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Evaluation of light measurements for indoor and outdoor classification using neural networks

Matthew B. Rhudy

Division of Engineering, Business, and Computing, Pennsylvania State University, Reading, PA, USA

***Corresponding author**:*
Matthew B. Rhudy
mbr5002@psu.edu

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ABSTRACT

The objective classification of outdoor time has the potential to benefit applications involving the effect of outdoor exposure on various health outcomes such as happiness, stress, or myopia. The focus of this work is the use of different combinations of multiple light measurements as inputs to an artificial neural network (ANN) to classify indoor and outdoor environments. Seven different light measurements are considered within this work: ultraviolet index, luminosity, color temperature, red light, green light, blue light, and clear light. ANNs are trained, validated, and tested using all combinations of these different light measurements as inputs. The classification accuracy of each of these variations is compared and used to determine the effectiveness of the individual measurements for classification purposes. The results of this work revealed that the color temperature measurement was particularly effective for detecting outdoor exposure when used in conjunction with at least one other measurement type. Additionally, it was found that the ultraviolet index may not be a necessary component for classification algorithms.

Keywords: artificial neural network; classification; light; sensor systems and applications

1. INTRODUCTION

Mental health has become an increasingly relevant consideration in recent years. The COVID-19 pandemic has created numerous stressors for people worldwide. Specifically, changes in social behavior patterns, such as physical or social distancing, as well as isolation and quarantine practices have led to a tendency for people to spend more time indoors during the COVID-19 pandemic (Soga et al., 2021; Lades et al., 2020). Earlier work in the field of psychology has demonstrated a link between outdoor time and greater overall happiness (MacKerron and Mourato, 2013), lower stress levels (Hartig et al., 2003; Thompson et al., 2012), lower mortality and disease rates (Maas, 2009), as well as lower anger, violence, and aggression (Kuo and Sullivan, 2001). This is further reinforced by more recent studies, which showed an overall decrease in subjective well-being during the pandemic due to this decrease in outdoor activity (Jackson et al., 2021; Stieger et al., 2021).

Since it is likely that these types of habits will continue for people across the world, methods for monitoring and analyzing indoor and outdoor exposure is an important consideration for human health and well-being. One of the limitations of previous studies regarding the effect of outdoor time is the reliance of self-reported survey data to determine the overall outdoor time. It is also possible that this exposure to outdoor environments is confounded with other measurements, such as physical activity (Cleland et al., 2008; Schaefer et al., 2014) or screen time (Burdette and Whitaker, 2005). It has been shown, however, that physical activity and exposure to natural environments can independently promote positive health effects (Frumkin, 2001; St Leger, 2003). Regardless, promoting outdoor time could naturally lead to increased physical activity, thus providing an overall health benefit (McCurdy et al., 2010). Therefore, the ability to objectively measure outdoor exposure could have numerous benefits for various research areas. In addition to mental health considerations, outdoor time has been shown to reduce the incidence of myopia (Xiong et al., 2017; He et al., 2015). There are likely many other potential uses for indoor/outdoor information. For example, it was shown that the accuracy of activity monitors varies between indoor and outdoor locations (Busse et al., 2009). Accurate information about the user's location could help to improve activity monitoring algorithms.

Currently, many consumers use health tracking devices for different purposes, such as monitoring physical activity through energy expenditure (e.g., calories burned), step counts, distance travelled, etc. Many users also benefit from other biometric data from wearable technology, such as heart rate monitoring during exercise. This information serves two primary purposes. The first is just simple tracking and logging. That is, users can keep track of their current progress so that they have an idea of what they are doing. The second, and perhaps more important purpose of this type of health monitoring, is to motivate users to do more, often to complete goals such as reaching 10,000 steps every day. This mindset could be extended to additional health metrics, such as their time spent outdoors. If there were a reliable way to objectively measure the time a person is spending outside each day, this information could be used to help motivate them to get outside more, which could directly impact their mental health. In order to accomplish this, a sensing system and corresponding detection algorithm must be employed to automatically determine at any given moment if a person is indoors or outdoors.

Various sensor systems have been explored for the purpose of outdoor detection. One primary category of classification algorithms for outdoor detection is the use of global positioning system (GPS) measurements (Tandon et al., 2013; Klinker et al., 2014; Kerr et al.; 2012). There are some limitations, however, with using this type of sensor. These sensors can be more expensive than other alternatives and require external communication with satellites to work properly. This communication requirement can lead to higher power consumption and susceptibility to issues related to outages, boundary issues, etc.

Other approaches take advantage of built-in smart phone sensors, such as accelerometers, proximity sensors, light sensors, and magnetometers. Machine learning algorithms, such as IODetector have been shown to be successful at making indoor/outdoor classification based on cell signal strength (Li et al., 2014; Radu et al., 2014; Wang et al., 2016; Zhou et al., 2012), or Bluetooth (Zou et al., 2016). These methods, however, like GPS, require external signal information for proper operation. The use of the mobile phone, while convenient, may not be representative of the user's environment when carried, e.g., inside a pocket or bag. A person may also choose to leave their phone somewhere inside while engaging in sports or other outdoor activities. Due to these limitations, alternative classification systems are desirable.

Various works have considered the use of different light measurements for indoor and outdoor classification. Light measurements provide a reasonable choice for outdoor classification applications due to their relative low cost and lack of reliance on external communication. Additionally, light sensors measure the current environmental conditions, which are particularly relevant when assessing environmental exposure. Some early work considered the use of light intensity for outdoor detection using receiver operating characteristic (ROC) analysis (Tandon et al., 2013), which was later improved (Flynn et al., 2014). A more recent work applied a machine learning algorithm, the support vector machine (SVM), using ultraviolet (UV) index along with light intensity and number of steps to classify the indoor or outdoor condition (Ye et al., 2019).

In previous related works, the use of light measurements and machine learning techniques have been explored. Specifically, these works investigated the use of UV index, luminosity, color temperature, and red, green, blue, and clear components of light. The data acquisition system is fully detailed, and ROC classification results are offered for the individual metrics in addition to a preliminary artificial neural network (ANN) classifier (Rhudy et al., 2020). This work was expanded from Rhudy et al. (2021), which offers a comparison of three different machine learning classifiers: SVM, ANN, and bagged tree (BT). This work considered the use of all seven light measurements as inputs to the machine learning classifiers. Although the BT classifier showed marginally better performance over the ANN classifier (Rhudy et al., 2021), the ANN classifier still reported very high classification accuracy at a much lower computational cost. Due to the eventual goal of implementing in real time on a wearable device, computational cost is of particular importance for this application. Thus, the ANN classifier was selected for use in this study.

As a follow up to these works, additional work is desired to explore the effectiveness of each of the individual measurements within an ANN classifier. Specifically, this work aims to identify which measurements provide meaningful information regarding indoor or outdoor condition. This could help to reduce the measurement set, thus reducing the overall cost of the system and the computational complexity of the algorithm.

2. MATERIALS AND METHODS

2.1 Materials

The experimental setup for this project consisted of a microcontroller, which sampled data from two different light sensors approximately once per minute and stored the data on a microSD card. The microcontroller was an Adafruit Feather 32u4 Adalogger (New York, USA) with a rechargeable 3.7 V 350 mAh lithium ion battery. The microcontroller interfaces through I2C communication with a TCS34725 (Adafruit Industries, New York, USA) to measure luminosity, color temperature, and red, green, blue, and clear components of light. Additionally, a GUVA-S12SD (Adafruit Industries, New York, USA) sensor measured UV index through an analog voltage signal. This sensing system was presented in full detail in Rhudy et al. (2020). A diagram of the data acquisition system wiring is given in Figure 1 along with a picture of the prototype system used for data collection, which is shown in Figure 2.

2.2 Protocol

Data collection was conducted under static conditions in various indoor and outdoor locations. A total of 3,640 indoor and 1,368 outdoor samples were collected. Each sample consists of seven light measurements: UV index, color temperature, luminosity, and red, green, blue, and clear components of light. Table 1 shows the full description of all collected data sets. Most of the data described in Table 1 were collected in the general area of Reading, PA, USA. However, the last three data files were collected in Egypt. Note that this data set was used in previous related studies (Rhudy et al., 2020; 2021).

2.3 Data analysis

In this study, various ANN systems were developed, which used different combinations of inputs from the light measurements. All ANNs were selected as feedforward neural networks with a single hidden layer, containing 13 nodes. The number of nodes was identified to maximize the performance of the ANN for classification. The overall data set was divided into 70% training data and 30% testing data for each of the considered machine learning classifiers. The training was repeated for each ANN variation using 1,000 unique permutations of the data sets. Each ANN used the same 1,000 variations of training and testing data to ensure one-to-one comparison of the different ANN models. All data analyses were performed using MATLAB (R2021a, Natick MA), including the neural network toolbox.

3. RESULTS AND DISCUSSION

Some preliminary work has already been published in (Rhudy et al., 2020), which investigated the classification accuracy using individual light measurements. This work used ROC curves to identify the discrimination accuracy between outdoor and indoor conditions using a fixed cutoff value. The cutoff values were selected as the maximum sum of sensitivity and specificity, which coincides with the maximum Youden's index (Le, 2006). The results from this work are shown in Table 2. The results in Table 2 indicate that the blue light measurement offered the highest classification accuracy for this data set, followed by the UV index, though all individual sensors performed with reasonable accuracy.

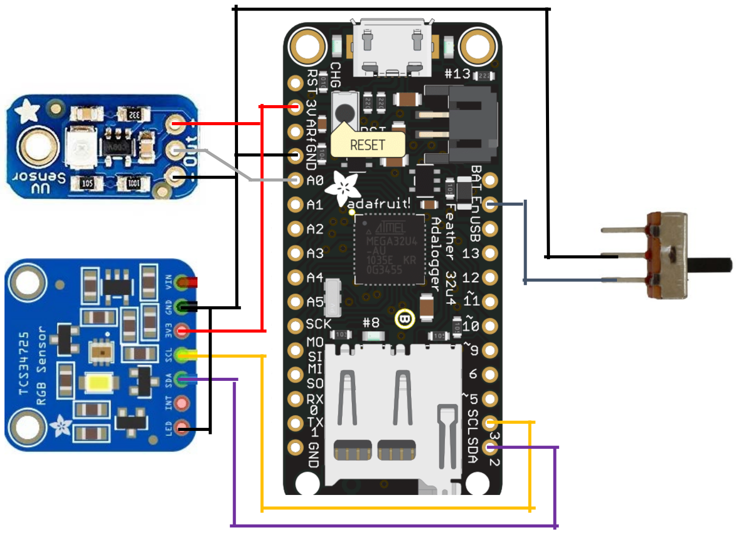

Figure 1. Diagram of the data acquisition system (Rhudy et al., 2020)

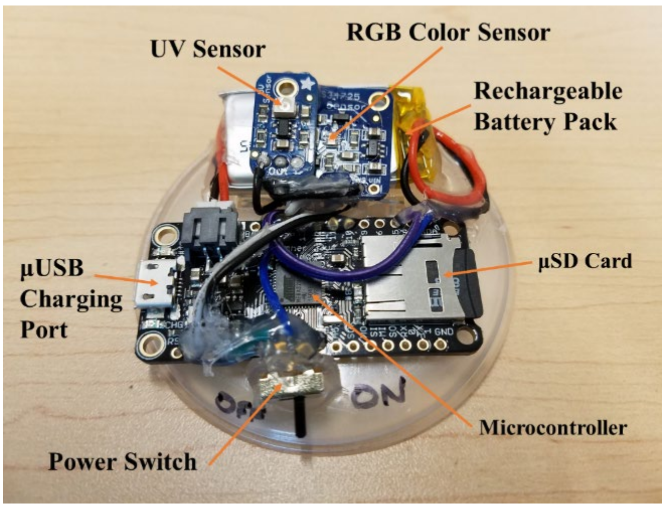

Figure 2. Picture of data acquisition system prototype (Rhudy et al., 2021)

Table 1. Description of data sets (Rhudy et al., 2021)

Description	Type	Month	Start time (Local)	Duration (HH:MM)	Weather
Classroom, 2 m from window	Indoor	January	09:00 AM	00:53	Sunny
Classroom, blinds down	Indoor	January	11:10 AM	00:35	Sunny
Classroom, blinds down	Indoor	January	09:05 AM	00:55	Sunny
Classroom, blinds down	Indoor	January	11:10 AM	00:53	Sunny
Apartment back step, shaded	Outdoor	January	01:15 PM	00:40	Sunny
Apartment, far from window	Indoor	January	01:56 PM	01:10	Sunny
Classroom, dark outside	Indoor	January	06:11 PM	00:39	Clear night
Classroom, blinds down	Indoor	January	10:35 AM	00:44	Sunny
Classroom, blinds down	Indoor	January	11:06 AM	00:46	Overcast
Classroom, blinds down	Indoor	January	08:57 AM	00:58	Overcast
Car windshield, direct sun	Outdoor	February	11:07 AM	04:21	Sunny
Café, next to large windows	Indoor	May	09:16 AM	00:36	Cloudy
Office desk, lights off	Indoor	May	01:58 PM	43:43	Partly Cloudy
House, blinds down	Indoor	June	03:18 PM	01:07	Cloudy
House under lamp (on)	Indoor	June	04:28 PM	01:19	Cloudy
House front lawn, direct sun	Outdoor	June	02:00 PM	00:57	Sunny
Outdoor swing	Outdoor	July	07:19 AM	01:07	Clear sky
Outdoor rocking chair under tree	Outdoor	July	08:27 AM	00:25	Sunny
House, bookshelf, lights off	Indoor	July	08:54 AM	01:10	Sunny
House, bench, lights off	Indoor	July	10:45 AM	01:19	Sunny
House, kitchen under LED lights	Indoor	July	12:24 PM	00:50	N/A
House by electric fireplace (on)	Indoor	July	01:16 PM	00:30	N/A
Outdoor deck chair, direct sun	Outdoor	July	01:48 PM	00:35	Sunny
Seesaw in shade	Outdoor	July	02:24 PM	00:35	Sunny
Chair under an outdoor roof	Outdoor	July	03:00 PM	00:38	Shaded area
Basement table, no windows	Indoor	July	07:44 PM	01:00	N/A
House roof (Egypt)	Outdoor	July	01:56 PM	05:38	Sunny
House roof (Egypt)	Outdoor	July	04:11 AM	08:50	Sunny
House, bedroom floor (Egypt)	Indoor	July	09:20 PM	01:37	N/A

Table 2. Classification accuracy from ROC analysis

Measurement	Sensitivity	Specificity	Youden's index
UV index	0.932	0.995	0.927
Color temperature	0.939	0.968	0.907
Light intensity	0.919	0.995	0.914
Red	0.904	0.999	0.903
Green	0.923	0.997	0.920
Blue	0.930	0.998	0.928
Clear	0.922	0.996	0.918

The performance of using all seven light measurements as inputs for the ANN revealed a sensitivity of 97.6% and specificity of 99.81% (Youden's index = 0.945), which showed a clear performance benefit over using the individual metrics. However, it is not clear if all seven metrics are necessary in order to obtain this higher performance accuracy (Rhudy et al., 2021). To investigate this further, all possible combinations of the seven considered light measurements were implemented as inputs to ANNs, resulting in 120 different combinations. For each ANN, the same 1,000 variations of training and testing data were used so that the comparisons were equivalent regarding their performance.

For each of the 120 different combinations, the performance was evaluated by calculating the sensitivity, specificity, and Youden's index. The classification results for the ANN variations with the top 5 highest Youden's index are presented in Table 3. The Youden's indices for each of the 2-input ANNs are shown in Figure 3, for 3-input ANNs in Figure 4, for 4-input ANNs in Figure 5, for 5-input ANNs in Figure 6, and for 6-input ANNs in Figure 7. For compactness, the following abbreviations were used in Table 3 and Figures 3 through 7: UV = UV index, CT = color temperature, L = luminosity, R = red light, G = green light, B = blue light, and C = clear light.

In addition to the results shown directly in Figure 3 through Figure 7, some additional observations were made regarding the different ANN combinations when ranked by Youden's index. Note in Table 3 that the color temperature measurement appeared in all top 5 ANN variations. In fact, the color temperature measurement was used in the top 42 ranked ANNs (out of the 120 combinations). This is particularly interesting, since the color temperature performed worse than all other light metrics except for red light when using only a single measurement as shown in Table 2. However, when used in combination with other light measurements, the color temperature served to improve the estimation performance.

Table 3. Classification accuracy for top 5 ANN combinations

ANN inputs	Sensitivity	Specificity	Youden's index
CT,B	0.9797	0.9981	0.9779
UV,CT,L,G,B,C	0.9776	0.9975	0.9751
CT,L,R	0.9761	0.9984	0.9745
CT,B,C	0.9755	0.9987	0.9741
CT,L,R,G,B,C	0.9762	0.9975	0.9737

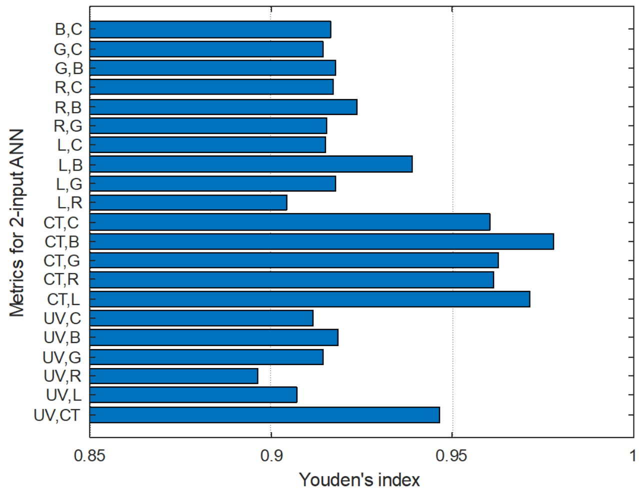

Figure 3. Classification accuracy for ANNs using 2 input metrics

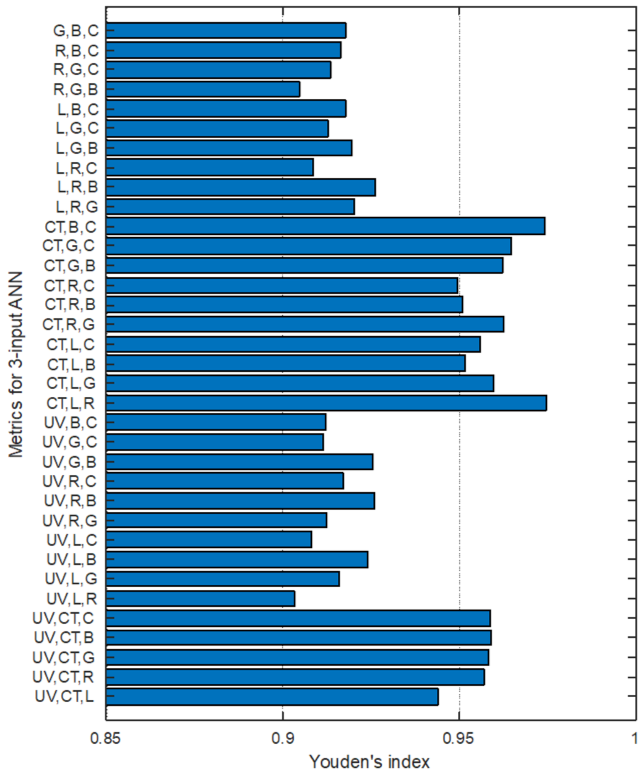

Figure 4. Classification accuracy for ANNs using 3 input metrics

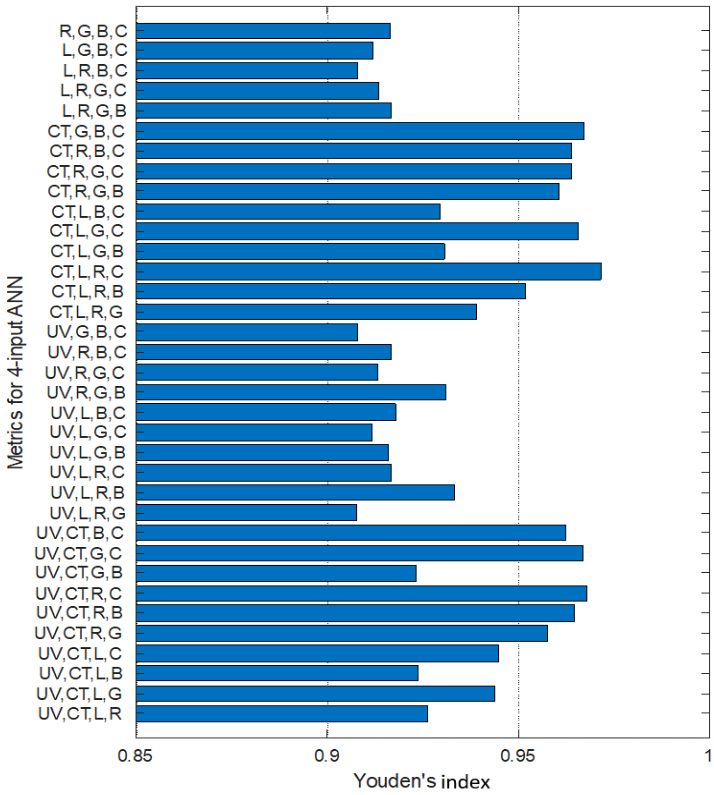

Figure 5. Classification accuracy for ANNs using 4 input metrics

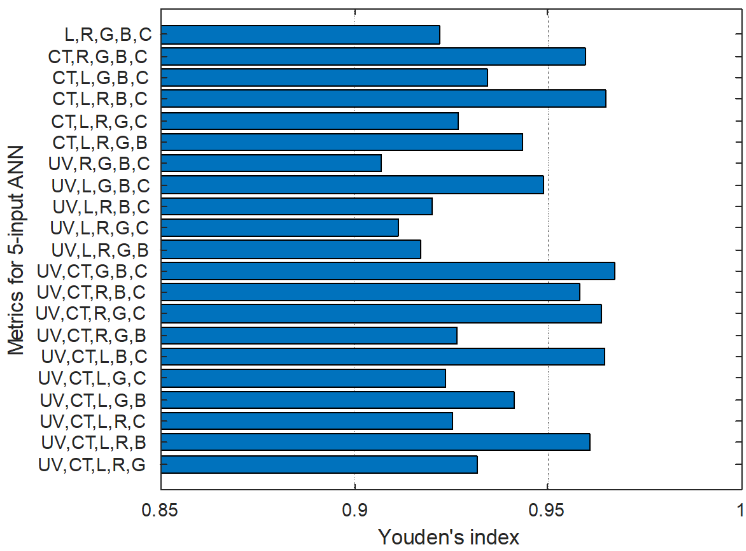

Figure 6. Classification accuracy for ANNs using 5 input metrics

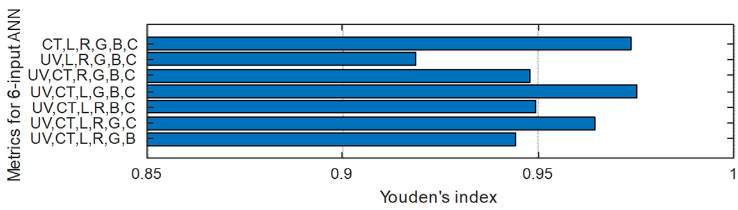

Figure 7. Classification accuracy for ANNs using 6 input metrics

It is also interesting to note that the classification accuracy of the ANN, which used all seven measurements ranks low on the list at 46. Often, one would expect greater performance when using more measurement data. However, as shown in Figure 7, some of the 6-input classifiers outperformed the full 7-input ANN. In fact, two of the top 5 combinations (Table 3) used 6 out of the 7 metrics. The second highest performing ANN used all measurements except the red light component. This indicated that the red light measurement may potentially be confusing the classification in the ANN. The red light measurement was also the one, which showed the worst classification accuracy (Table 2).

Surprisingly, four out of the five best performing ANN classifiers did not use the UV index. UV exposure is known to be higher in outdoor locations, so this measurement was expected to provide a meaningful indication of indoor or outdoor condition. This is particularly interesting in this application though, because the measurement is provided from a separate sensor. Future iterations of this hardware could consider omitting the UV sensor since it does not lead to a significant improvement in classification accuracy.

As an additional comparison analysis, for each light measurement, two groups were created: one group containing all ANN combinations with that light measurement, and the other group containing all ANN combinations without that light measurement. Then, a two-sample t-test was used to see if there were significant differences in the classification accuracy between the two groups. Only the color temperature demonstrated significant difference between the two groups ($p<0.001$). This is further indication that the color temperature measurement can help to improve the classification accuracy. To further illustrate these results, a box plot of the classification accuracy for ANN combinations with and without the color temperature are shown in Figure 8. The classification accuracy significantly improved when using classifiers with the color temperature measurement. Though not statistically significant, the blue light measurement showed an increase in classification accuracy between the two groups. It is interesting to note that the other five measurements showed a decrease in classification accuracy between the two groups, though not statistically significant.

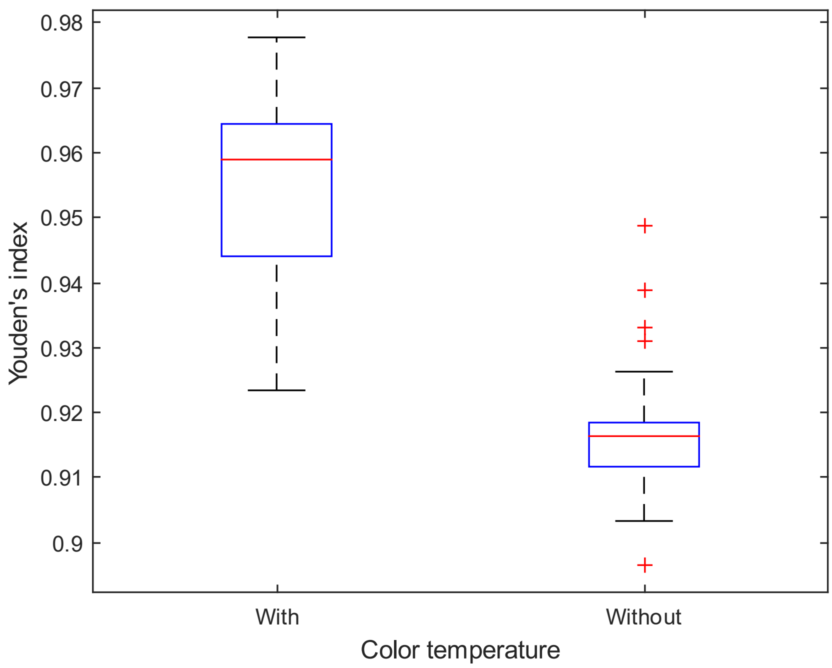

Figure 8. Box plot of classification accuracy for ANN combinations with and without the color temperature measurement as an input

4. CONCLUSION

This work investigated the use of different light measurements within ANNs for indoor or outdoor classification. The results indicated that the greatest classification accuracy was obtained when using only two of the light measurements: color temperature and blue light. This combination of sensor measurements led to a Youden's index of 0.9779, which is a very high classification performance. The color temperature measurement was shown to offer the best performance improvement when used in conjunction with other light sensors. Overall, this work determined that the use of all seven considered light measurements is likely unnecessary for indoor and outdoor classification, and a reduced measurement set could be considered in future applications.

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