USING SMARTPHONE EXIF DATA TO CLASSIFY LIGHTING CONDITIONS FOR OUTDOOR AUGMENTED REALITY

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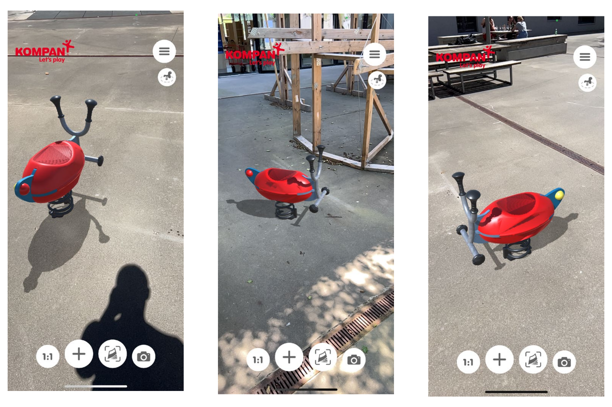
1 PROBLEM

We address the problem of illumination consistency for outdoor Augmented Reality (AR).
For outdoor AR it breaks the illusion, if augmented objects are shaded, and cast shadows in ways that are not consistent with the illumination conditions of the real scene.



Three screenshots from commercial AR app (Kompan AR) showing examples of AR objects with shadows that are inconsistent with real scene illumination.

2 RELATED WORK

Most related work rely on direct image analysis, using either model-based [2] or neural approaches [3] to estimate the illumination conditions in the scene. Since these approaches work on the pixel information they typically require immense amounts of training data, and/or have difficulties handling scenario variation. The raw pixel values also do not carry information about the big dynamic range changes experienced in outdoor scenarioes.

3 OVERVIEW

We explore if it is possible to use only EXIF information from the camera (ISO, exposure time, shutter speed, and aperture). In the EXIF standard shutter speed is very similar to Exposure Value (EV). The idea is based on the research by Ghazali et al. [1].

We train a range of machine learning models to use EXIF data as feature vectors, and classify scenes into four illumination classes:

- SUN (scene is in direct sunlight)
- NO SUN (scene is in complete shadow)
- SHADE FROM SUN (camera is in direct sunlight, imaged scene is in shadow)
- SUN FROM SHADE (camera is in shadow, imaged scene is in direct sunlight)

The classification runs in real-time on a standard consumer smartphone.

4 METHODOLOGY

Classical machine learning approaches tested:
Random Forrest (**RF**), Extra Trees (**ET**), Decision Tree (**DT**), K-Nearest Neighbour (**KNN**), Gradient Boosting (**GB**), Support Vector Classifer (**SVC**), Logistic Regression (**LR**), Naive Bayes (**NB**).

Neural approaches tested:
Convolutional Neural Network (**CNN**) and Multi-layer Perceptron (**MLP**)

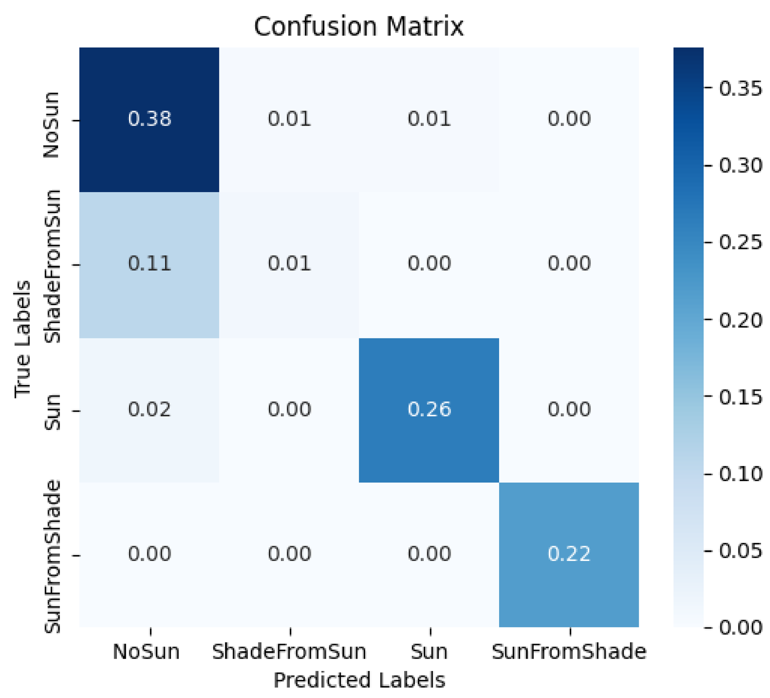
MLP: 3 fully connected layers plus softmax layer
CNN: 1D-convolutional and ReLu layers, 2 fully connected layers plus softmax layer

MLP performs best with an F1-score of 0.834

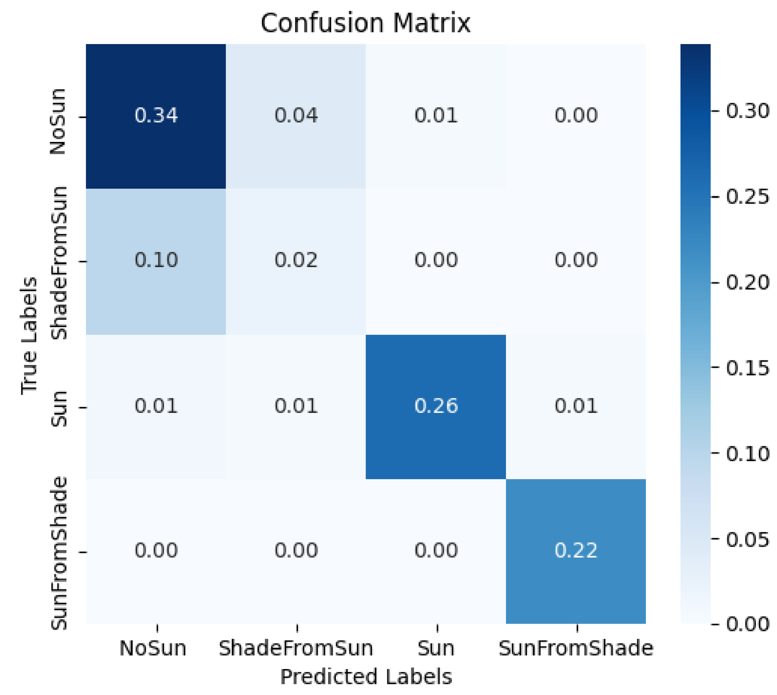
Dataset:
325 SUN
317 NO SUN
103 SHADE FROM SUN
205 SUN FROM SHADE

SUN | NO SUN | SHADE FROM SUN | SUN FROM SHADE

For visualization the trained MLP model is implemented as part of an AR app through Unity Sentis.



Confusion matrix MLP



Confusion matrix CNN

5 RESULTS

SUN | SUN | NO SUN | NO SUN | SUN FROM SHADE | SHADE FROM SUN | NO SUN

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

AFFILIATIONS

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REFERENCES

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[2] LIU C., WANG L., LI Z., QUAN S., XU Y.: Real-Time Lighting Estimation for Augmented Reality via Differentiable Screen-Space Rendering. IEEE Transactions on Visualization and Computer Graphics 29,4 (2022), 2132–2145. 1

[3] MA H., FENG S., XIAO X., DONG C., CHENG X.: Image Shooting Parameter-Guided Cascade Image Retouching Network: Think Like an Artist. IEEE Transactions on Multimedia (2024). 1