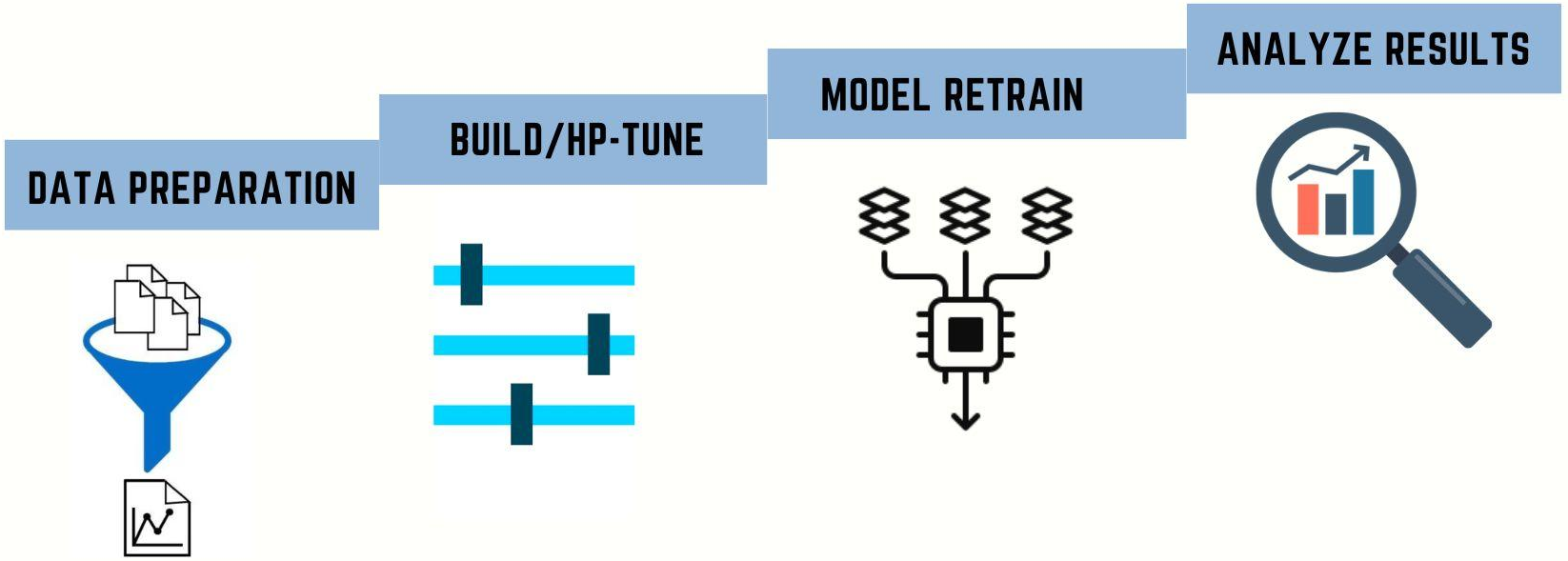
Convolutional Neural Network (CNN) 2D - RGB and 1D - Grayscale



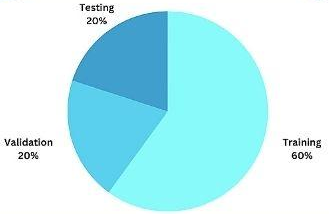
Multiclass Logistic Regression - Grayscale



Model Experiment Process

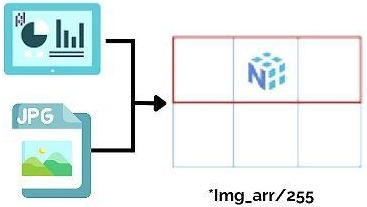


2. Generate an equal number of images from each class



4. Split the images to comprise 60% training, 20% validation and 20% testing

1. Choose only images of size 150x150x3



3. Convert list of labels and images to numpy arrays

5. Shuffle the images and labels together.

Data Preparation and Transformation

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Convolutional Neural Network 2D

Input 150x150 pixels x 3 (RGB)

Preprocessing

Convolution 2D

16 layers + ReLU + 3x3 kernel size

Subsampling

Max pooling 2x2 size

FLATTEN

BUILDINGS

FOREST

SEAS

MOUNTAINS

STREETS

GLACIERS

OUTPUT LAYER

FEATURE EXTRACTION

SOFTMAX CLASSIFICATION

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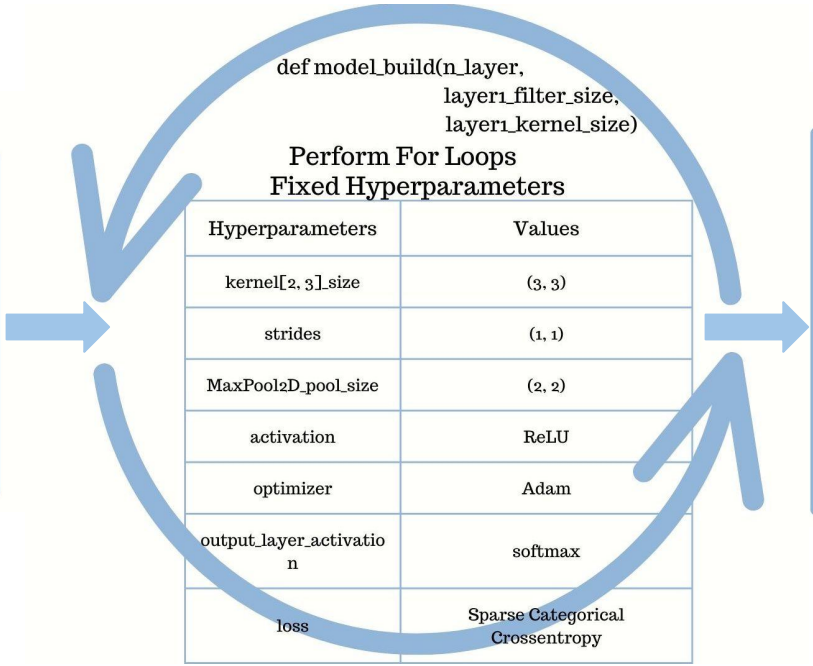
Hyperparameter Tuning

INPUT

Hyperparameters to vary

Hyperparameters	Values
n_layers	1, 2, 3
layer1_filter_size	64, 32, 16
layer1_kernel size	(5, 5), (3, 3), (1, 1)



Hyperparameters	Values
kernel[2, 3]_size	(3, 3)
strides	(1, 1)
MaxPool2D_pool_size	(2, 2)
activation	ReLU
optimizer	Adam
output_layer_activation	softmax
loss	Sparse Categorical Crossentropy

OUTPUT

Cases	loss	accu	val_loss	val_accu
[1,64,(5,5)]	0.0xxxa1	0.0xxxa2	0.0xxxa3	0.0xxxa4
[1,64,(3,3)]	1.0xxxb1			
[1,64,(1,1)]	2.0xxxc1			
[1,32,(5,5)]	0.0xxxd1			
...	...	...	...	...
[3,16,(1,1)]	0.0xxxn1			

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Model Retrain: Apply CNN_2D Optimum Case

	train_loss	train_accu	val_loss	val_accu	filter1_size	kernel1_size	num_conv_layers	build_minutes
0	0.0031	0.9999	0.0361	0.9905	64.0	(5, 5)	1	8.879024
1	0.0058	0.9996	0.0347	0.9911	32.0	(5, 5)	1	4.789623
2	0.0077	0.9997	0.0368	0.9895	16.0	(5, 5)	1	3.473544
3	0.0033	0.9998	0.0263	0.9930	64.0	(3, 3)	1	6.649201
4	0.0040	0.9998	0.0288	0.9924	32.0	(3, 3)	1	4.994755
5	0.0081	0.9998	0.0299	0.9933	16.0	(3, 3)	1	2.412871
6	0.0824	0.9823	0.1419	0.9705	64.0	(1, 1)	1	6.837631
7	0.1238	0.9722	0.1747	0.9559	32.0	(1, 1)	1	3.754270
8	0.1947	0.9533	0.2762	0.9194	16.0	(1, 1)	1	2.064861
9	0.0596	0.9861	0.0870	0.9832	64.0	(5, 5)	2	13.014805

CNN_2D *Model Retrain* at optimum HPs over more epochs

HYPERPARAMETERS	VALUES
Epochs	**10** [5, 10, 15]
No. of CNN Layers	**1** [1, 2, 3]
Filter Size	**64** [64, 32, 16]
Kernel Size	**(3, 3)** [(5, 5), (3, 3), (1, 1)]
MaxPool2D Size	*(2, 2)*
Conv2D activation	*ReLU*
Output Activation	*Softmax*
Optimizer	*Adam*
Loss	*SCC*

	loss	accuracy	val_loss	val_accuracy
0	1.242730	0.703500	0.318093	0.920368
1	0.130304	0.969546	0.085889	0.981599
2	0.026977	0.996511	0.052284	0.991434
3	0.008711	0.999471	0.027462	0.992703
4	0.003313	0.999789	0.026319	0.993020
5	0.001790	1.000000	0.036934	0.991434
6	0.001181	1.000000	0.026425	0.993338
7	0.000731	1.000000	0.026440	0.993655
8	0.000528	1.000000	0.026746	0.993338
9	0.000399	1.000000	0.025375	0.995241

Analyze Results: CNN_2D Classification Report

There are no indication of bias in the classes, 0 - 5. They are tightly grouped together between > 0.98 and < 1 in all metrics.

Classes

0 - Buildings
1 - Forests
2 - Glacier
3 - Mountains
4 - Sea
5 - Street

	precision	recall	f1-score	support
0	0.9978	0.9803	0.9890	458.0000
1	1.0000	1.0000	1.0000	508.0000
2	0.9944	0.9832	0.9888	537.0000
3	0.9852	0.9962	0.9907	533.0000
4	0.9894	1.0000	0.9947	466.0000
5	0.9908	0.9954	0.9931	651.0000
accuracy	0.9927	0.9927	0.9927	0.9927
macro avg	0.9929	0.9925	0.9927	3153.0000
weighted avg	0.9927	0.9927	0.9927	3153.0000

Precision - Percentage of correct positive predictions relative to total positive predictions.

Recall - Percentage of correct positive predictions relative to total actual positives.

F1-score - A weighted harmonic mean of precision and recall: 2 * (Precision * Recall) / (Precision + Recall)

Support - These values tell us how many images belong to each class in the test dataset.

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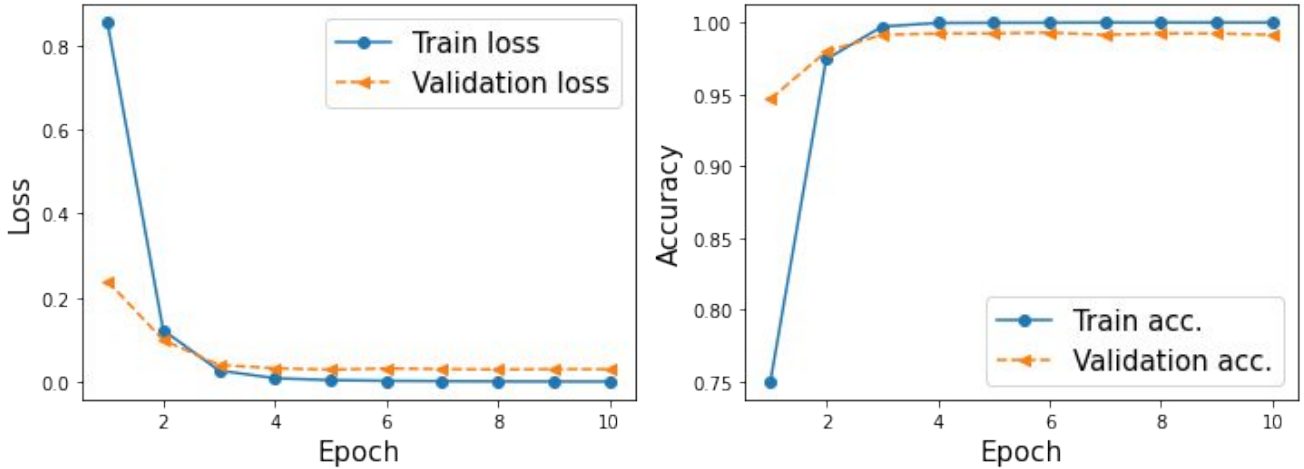
Analyze Results: CNN_2D Loss and Accuracy Plots



There are no indications of over-fitting as can be seen above where the plots converged almost from the start.

Convolutional Neural Network 1D

Input 150x150 pixels x
1 Grayscale

Preprocessing

Convolution 1D

256 layers + ReLU + kernel size = 1

Subsampling

Max pooling size = 2

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BUILDINGS
FORESTS
SEAS
MOUNTAINS
STREETS
GLACIERS

OUTPUT LAYER

FEATURE EXTRACTION

SOFTMAX CLASSIFICATION

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CNN_1D: Hypertune and Apply Optimum Case

	train_loss	train_accu	val_loss	val_accu	filter1_size	kernel1_size	build_minutes
0	1.0878	0.6101	1.0513	0.6164	512.0	7	1.086736
1	1.0349	0.6254	0.9917	0.6304	256.0	7	0.785027
2	1.1566	0.5726	1.1152	0.6028	128.0	7	0.524590
3	1.0901	0.5986	1.0910	0.5945	64.0	7	0.366595
12	0.1582	0.9662	0.1822	0.9578	512.0	1	0.568469
13	0.1595	0.9712	0.1890	0.9626	256.0	1	0.362797
14	0.2300	0.9508	0.2843	0.9334	128.0	1	0.233020
15	0.3917	0.9005	0.4112	0.8877	64.0	1	0.214232

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CNN_1D *Model Retrain* at optimum HPs over more epochs

HYPERPARAMETERS	VALUES
Epochs	**15** [5, 10, 15, 20]
No. of CNN Layers	**1** [1, 2, 3]
Filter Size	**256** [512, 256, 128, 64]
Kernel Size	**1** [7, 5, 3, 1]
MaxPool1D Size	*2*
Conv2D activation	*ReLU*
Output Activation	*softmax*
Optimizer	*Adam*
Loss	*SCC*

	loss	accuracy	val_loss	val_accuracy
0	1.189192	0.546791	0.888876	0.685596
1	0.699524	0.767685	0.628770	0.802348
2	0.426931	0.878503	0.480725	0.842957
3	0.259817	0.939516	0.262416	0.938769
4	0.159511	0.971238	0.188955	0.962563
5	0.114062	0.980015	0.135424	0.976840
6	0.065054	0.992704	0.096758	0.985089
7	0.042953	0.996616	0.099908	0.982551
8	0.031719	0.997674	0.074131	0.986675
9	0.019681	0.998202	0.086057	0.986041
10	0.016538	0.998731	0.149400	0.969226
11	0.019724	0.998625	0.070287	0.988261
12	0.009439	0.999683	0.072023	0.988579
13	0.005027	1.000000	0.067441	0.989213
14	0.003959	1.000000	0.066436	0.987944

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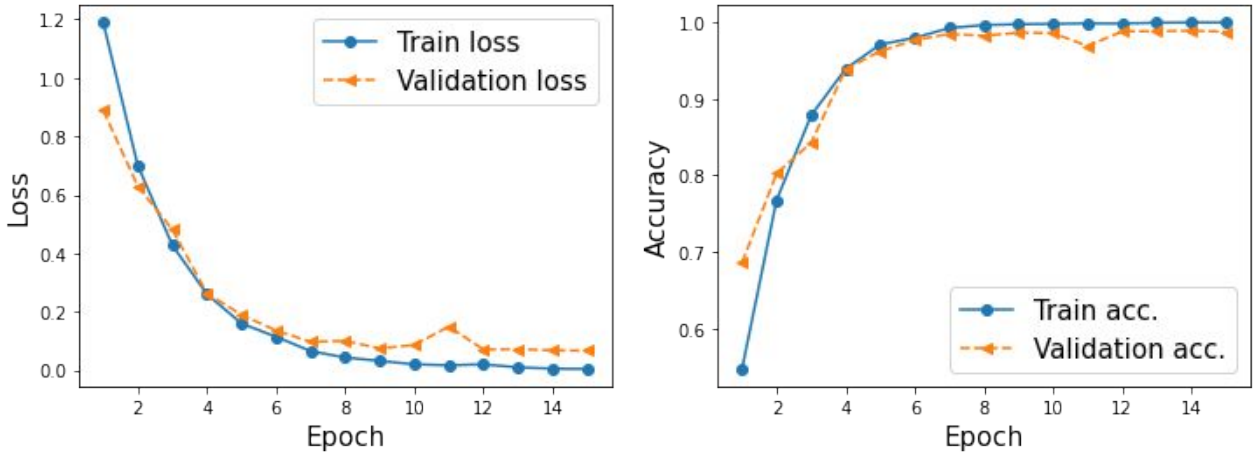
Analyze Results: CNN_1D Classification Report

The results here are only slightly poorer than in CNN_2D. However, the grouping is still tight and with no class showing any obvious *bias* over another.

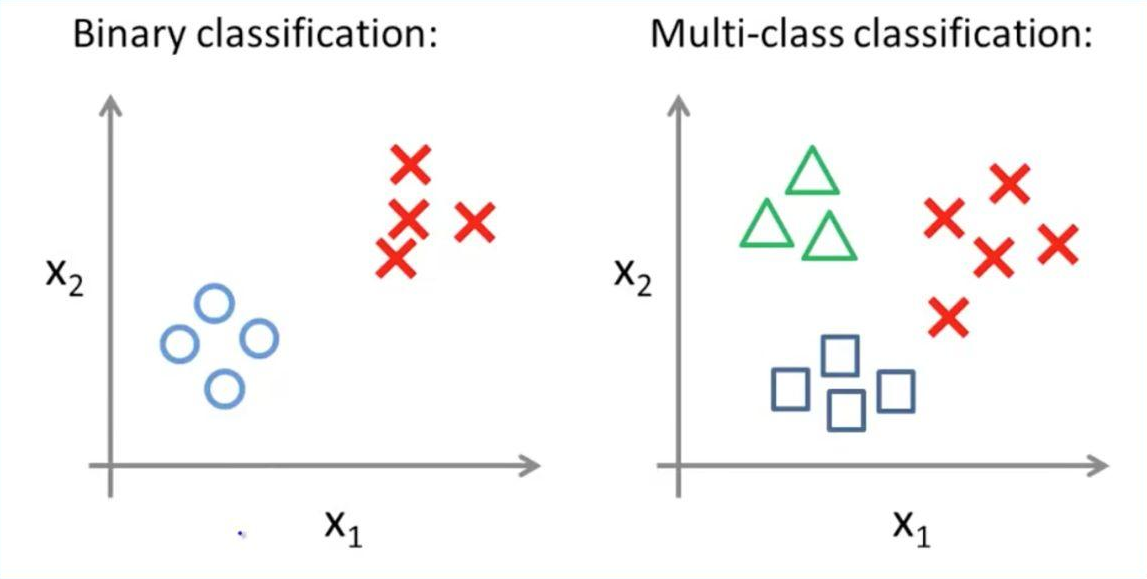
	precision	recall	f1-score	support
0	0.9890	0.9847	0.9869	458.0000
1	0.9941	0.9882	0.9911	508.0000
2	0.9814	0.9832	0.9823	537.0000
3	0.9906	0.9887	0.9897	533.0000
4	0.9786	0.9807	0.9796	466.0000
5	0.9847	0.9908	0.9877	651.0000
accuracy	0.9864	0.9864	0.9864	0.9864
macro avg	0.9864	0.9861	0.9862	3153.0000
weighted avg	0.9864	0.9864	0.9864	3153.0000

Analyze Results: CNN_1D Loss and Accuracy Plot



The plots here also show a converging pattern. But unlike in CNN_2D, the validation line show a bit of a bump at the 3rd and 11th epoch.

Multi-class Logistic Regression- Grayscale



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MCLR *Model Retrain* at optimum HPs over more epochs

HYPERPARAMETERS	VALUES
Epochs	**50** [10 - 60, step: 10]
Learning Rate	**0.001** [0.01, 0.001]
Batch Size	**32** [16, 32, 64]
Optimizer	**Adam** [SGD, Adam]
Output Activation	*softmax*
Loss	*Sparse Categorical Crossentropy (SCC)*

	loss	accuracy	val_loss	val_accuracy
0	2.321057	0.326319	2.214630	0.348985
1	1.672324	0.434387	1.581540	0.468274
2	1.367396	0.534842	1.484961	0.494607
3	1.180820	0.609073	0.907844	0.701777
4	1.017916	0.661521	1.179285	0.582487
45	0.072881	0.979380	0.146761	0.968274
46	0.227095	0.944697	0.113168	0.977792
47	0.064674	0.980226	0.132256	0.971129
48	0.355281	0.921857	1.055452	0.758883
49	0.083987	0.975256	0.108018	0.980013

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Analyze Results: MCLR Classification Report

Although MCLR is the worst of the three in terms of loss and accuracy, the classification report still show no indication of bias and it still achieved a fairly decent accuracy score of 0.98.

	precision	recall	f1-score	support
0	0.9846	0.9782	0.9814	458.00
1	0.9980	0.9665	0.9820	508.00
2	0.9814	0.9832	0.9823	537.00
3	0.9637	0.9962	0.9797	533.00
4	0.9656	0.9635	0.9646	466.00
5	0.9862	0.9877	0.9870	651.00
accuracy	0.9800	0.9800	0.9800	0.98
macro avg	0.9799	0.9792	0.9795	3153.00
weighted avg	0.9802	0.9800	0.9800	3153.00

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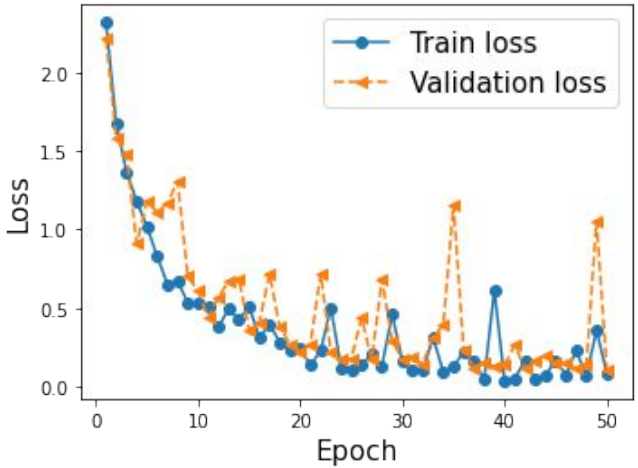
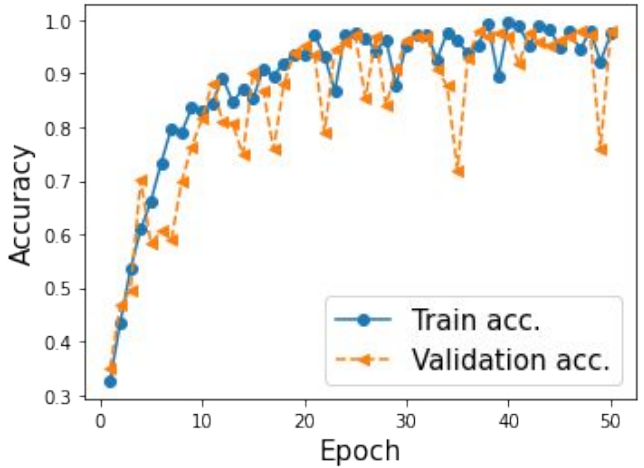
Analyze Results: Multi-class Logistic Regression (MCLR) Loss and Accuracy Plot





The path taken to achieve a > 0.98 score is erratic as shown above.

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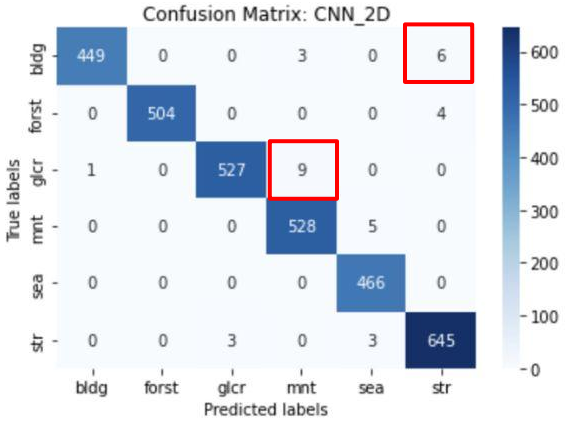
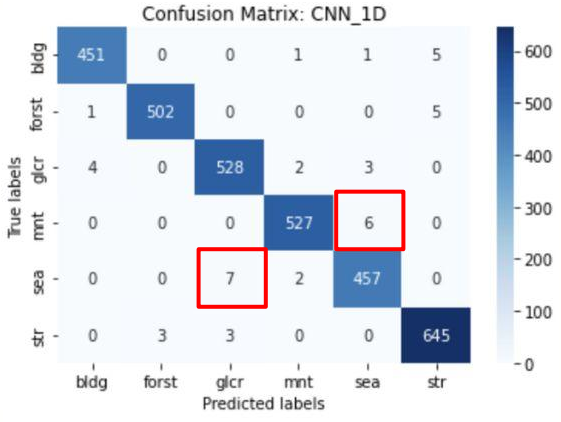
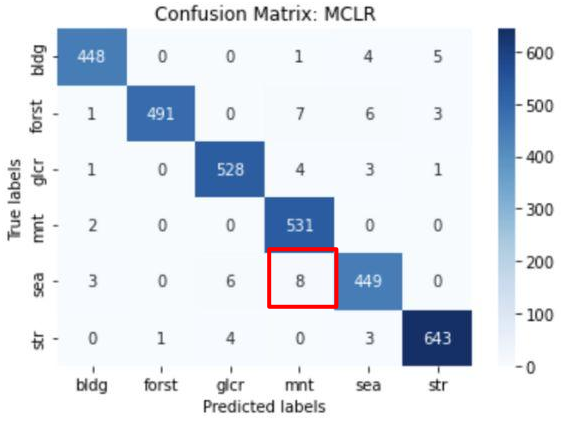
Comparing Confusion Matrices







The confusion matrices vary in results. CNN_2D errors were mostly mountains vs. glaciers and street vs. buildings; CNN_1D: sea/glaciers and sea/mountain; MLCR: sea/mountain and forest/mountain

Conclusion: Model vs. Test Data

For our use case, model training will occur offline so training times don't matter. Therefore, due to its slightly higher classification accuracy, we would recommend a 2D CNN for classifying images in a production environment.

model.evaluate( )	Loss	Accuracy
CNN_2D	**0.030794**	**0.992705**
CNN_1D	**0.066340**	**0.986362**
MCLR	**0.150250**	**0.980019**

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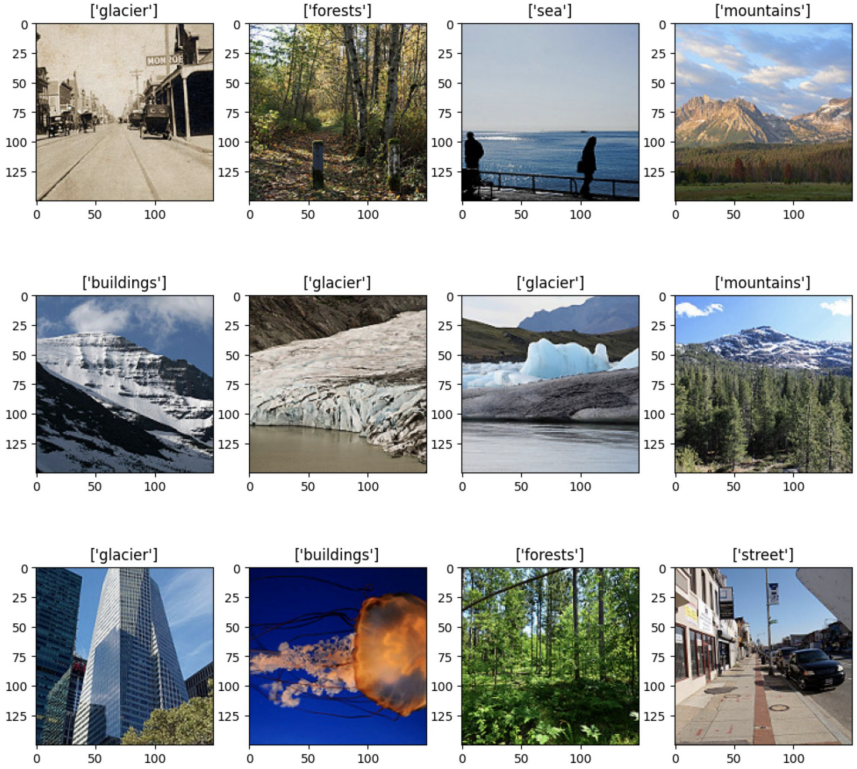
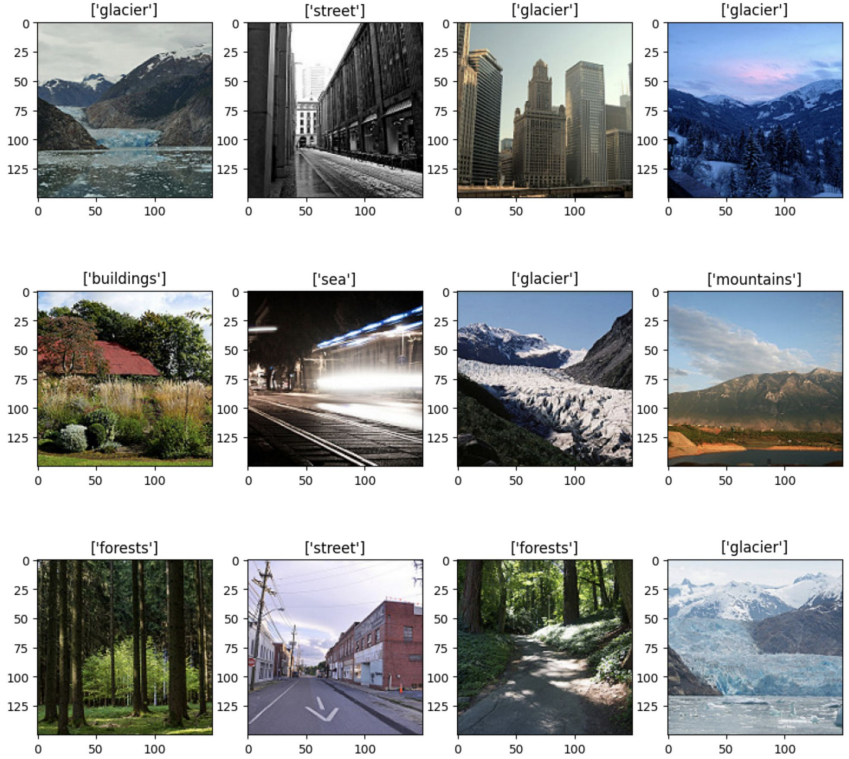
Conclusion: Final Test





Thank you.

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