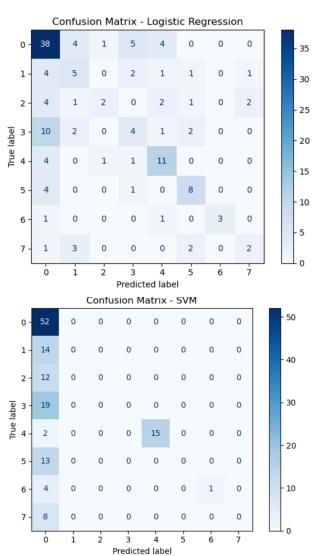
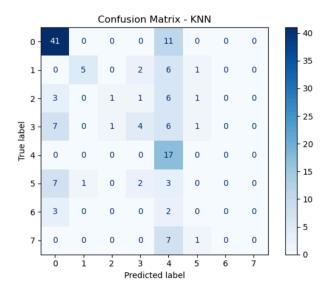
V1 CNN:

MobileNetV2 results:

Logistic Regression Accuracy: 0.5214285714285715

SVM Accuracy: 0.4857142857142857 KNN Accuracy: 0.4857142857142857

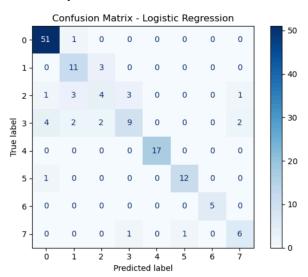


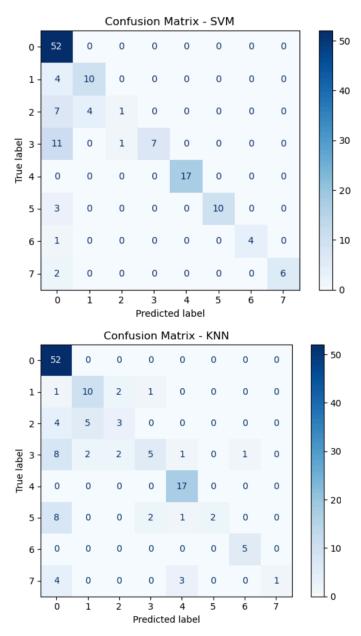


ResNet50 Results:

Logistic Regression Accuracy: 0.8214285714285714

SVM Accuracy: 0.7642857142857142 KNN Accuracy: 0.6785714285714286

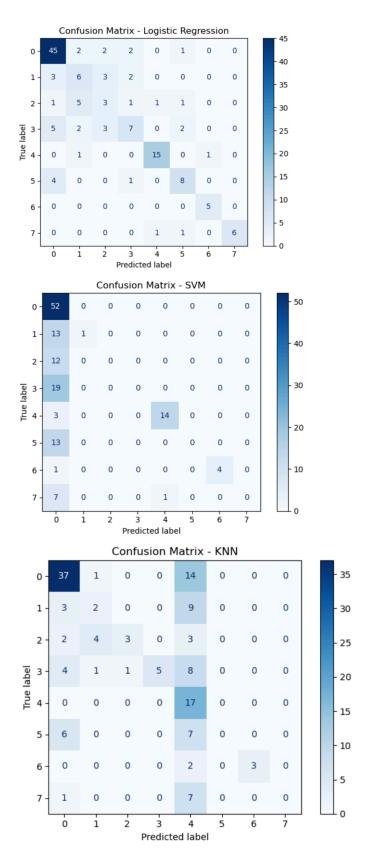




EfficientNetB0 results:

Logistic Regression Accuracy: 0.6785714285714286

SVM Accuracy: 0.5071428571428571 KNN Accuracy: 0.4785714285714286

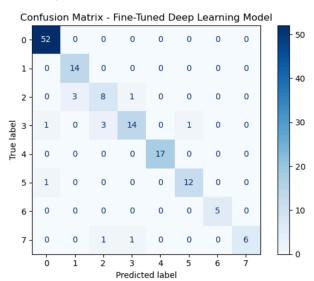


CNN V2 without data augmentation:

ResNet50 results:

Fine-tuned Custom Model Accuracy: 0.9143 Logistic Regression Accuracy: 0.8286

SVM Accuracy: 0.8214 KNN Accuracy: 0.7429



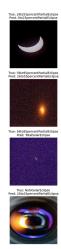
Classification Report - Fine-tuned Custom Model

	precision	recall	f1-score	support
0	0.96	1.00	0.98	52
1	0.82	1.00	0.90	14
2	0.67	0.67	0.67	12
3	0.88	0.74	0.80	19
4	1.00	1.00	1.00	17
5	0.92	0.92	0.92	13
6	1.00	1.00	1.00	5
7	1.00	0.75	0.86	8
accuracy			0.91	140
macro avg	0.91	0.88	0.89	140
weighted avg	0.92	0.91	0.91	140

Total misclassified images: 12





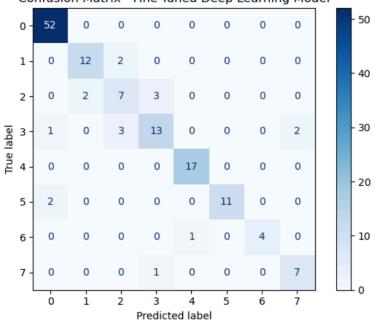


EfficientNetB0 results:

Fine-tuned Custom Model Accuracy: 0.8786 Logistic Regression Accuracy: 0.8000

SVM Accuracy: 0.7714 KNN Accuracy: 0.7143





Classification	n Report -	Fine-tuned	Custom Mod	el
	precision	recall	f1-score	support
0	0.95	1.00	0.97	52
1	0.86	0.86	0.86	14
2	0.58	0.58	0.58	12
3	0.76	0.68	0.72	19
4	0.94	1.00	0.97	17
5	1.00	0.85	0.92	13
6	1.00	0.80	0.89	5
7	0.78	0.88	0.82	8
accuracy			0.88	140
macro avg	0.86	0.83	0.84	140
weighted avg	0.88	0.88	0.88	140

Total misclassified images: 17



True: 26to55percentPartialEclipse Pred: 56to95percentPartialEclipse



True: 26to55percentPartialEclipse Pred: 56to95percentPartialEclipse



True: 56to95percentPartialEclipse Pred: 26to55percentPartialEclipse



True: 56to95percentPartialEclipse Pred: 26to55percentPartialEclipse



True: Flats Pred: Darks

Misclassified Images - Fine-tuned Model

True: 0to25percentPartialEclipse Pred: 26to55percentPartialEclipse



True: 26to55percentPartialEclipse Pred: 0to25percentPartialEclipse



True: 56to95percentPartialEclipse Pred: NotASolarEclipse



True: 56to95percentPartialEclipse Pred: NotASolarEclipse



True: DiamondRing_BaileysBeads_SolarEclipse Pred: TotalSolarEclipse



True: NotASolarEclipse Pred: 56to95percentPartialEclipse



True: 26to55percentPartialEclipse Pred: 56to95percentPartialEclipse



True: 56to95percentPartialEclipse Pred: TotalSolarEclipse



True: 56to95percentPartialEclipse Pred: 26to55percentPartialEclipse



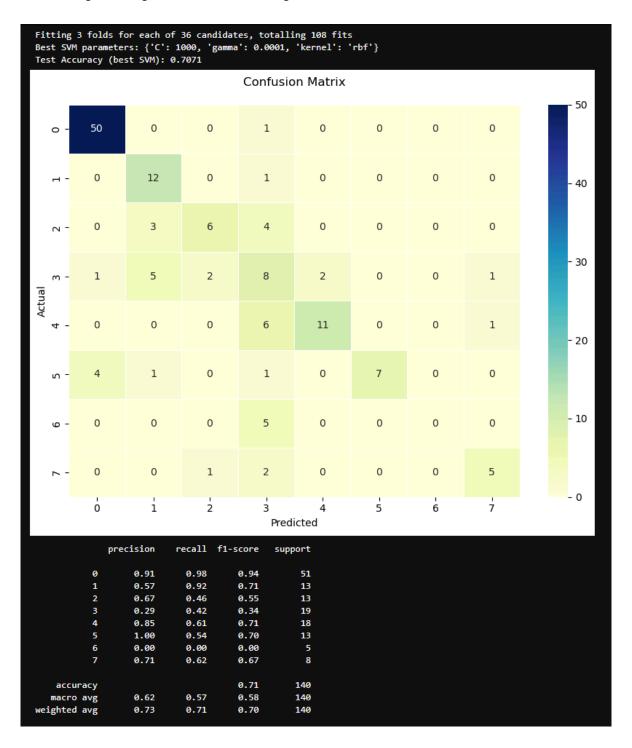
True: DiamondRing_BaileysBeads_SolarEclipse Pred: TotalSolarEclipse



SIFT + BoVW + SVM/LR

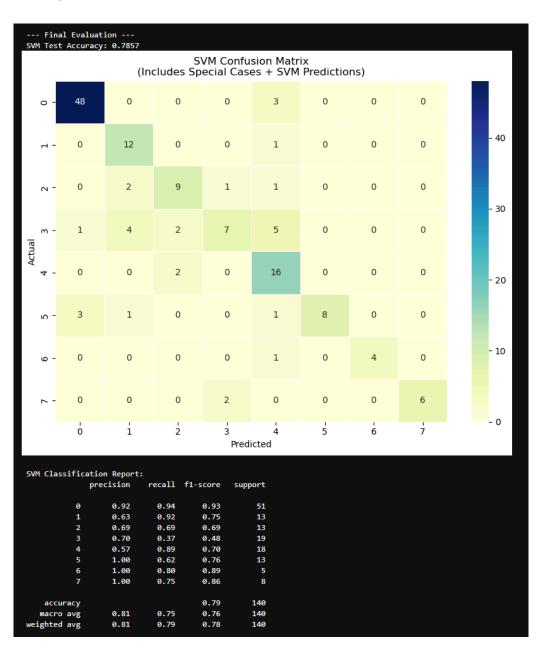
First Pipeline

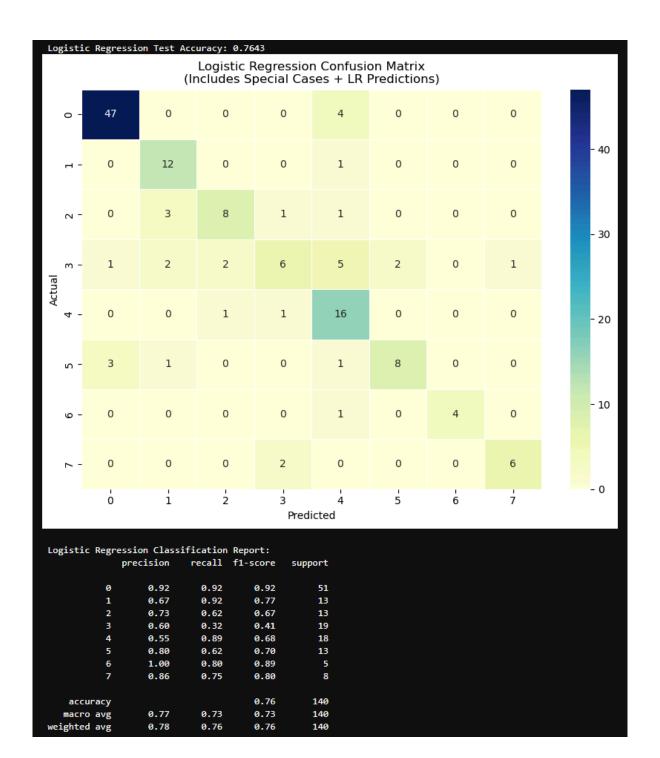
Our first attempt at using SIFT and BoVW did not use pre-classification of dark and flat images. Instead we went directly by trying to run all images through SIFT and BoVW and then through SVM and Logistic Regression. The following were our best results:



Second Pipeline

No matter what parameters we changed we could not get a higher accuracy. So we decided to look at what images were mostly being misclassified based on the confusion matrix and we can see that 6(flats) had no correct predictions and 4(darks) could do better. We decided that we could classify these two beforehand since the key feature in each of these classes was simply the unbalanced histograms. Darks would have more of their peaks towards 0 and flats (brighter images) would have more of their peaks closer to 255. Using this information and intensities of these images, along with the dominant pixel value, we went ahead and tried classifying these images before running the rest of the images through SIFT, BoVW, and SVM/LR. With this we got the following results (best):





Overview of what was tried (for SIFT/BoVW/SVM/LR) and what the outcomes were:

- As stated, first we did not try dark and flat classifying before SIFT. Everything was running through sift and the best accuracy we were able to get (with varying ALL parameters) was about 70%.
- Now pre-classifying flats and darks through statistical thresholding, bumped the accuracy to our best accuracy of about 79%.
- With this approach our accuracy varied from 74% up to 79%. We tried sharpening
 the images since SIFT looks for keypoints that come from corners and edges (for
 example) because some eclipse images had good edges and points that stuck out, but
 we actually got a worse accuracy even with pre-classification i was getting around
 62%.
- We tried using a different preprocessing method for dark/flat classification than for sift but the accuracy went down to 66%. I believe we had tried no CLAHE for flat/dark classification and no Gaussian Blur for SIFT/BoVW.
- Parameters we played with and added:
 - sift = cv2.SIFT_create(contrastThreshold=0.03, edgeThreshold=5)
 - o Image size
 - Threshold values
 - def classify_flat_or_dark(img, flat_std_thresh=8,
 dark_mean_thresh=25, dark_std_thresh=6, path=""):
 - o Minikmeans instead of regular KMeans
 - Lowered the accuracy
 - Vocab size

• Best: 345

Larger: Lowered the accuracySmaller: Lowered the accuracy

- Added grid search
 - Improved by about 1% as our parameters before were almost all the same except for gamma, but always good to have