# Using Smartphone EXIF Data to Classify Lighting Conditions for Outdoor Augmented Reality

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**Abstract**

*Correctly matching real-world environment lighting conditions is an important step in making Augmented Reality content better fit with surrounding real objects. It is also the first step in larger, more complex problems like object relighting, shadow estimation, surface shading, etc. Dynamic classification of lighting conditions thus needs to be robust and lightweight. In this paper, we investigate the suitability of using pure EXIF data for classifying outdoor lighting conditions in four broad categories using a variety of shallow machine learning models. We gather a dataset of images together with EXIF metadata to test different models and show the results from the best-performing one in a real-time Augmented Reality application on a smartphone.*

**CCS Concepts**

• ***Computing methodologies*** → ***Computer graphics; Machine learning; Mixed / augmented reality;***

## 1. Introduction

Accurate lighting and shadows are essential for immersive Augmented Reality (AR). Estimating lighting conditions enables adaptive shading and consistent shadow casting. Traditional approaches rely on direct image analysis, including object and shadow segmentation, depth estimation, normal maps, and BRDFs [LWL*22]. Alternatively, some methods leverage EXIF metadata [QFQW21, MFX*24]. Qian et al. [QFQW21] found that incorporating a simple CNN with EXIF data yielded optimal results, highlighting the need for a more refined approach to utilizing EXIF data for illumination and shadow estimation.

This paper explores using EXIF data to classify outdoor AR lighting conditions. Leveraging simple EXIF data allows for smaller models with lower data requirements. We capture images at different times of day across two months, collect their EXIF data, and train multiple machine learning models. We try to classify the lighting conditions in the images into four main categories that can be used later to dynamically change shadow intensity in augmented reality applications - looking at a sunny space from a sunny position *Sun*, looking at an overcast space from an overcast position *NoSun*, looking at space in shadow from a sunny position *ShadeFromSun* and looking at a sunny space from a position in shadow *SunFromShade*. We test both classical statistical machine learning models with the Gradient Booster Classifier, achieving an F1-Score of 0.785 and our proposed shallow CNN and MLP models reaching an F1-Score of 0.821 and 0.834, respectively. We demonstrate the feasibility of the model in an AR application and plan to implement it as part of a larger AR lighting and shadow estimation pipeline.

## 2. Methodology

To explore EXIF data for classifying AR lighting conditions, we collect 950 images from four smartphones across four categories. Each image is taken at a 45-degree angle and a comfortable viewing height for AR visualizations on the ground. Captured in October and February, the dataset includes diverse weather and ground conditions from various outdoor locations. From those 325 *Sun*, 317 *NoSun*, 103 *ShadeFromSun* and 205 *SunFromShade* images. We extract EXIF data from each image and use common smartphone-captured features—ISO, exposure time, shutter speed, aperture —for model training. Shutter speed in the EXIF standard is similar to Exposure Value (EV). Analyzing these features' correlation with the four categories, we find shutter speed has the highest correlation with 0.89, followed by exposure time (0.66), ISO (0.35), and aperture (0.11). Having the captured data, we select several machine learning models to train.

We choose 8 classical statistical models that have been successfully used on tabular EXIF data [GKZ20] - Random Forest (RF), Extra Trees (ET), Decision Tree (DT), K-nearest Neighbors (KNN), Support-Vector Classifier (SVC), Gradient Boosting (GB), Logistic Regression (LR), and Naive Bayes (NB). Together with these, we create a CNN with 1-dimensional convolutions and a multi-layer perceptron (MLP). The CNN consists of a 1D-convolutional and Relu layers followed by 2 fully connected layers, while the MLP consists of 3 fully connected layers, both ending with a softmax layer. The chosen depths were selected after evaluating various ones and choosing the best-performing ones. We decided to test the CNN architecture based on the ideas proposed





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Table 1: Results from the different models on the EXIF data. The trained models are Random Forest (RF), Extra Trees (ET), Decision Tree (DT), K-nearest Neighbors (KNN), Support-Vector Classifier (SVC), Gradient Boosting (GB), Logistic Regression (LR), Naive Bayes (NB), our proposed shallow MLP and CNN models.

| **Classifier** | **RF** | **ET** | **DT** | **KNN** | **SVC** | **GB** | **LR** | **NB** | **MLP** | **CNN** |
|---|---|---|---|---|---|---|---|---|---|---|
| F1-score | 0.769 | 0.751 | 0.771 | 0.779 | 0.675 | 0.785 | 0.672 | 0.551 | **0.834** | 0.823 |


**(a)** ✓ *Sun* **(b)** ✓ *Sun* **(c)** ✓ *noSun* **(d)** ✓ *SunFromShade* **(e)** ✗ *noSun -> Sun* **(f)** ✗ *NoSun -> ShadeFromSun*

**Figure 1:** *Visualizations from the example AR app. From left to right - correct detections for Sun (Figure 1a), another Sun (Figure 1b), NoSun (Figure 1c) and SunFromShade(Figure 1d) classes. After that are error visualizations when NoSun was detected, but should have been Sun (Figure 1e) and when NoSun was detected but it should have been ShadeFromSun (Figure 1f)*

by [QFQW21]. Both models were trained with a batch size of 16 and a learning rate of 0.004 for 20 epochs, after which the observed loss did not change meaningfully. The dataset is divided into training/testing at a ratio of 80/20. All models had a Grid Search done on their parameters with 5 Cross-Validation folds.

## 3. Results

For each model, we calculate the combined F1-score to assess precision and recall, as shown in Table 1. The MLP model outperforms all other models. Classical approaches also yield good results with Gradient Boosting performing the best among them. Both the CNN and MLP have the most problems while trying to distinguish *ShadeFromSun* label, where almost all of the *ShadeFromSun* labels were classified as *NoSun*. This can be attributed to the fact that this class has the smallest amount of data, and if we inspect the EXIF features, we can see it has a lot of overlap with the *NoSun*, especially in shutter speed. Some of the images contain snow patches and puddles that have also influenced the camera parameters. For a demonstration, we implement the best-performing architecture as an ONNX model, in a Unity AR application, through the use of Sentis. In the application, we adjust the augmented objects' shadow strength and color based on the output label from the classifier through the use of a custom shadow shader. If the output label *(Sun)* the shadow is very strong, and basically no shadow for label *(NoSun)*. Examples of the augmented shadows at different lighting conditions are shown in Figure 1. The proposed light classification model is very lightweight, generating results in an average of 1.2 milliseconds on a regular consumer smartphone, making it suitable for real-time use or as a part of a larger relighting solution.

## 4. Conclusions

We presented our initial work in utilizing readily available EXIF data from phone cameras to dynamically classify the lighting conditions of outdoor scenes in four rough classes. We saw that a fully connected MLP provides the best performance, but has problems with one of the classes because of similar EXIF values to others. We implemented the proposed model as part of a demonstration AR application. For future work, we plan to use it as part of a larger shadow estimation application, where it will provide initial information about the lighting conditions and its output will be combined with a network that gathers weather and sun position metadata from geo-location, as well as phone internal sensor data.

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