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Research Article

Performance Comparisons of Machine Learning Methods of PLA-based Photochromic Material UV Sensor

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Abstract **–** A simple method for measuring of ultraviolet (UV) radiation or index values is introduced. In this study, which aims to use machine learning models to accurately analyze a changing color scale and make predictions about the magnitude of the external stimulus that causes color change, the photochromic Polylactic acid (PLA) material that changes color under UV light was video recorded with a smartphone camera. Then, by interpreting the data sets created from these images with machine learning models, a relationship was established between the current applied to the UV light source and the color. Video images taken with the smartphone camera were augmented with screen captures of 25 consecutive seconds, enabling the regression models used to make more accurate predictions. 9 different regression models were used, their performances were evaluated according to cross-validation results. Then, model performances were improved by using appropriate hyperparameters. Better accuracies were achieved especially in CatBoost Regression model. The findings of the study showed that UV intensity or index values can be determined with high accuracy with the existing smart phone camera without the need for any device.

Keywords – UV, PLA, Photochromic, Camera, Machine Learning

I. INTRODUCTION

The uses of ultraviolet (UV) rays and the harms or benefits of these rays are quite diverse [1], [2]. UV rays occur naturally as part of sunlight and are also used artificially in many different areas. Besides sunlight, artificially produced UV rays are also used in medical treatments, skin health products, research and industrial processes. One of the most common uses of UV rays is in sunscreen products. These products are used to protect the skin from the harmful effects of UV rays. Additionally, UV rays are also used in some medical treatments such as photodynamic therapy [3]. However, excessive exposure to UV rays can cause serious health problems such as skin cancer.

Measuring UV ray levels provides important data to obtain information about their positive and negative effects. UV measurements are provided by UV–vis absorption spectrophotometers, portable UV meters and smart phones connected to them, and image sensors in smart phones [4], [5]. In this study, a new method for UV light measurement was developed. In this method, 3D printable filaments, which are a product of Polylactic Acid (PLA) Photochromic materials that change color under UV light, were used [6]. Although PLA has high mechanical strength and superior thermal processability, using it pure is far from functional [7]. Photochromic materials were produced by taking advantage of the UV resistance of PLA materials under UV light [8]. The method developed in this study; It is based on taking images of the photochromic material with the help of a camera and establishing a relationship between the color and the UV light falling on the material with the help of artificial intelligence technologies. Color detection can be detected with the help of sensors or cameras [9], [10]. For example, voltage values read on a sensor designed using a photodiode will provide information about the RGB values of the color of the material [11]. However, these voltage values have the disadvantage of not being able to determine which area of the material in question is color detected.

In this study, the reason why color detection with a camera was preferred to detection with sensors was to minimize the effect of non-homogeneous color changes in the material on color perception. This was achieved with software technologies that include image processing and artificial intelligence modeling that has begun to enter every aspect of our lives. The method used in this study can eliminate the need for UV–vis absorption spectrophotometers and Portable UV meters, as it can be applied with our mobile smart phones, which are easily available today.

II. MATERIALS AND METHOD

In the study, eSUN UV 1.75 mm thick purple/white color changing filament was used as the material whose images were taken with the camera of smart phone. These filaments were printed on a 3D printer in dimensions of 30x20 mm as in Figure 1.

Fig. 1 Photochromic PLA material

To observe the color change of the photochromic material, a special experimental setup shown in Figure 2 was created and a professional color box was used in this setup.

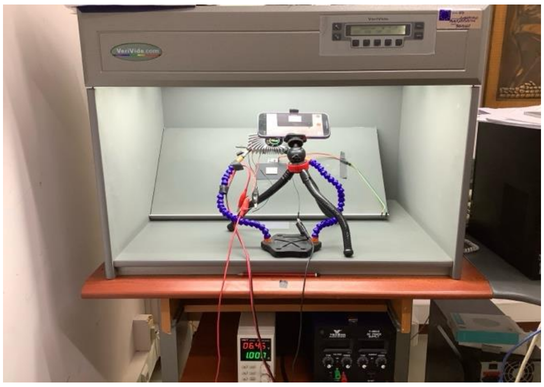


Fig. 2 Photochromic PLA material

The images were recorded as a video under UV light with the iphone 14 pro max camera at 4K resolution and 60 frame rate for 30 seconds. The iphone camera was operated in automatic white balance mode.

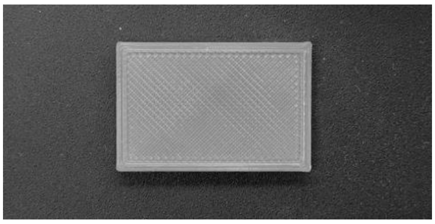
Screen captures of the videos taken in the experiment were taken once a second from the 1st to the 25th second. The UV light source, which enables the color change of the photochromic material, was applied to the material at different current levels. The effect of UV light on the material was examined using a total of 25 different current levels. These consist of 25 equal ranges from 1.5 A to 300 mA. A total of 625 observations were obtained at 25 different time points, 25 different current (Ampere) levels. These observations allowed obtaining detailed information about the color change of the photochromic material.

The images used to create the dataset were passed through a series of image processing stages. These stages are the methods used to analyze and process the obtained images. The stages are

Application of Grayscale,
Thresholding and Binarized Image Creation,
Morphological Operations,
Masking,
Making Transparent,
Cropping,

respectively. Pictures of these processes are shown in Figure 3.

a. Original image



b. Grayscale

c. c. Binarize (make it two-color)

d. D. Masking (Adding the relevant area to the white part)

e. Make Transparent.

f. Croped image

Fig. 3 Image processing stages.

After these processes were completed, the data set was created. The features used in the dataset are color attributes. A total of 10 features were extracted. In addition, columns such as Seconds and UV current have been added to the data set.

Since UV current (ampere) is a continuous value, regression analysis was used. The regression models used are as follows.

```
model_names = [
        "Linear Regression",
        "Decision Tree",
        "Random Forest",
        “GradientBoostingRegressor”
        "K-Nearest Neighbor",
        " MLPRegressor ",
        " GaussianProcessRegressor ",
        "XGBoost",
        "CatBoost"
    ]
```

Kilic et al. used machine learning classification models when detecting non-enzymatic glucose using a mobile smart phone and achieved a success rate of 93% [12]. Regression models were used in the study in this paper.

III. Results

In the experimental setup in this study, a data set was created by shooting 25 videos under a light source with a color temperature of 6500K for 25 different current values applied to the UV source. 25 screenshots were taken, one per second. A total of 625 images were obtained. These images went through image processing and subsequent extraction of color features in preparation for use as a data set in machine learning. 10 color features consisting of average values and intensity were extracted for each channel of RGB, HSV, Lab color spaces. Since texture attributes negatively affected the dataset, these attributes were removed from the images. 625x12 data set was created by adding seconds and current(ampere) features.

After the regression models were found to be suitable for machine learning, they were passed through cross-validation stages to evaluate the performance of these regression models. The results are seen in Table 1.

In Table 1, a smaller MSE value indicates that the model makes better predictions. Additionally, values such as "0.00" are expected to appear. The standard deviation is also expected to be lower, indicating that the model makes more accurate predictions.

Table 1. Cross Validation results

Model	Mean Squared Error (MSE)	Standard Deviation
Linear Regression	0,01	0
Decision Tree	0,01	0
Random Forest	0	0
K-Nearest Neighbors	0,01	0
Artificial Neural Network	0,13	0,02
Gaussian Process	0,15	0,06
Gradient Boosting	0	0
XGBoost	0	0
CatBoost	0	0

Performance criteria of the training are as in Table 2. In the performance criteria, the R2 score being close to 1 and the others being low shows how well the model can predict the real values.

Table 2. Performance measures of training

Model	Mean Squared Error (MSE)	Standard Deviation	R² Score	Mean Absolute Error (MAE)	Mean Absolute Percentage Error
Linear Regression	0,01	0,1	0,94	0,07	0,10
Decision Tree Regressor	0,01	0,09	0,95	0,06	0,08
Random Forest Regressor	0,00	0,07	0,97	0,05	0,06
Gradient Boosting Regressor	0,00	0,06	0,97	0,05	0,06
KNeighbors Regressor	0,01	0,08	0,95	0,06	0,06
MLP Regressor	0,02	0,14	0,85	0,11	0,14
Gaussian Process Regressor	0,10	0,31	0,37	0,20	0,25
XGB Regressor	0,01	0,07	0,97	0,05	0,07
CatBoost Regressor	0,00	0,05	0,98	0,04	0,04

The accuracy results for 6 different observations are as in Table 3.

Table 3. 6 accuracy results for different observation

Model	Accuracy_1	Accuracy_2	Accuracy_3	Accuracy_4	Accuracy_5	Accuracy_6
Linear Regression	87,6	95,7	99,36	97,97	93,8	83,67
Decision Tree Regressor	95,24	93,75	88,89	95	96,74	95
Random Forest Regressor	89,64	94,44	93,39	95,7	93,69	89,15
Gradient Boosting Regressor	95,07	91,35	95,06	97,8	93,29	88,97
K-Neighbors Regressor	97,14	97,5	94,44	98	96,74	95
MLP Regressor	85,87	86,46	91,06	96,82	99,82	85,87
GaussianProcessRegressor	99,3	61,58	94	27,8	98,02	99,3
XGBRegressor	90,9	89,82	94,84	94,93	91,07	94,46
CatBoostRegressor	**98,84**	**95,1**	**97,43**	**99,76**	**99,36**	**99,17**

The current values applied to UV are as in the list below.

[0.7, 0.8, 0.9, 1, 0.982, 1.0] Ampere.

The CatBoost Regression model has shown very good success in predicting these amperage values. These results are provided for screenshots at the 20th second of the prediction videos.

IV. DISCUSSION

In this study, the changing color values of a PLA photochromic material produced from a 3D printer under constant light and temperature conditions, changing in varying UV light intensities, were recorded with a camera. Data sets containing color attributes were created from camera recordings. Very good results were obtained in some of the 9 regression models using machine learning data sets. The results show that the color change in the photochromic material is directly related to the current value applied to the UV light source.

The high percentage accuracy of the predictions is for a color temperature of 6500 Kelvin. Creating a data set for different color temperatures has been the subject of subsequent studies. In addition, photochromic material may lose its color changing properties when exposed to UV radiation for a certain period of time. [13]. For this reason, it may be necessary to replace the material subject to the experiment with an unused one.

When you look at the pattern in the cropped image, it is seen that the colors in the patterns are not distributed homogeneously. For more precise results, it would be useful to use image processing algorithms to focus on the relatively more homogeneous colors found in the photochromic cartridge with a different pattern newly printed from a 3D printer.

These results cannot achieve the same accuracy values in different lighting conditions at different times. This problem can be resolved by creating a data set by measuring the amount of light from the UV light source instead of the current applied to the UV light source of the predicted target variable. This version of the study shows that it can give accurate results when the temperature of the UV source and the environment are the same.

V. CONCLUSION

An alternative and simple method was developed to evaluate the UV radiation quantities such as UV intensity or UV index values. By supporting machine learning techniques, one can estimate with high accuracy the levels with the existing smart phone camera, without the need for measuring devices. Although the method has some limitations, such as utilizing only one smart phone and maintaining a constant color temperature, we expect more widely applicable results with an expanded.

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