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Classification of Lighting Design Aspects in Relation to Employees' Productivity in Saudi Arabia

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Abstract: Though the average employee spends a third of their day inside an office, designing a productive workspace can be challenging for designers. However, lighting design is a critical factor for the wellbeing of the employee. With the increasing number of local and international companies opening in Saudi Arabia, it is important to study the effect of natural and artificial lighting on the productivity of employees in the office environment. It is essential to consider that employee productivity leads to economic productivity. A questionnaire was shared with the employees of the head office of Ensan Charity for Orphans Care to collect data on the preferences of staff on the current lighting design in their offices. Office design is one of the most important aspects in need of special attention, since employees spend more than eight hours daily at their offices. Lighting design is one of the key aspects of office design that has a direct impact on employees' satisfaction and productivity. The aim of this study was to discover employees' preferences for office design in Saudi Arabia. The collected data are analyzed to uncover employee preferences as well as to predict two key design aspects using machine-learning techniques. The two design aspects of concern are direct sunlight in the office environment and manual control of light intensity. This research aimed to help improve the design of the office environment according to employees' preferences and international standards through investigating sustainable lighting design elements. A further challenge to be overcome was the need for further data collection as it relates to the two design aspects mentioned above. This paper demonstrates relatively high prediction accuracies of the mentioned design considerations using a variety of machine-learning algorithms.

Keywords: economic productivity; office design; lighting design; employee satisfaction; machine learning

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1. Introduction

Lighting design has been the subject of much research around the globe in the past few decades, and researchers have been studying the influence of natural and artificial lighting covering all environments and spaces, whether to influence the mood of users or simply to add to the beauty of the space [1,2]. In Saudi Arabia, research on this topic is growing as well, especially in critical spaces, such as hospitals, educational buildings [3], and work environments [4,5]. However, most studies in Saudi Arabia are more concerned with energy consumption in relation to natural and artificial lighting [4]; almost none have focused on the psychology of the users of a space in regard to lighting design. A study conducted in Riyadh measured visual comfort in relation to natural light through different types of glass windows [5]. Consequently, apart from the limited lighting research in this area, it was found that, to the best of the researchers' knowledge, collaboration between the educational sector and engineering companies to support non-profit organizations with meaningful design has not been developed in Saudi Arabia. This gap has led to the establishment of the present study, which focuses on adding to the knowledge of designers, as well as helping non-profit organizations to empower employee satisfaction and increase productivity through design. The main aim of the study was to increase the productivity of employees, which ultimately leads to economic productivity.

This research was initiated by the East Consulting Engineering Company (ECEC),who designed the new headquarters for Ensan Charity, and Prince Sultan University. Ensan Charity is a non-profit organization that was established in 1999. The Charitable Association for Orphans Care in Riyadh (Ensan), headed by His Royal Highness, Governor of Riyadh Region, was registered with the Ministry under No. (166) and dated 8/28/1420 AH in accordance with the provisions of the Charitable Associations and Institutions Regulations and their implementing rules, and its articles of association were published in Umm Al-Qura newspaper (Issue 3783) issued on 11/12/1420 AH (https://ensanonline-com.translate.goog/Pages/founding-assembly.html?_x_tr_sl=ar&_x_tr_tl=en&_x_tr_hl=en&_x_tr_pto=sc (accessed on 25 December 2022)). The ECEC and Prince Sultan University initiated this research as an attempt to create a beneficial engagement between the three parties involved in this research. The idea was welcomed by the Charity, with an initial approval granted to start designing the research using the plans produced by the ECEC. The next step was identifying the critical elements to be included in a questionnaire to lead the research. Researchers from the university collected and analyzed data to uncover employees' preferences in relation to lighting design, as well as to predict two important design aspects using machine-learning techniques. Consequently, the contributions of this paper are as follows:

1. The collected data are analyzed to compare the relationship between the employees' current conditions in their offices, the amount of time they spend there, and their lighting preferences for their future offices for the purposes of achieving a sustainable work environment.
2. Two different lighting-related design considerations are predicted using machine-learning techniques for the purposes of easing future office designs and limiting the need for further data collection, which in turn creates a potentially sustainable lighting design process. This contribution also includes ranking the utilized machine-learning algorithms.

These two contributions above aim to fill an existing gap in practice that pertains to data collection for lighting design considerations. More specifically, the second contribution of this paper addresses the fact that the cited literature, as will be seen next in the "machine learning in building design" section of the literature review, uses the collected data for prediction purposes. This paper follows the same procedure of the cited literature. In addition, this paper aims to establish design guidelines based on the predicted results of six different machine-learning algorithms. Consequently, the need for future data collections may be eliminated due to the design guidelines that are achieved as a result of the machine-learning prediction scheme. The use of a variety of machine-learning techniques also provides a wide spectrum of prediction scheme choices for future design considerations.

1.1. Natural Light

Natural light is the most preferred light used by interior designers in an interior environment due to its full color spectrum, which has a CRI of 100. CRI or the color-rendering index indicates the ability of light to render the color of an object using a scale from 0 to 100, in which 0 equals a bad rendering (the light does not show the true colors of objects) and 100 is perfect (the light shows the true colors of objects) [1]. Daylight can influence the workers' performance on many levels, such as in terms of the visual system, the circadian system, and the perceptual system [2].

One of the most common artificial lighting sources currently used are light-emitting diodes (LEDs) because of their high CRI and low energy consumption. The color-rendering index is an important parameter of LED lights because of its impact on users' perception of the interior space. LEDs are very similar to daylight due to their ability to provide a variation of the spectral content, which basically means that the colors of interior environments will look more vivid and true. This will affect users' mood, productivity, and wellbeing in general [6]. A comparison between various types of LED lights and other types of lighting sources showed that RGB mixed white LEDs are the most suitable light source for office tasks such as reading [7]. On the other hand, correlated color temperature (CCT) indicates the appearance of light, or the color of the light being cool or warm. A study compared the effect of the relationship between daylight and artificial light on users' visual comfort, alertness, and general wellbeing and found a correlation between CCT and daylight. The group that was exposed to more daylight during the afternoon time was more alert than the group that experienced dim artificial lights. However, high CCT correlated with daylight was reported to cause glare and visual discomfort by the users [8].

Moreover, natural light has a better effect on melatonin levels when compared to artificial lighting. When two groups of workers with or without windows in their offices, the group that had no access to daylight showed lower melatonin levels by evening time, which would result in sleep disturbances [9]. On the other hand, Marans and Yan (1989) compared open and private office designs in aspects of privacy and lighting conditions. The results showed that privacy concerns had more impact than the lighting condition in open offices when compared with private offices. When evaluating the working environment, employees in private offices emphasized the quality of the lighting [10].

1.2. Artificial Light

Since a contemporary lifestyle requires indoor presence during 90% of the daytime, new office designs require the creation of an environment that enhances the wellbeing of the employee. This includes providing the appropriate amount of light (natural/artificial) for workers to perform a variety of assigned tasks [10].

According to Katabaro and Yan's (2019) research on office workers at an administrative office at Mbeya University of Science and Technology, poorly designed work environments can negatively impact employees' productivity and work efficiency. Workers who are in this situation are also susceptible to occupational diseases such as headaches, visual discomfort, fatigue, and eye irritation. As a result, a healthy workplace setting for employees should be a fundamental right. A poorly designed workplace can have a detrimental effect on employees' productivity and efficiency [11].

Additionally, Ali et al. (2015) correlated office workers' performance with their physical health influenced by the work environment. Their research conducted in 2015 on office workers in three universities in Malaysia found that an unpleasant working environment in the office contributes to health problems and raises the rate of absenteeism. Employee performance is impacted by high levels of employee absenteeism, because it lowers productivity [12].

1.3. Light and Productivity

Productivity is defined as the behavior of a human that serves their personal wellbeing and the development of related groups. "It is measured by the rate of the output per unit of input" [13]. In other words, a person measures their productivity according to the success they achieve on a task after a specific amount of effort.

A conceptual framework introduced by Boyce, Hunter, and Howlett (2003) showed that the visual performance of workers is influenced by lighting in four aspects: retinal illuminance, retinal image quality, color difference, and luminance contrast [14]. In a study conducted by Zhang et al. (2020) in Japan measuring the impact of dynamic LED lighting in office design, the overall wellbeing of the workers improved due to the dynamic lighting used in the model they created. The study measured many parameters in the office environment modules such as lighting, thermal environment, air quality, and acoustic environment using wireless real-time sensors. The final result of the study showed a positive to mixed impact on alertness, especially in the afternoon time. However, the employees experienced a negative impact on sleep quality and duration after being exposed to dynamic lighting [15].

1.4. Machine Learning in Building Design

Machine learning is a method that uses computer programs to learn from data. It is used in buildings to optimize building performance according to previous data that are usually related to energy consumption [16]. Moreover, advanced machine-learning algorithms have been used to predict preferences for building environments [17]. Research on the correlation of lighting control with users' satisfaction used a Q-learning algorithm to improve the built environment. The study measured three main aspects of design, which were HVAC, light, and blinds, in order to improve automated lighting control [18]. The Q-learning framework provides personalized service after learning the users' preferences [18]. In addition, machine-learning predictions were used instead of building simulation programs. A study conducted by Nourkojouri et al. (2021) measured the characteristics of daylight in relation to visual comfort. The prediction applied different physical features in the built environment, such as rooms, the dimensions of windows, the number of windows, the shading devices used, and the orientation of the rooms, to predict the best measures for visual comfort [19].

Machine-learning techniques are used broadly to maintain sustainable energy consumption in buildings. A study was conducted by Han et al. (2023) on an office building and a living laboratory building [20]. The study analyzed the energy consumption of the building for the past two years. The data contained the energy consumption of heating/cooling systems, water heating, lighting, and plug loads. This type of deep analysis for energy consumption has not been implemented in research in Saudi Arabia and could improve design solutions. It is worth mentioning that the aforementioned study utilized linear regression (LR), polynomial regression (PR), and decision trees (DT) [20].

Moreover, machine learning is associated with visible lighting communication in 6G communication technologies. A novel framework for smart building systems was proposed by Ma et al. (2022) [21]. The framework suggested applying multi-layers for smart building based on trained machine-learning algorithms that provide complex communication services for users. Additionally, a study by Ibrahim et al. in 2021 investigated four different approaches to positioning visible light communications (VLC) in building simulations and used machine learning to predict the best positioning of the lighting system in buildings in Saudi Arabia. The study used the k-nearest neighbor machine-learning algorithm [22].

Even though machine-learning algorithms are widely used in building performance systems, energy consumption, and smart building frameworks, there is a gap in the literature on the use of machine learning in the interior design field, especially in Saudi Arabia. The field of interior and environmental design is new in Saudi Arabia, with very little literature discussing the impact of the interior environment on users' performance and preferences. The significance of this study is to better understand the preferences of users in cities with high temperatures caused by extreme sunlight and clear skies most of the year, such as the city of Riyadh, Saudi Arabia. It is generalized that most people in Riyadh prefer to have heavy curtains to avoid the heat caused by sunlight. However, the preferences of users have recently changed. Office designs in Saudi Arabia are a replication of old designs that do not consider users' preferences. This paper attempts to provide an evidence-based design solution for future designs.

In this paper, six different machine-learning algorithms were used to predict two different design aspects in relation to lighting in the workplace. As will be discussed further in the paper, the two predicted design aspects are direct sunlight and manual control of the light intensity in the office space. The justification for this study stems from the need for data collection for the purposes of design aspect considerations in office design as they relate to lighting. This paper proposes the use of machine-learning techniques as an attempt to eliminate the need for future data collection as it pertains to lighting design considerations. When the preferences of office employees are mapped to predict the optimum design features that directly influence their productivity, future lighting design considerations are expected to be made simple and intuitive. The general problem is lighting design aspects, and the specific problem is the data collection burden for determining those design aspects. For this reason, this paper proposes a data-driven approach that attempts to eliminate the need for future data collection and utilizes the predicted results as a design guide.

2. Materials and Methods

The research was conducted as a collaboration between the ECEC architecture consulting company and Prince Sultan University to uncover employees' preferences in relation to office design and its impact on their productivity. The ECEC is designing the new head office of Ensan Charity. A questionnaire of 31 questions was shared with Ensan Charity employees. The questions were divided into two sections: Section 1 was related to the current situation, and Section 2 was related to future office design preferences. The questions pertained to three main aspects of design, including natural light, artificial light, and color preferences in the office environment. Fifty-two participants answered the questionnaire out of 100 employees from both genders. As is shown in Section 2.2, the dataset was preprocessed and used throughout the research for the purposes of consistency.

2.1. Lighting Design Preferences

In this section, a subset of the collected data was analyzed to uncover some of the employees' preferences and behaviors. For the current research, only questions related to natural lighting were analyzed. The employees' current lighting intensity was compared to their preference for natural light, having a view, and having curtains in their future offices. Moreover, the intensity of natural lighting in the office was compared with the number of hours the employee spent in the office. Different aspects of lighting design are studied in the next subsection of the methodology.

2.2. Lighting Design Prediction

The dataset used in this research was based on a survey collected from office employees. The employees were asked to answer a series of questions. These questions were meant to extract the perspectives of employees in relation to productivity in the workplace as influenced by key design aspects of the office space. The questions of the survey were used as variables for the purposes of the machine-learning portion of this paper's contribution. It is worth mentioning that the survey was informed by a literature review that was conducted.

There were 52 participants; however, one of them declined to participate in the survey. As a result, the dataset consisted of 51 rows for participants and 32 columns for variables. Variables with 6 or more class labels were not considered as input to the machine-learning algorithm to account for the dimensionality balance of the dataset. Table 1 below shows the details for variable selection. The maximum number of class labels for every variable is also shown in Table 1. True response labels show the actual participants' response range as compared to the maximum, possible, response range. In addition, V32 was not considered as input in the machine-learning model due to its being open-ended. It is worth mentioning that variables with 6 or more class labels would hinder the machine-learning algorithm's ability to produce accurate results, as the vector combinations would result in insufficient repetition; repetition is necessary for training the algorithms.

After variable selection and as another preprocessing step, records with null values within the selected columns were removed and not considered for further processing. As a result of the variable and record dimensionality reduction, the dataset used in this paper had a size of 44×25.

Table 1. Dataset description.

Variable Code	Variable Description	Selected for Processing (Yes/No)	Maximum Number of Class Labels	True Response Labels
V1	Agree to participate	No	2	2
V2	# of people in shared office space	Yes	3	3
V3	Daily hours spent sitting at desk	Yes	2	2
V4	Design factors that affect satisfaction with your current office	No	6+	6+
V5	Direct sunlight in current office	Yes	2	2
V6	Intensity of natural light	Yes	3	3
V7	Intensity of artificial light	Yes	3	3
V8	Satisfaction with natural light	Yes	5	5
V9	Satisfaction with artificial light	Yes	5	5
V10	Focus rating in current lighting conditions	Yes	5	5
V11	Daily light source in current office	Yes	3	3
V12	Lighting health effects	No	6+	6+
V13	Factors causing dissatisfaction with current office conditions	No	6+	6+
V14	Reflective vs. absorbant surfaces in current office	Yes	3	3
V15	Surface colors in office	Yes	3	3
V16	Importance of natural light in office	Yes	5	4
V17	Open floor space preference	Yes	5	5
V18	Preference for natural light, artificial light, or both in the workplace	Yes	3	3
V19	Importance of having a view	Yes	5	3
V20	Importance of sunlight	Yes	5	4
V21	Importance of curtains	Yes	5	5
V22	Importance of controlling office temp	Yes	5	3
V23	Wall/floor color intensity preference	Yes	5	3
V24	Furniture color intensity preference	Yes	5	5
V25	Preference for mixing dark and light colors in the workspace	Yes	5	5
V26	Colors affecting mood in the workplace	Yes	2	2
V27	Lighting affecting mood in the workplace	Yes	2	2
V28	Importance of manually controlling light intensity	Yes	2	2
V29	Design aspect preferences in the workplace	No	6+	6+
V30	Flooring preference	No	6+	6+
V31	Productivity affected by noise and temp	Yes	3	3
V32	What can be added in office design to increase productivity and focus	No	-	-

The dataset of selected variables was then split into X_i and Y_j, where i denotes the index of the selected variables, with the exception of variables V5 and V28, where they are denoted by j as the dependent variables to be predicted based on the independent variables X_i. The choice of predicting V5 that is related to whether direct sunlight exists in the workplace stems from the fact that this is intuitively one of the major considerations for lighting design. The second dependent variable to be predicted, V28, is related to the importance of manually controlling light intensity. The machine-learning algorithms' predictions of responses for these two variables is crucial for future lighting design considerations.

Python programming [23] was used for the entire portion of this paper that is related to machine learning and classification. A NumPy [24] seed in the range of [0, 9] was used for processing the data for the purposes of reproducibility. A total of 6 different machine-learning algorithms were used in this paper to classify the labels of the two dependent variables, V5 and V28. The machine-learning classifiers used were decision trees (DT), adaptive boosting (AB), random forest (RF), k-nearest neighbors (KNN), support vector machines (SVM), and multilayer perceptron (MLP) classifiers. All parameter settings were left at the default values as per the Scikit learn library inputs [25].

Machine-learning algorithms can be used in almost all types of applications. In this paper, machine-learning techniques were used to classify binary labels for the purposes of improving future lighting design consideration while limiting the need for further data collection. The following provides a brief account on each of the machine-learning classifiers used in this paper for the purposes of predicting class labels.

A decision tree is an easy-to-interpret machine-learning algorithm [26]. It essentially works by means of splitting into two different possible outcomes at each level. Splits are further branched until the final layer at which the classification occurs. Adaptive boosting combines weak learners to establish a stronger learner [27]. An example of a weak learner algorithm can be a decision tree. A random forest is a voting system that is intended to determine the best decision tree out of a collection of decision trees [26]. Each decision tree in the random forest is associated with a subset of the dataset itself. The k-nearest neighbor algorithm can be used for classification, such that the output of a specific input is the output majority of its neighboring inputs [28]. The value of k can be set to any integer but is usually optimized depending on the dataset. Support vector machines are one of the most popular linear classifiers for high-dimensional data [29]. However, in this paper, it was observed that SVM could perform reasonably well with low-dimensional data. A multilayer perceptron or an artificial neural network, in its simple form, is a collection of nodes that are connected by weights for mapping input to output nonlinearly [30]. The applications of neural networks are ubiquitous across most fields of science and engineering.

The data were read with the Pandas library [31]. The dataset was then configured to create one-hot-encoding for each of the categorical variables used as a predictor. The process of one-hot-encoding creates dummy variables that are derived from each variable, with categories as its values. For example, a binary response variable, such as V27, would be replaced by two different variables, V27_Yes and V27_No, with actual values alternating between 0 and 1 depending on the two created columns. This process ensures a smooth input to the abovementioned machine-learning classifiers.

At this stage, the identification of dependent and independent variables occurs. Variables V5 and V28 were designated as the dependent variables Y_j to be predicted, whereas the remaining variables were designated as independent variables X_i. The dataset was then split into 70% for training and 30% for testing. The machine-learning algorithms were trained on the training portion of the data and tested against the testing portion. In essence, the algorithms use the true labels in the training portion and attempt to predict the labels in the testing portion. Shuffling was enabled in the train/test split to ensure that random sampling with replacement was performed according to the initial setting of the NumPy seed.

Each of the 6 classifiers, at the range of seeds, was then trained on the training portion for the purposes of predicting the class labels of the testing portion of the dataset. To test the accuracy of predicting the class labels, an accuracy score was calculated. The accuracy score equation is based on the following confusion matrix as shown in Table 2 for a binary classification of two class labels, yes and no.

Table 2. Confusion matrix.

	Predicted Yes	**Predicted No**
Actual Yes	True positive (TP)	False negative (FN)
Actual No	False positive (FP)	True negative (TN)

The accuracy score equation is then:

$$Accuracy\ Score\ (AS) = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

Finally, the 6 studied machine-learning algorithms are compared in terms of their accuracy in predicting the two relevant dependent variables, V5 and V28, on the testing set for the purposes of exploiting the prediction in future design considerations as they relate to lighting.

3. Results

3.1. Comparative Analysis

Fifty-two participants answered the survey. As mentioned earlier, the survey had two parts. Part one inquired about the current office conditions in terms of natural and artificial lighting intensity, having a view or a window, and users' satisfaction. The second part included the employees' preferences for the future office design. Questions included the users' preferences for the main aspects of the office environment, such as natural and artificial lighting, color preferences between dark or light colors, and lighting and temperature control. It should be noted that the dataset used to produce the results in this Section 3.1, was of the dimensions 44×25 to be consistent with Section 3.2.

The intensity of natural lighting in the office was compared with the number of hours the employee spent in the office. Only five employees spent more than 6 h in high light intensity conditions. Twelve participants spent more than 6 h in moderate lighting conditions, and 16 of the participants spent more than 6 h in low-intensity lighting conditions.

The following part of this section compares the intensity of light in the current offices with a variation of the variables measuring the employees' satisfaction of their current office and their preferences for the future offices. The variables are: satisfaction with natural lighting, importance of natural lighting, importance of having a view, importance of sunlight, and importance of having curtains.

The five participants described above with intense natural light in their offices had an average natural lighting satisfaction score of 4.4/5 and a 4.8 importance score for natural light. They thought that having natural light and a view were very important elements of design. All of them answered that having curtains was very important as well.

The twelve participants described above with moderate natural light in their offices had an average natural lighting satisfaction score of 3.8/5 and a 4.6 importance score for natural light. This subgroup also agreed with the importance of having natural light, a view, and curtains in the office.

The sixteen participants described above with low natural light in their offices had an average natural lighting satisfaction score of 1.6/5 and a 4.4 importance score for natural light. This subgroup also agreed with the importance of having natural light, a view, and curtains in the office.

3.2. Lighting Design Prediction Results

After applying the prediction methodology in Section 2.2, master tables of accuracy scores were generated for each of the two predicted variables, V5 and V28, as shown in Tables 3 and 4, respectively.

For the purposes of enhancing the visual presentation and allowing for a clear comparison, the following two figures were constructed. The average accuracy scores for each of the studied machine-learning algorithms were plotted for variables V5 and V28 in Figures 1 and 2, respectively.

Table 3. Classification accuracy of variable V5 using machine-learning algorithms.

		Prediction Algorithm					
		DT	AB	RF	KNN	SVM	MLP
Seed	0	78.57	85.71	78.57	85.71	100.00	100.00
	1	71.43	64.29	92.86	85.71	64.29	85.71
	2	64.29	71.43	85.71	78.57	78.57	85.71
	3	71.43	100.00	100.00	85.71	92.86	100.00
	4	78.57	85.71	85.71	71.43	78.57	78.57
	5	71.43	78.57	92.86	71.43	78.57	92.86
	6	78.57	78.57	78.57	85.71	78.57	71.43
	7	78.57	100.00	100.00	100.00	92.86	85.71
	8	78.57	71.43	78.57	71.43	64.29	71.43
	9	71.43	78.57	85.71	92.86	92.86	92.86
Statistics	Average	74.29	81.43	87.86	82.86	82.14	86.43
	Standard Deviation	4.99	11.76	8.28	9.64	12.26	10.35
	MAX	78.57	100.00	100.00	100.00	100.00	100.00
	MIN	64.29	64.29	78.57	71.43	64.29	71.43

Table 4. Classification accuracy of variable V28 using machine-learning algorithms.

		Prediction Algorithm					
		DT	AB	RF	KNN	SVM	MLP
Seed	0	64.29	64.29	71.43	85.71	85.71	78.57
	1	64.29	71.43	78.57	71.43	78.57	64.29
	2	85.71	57.14	85.71	78.57	78.57	85.71
	3	64.29	64.29	78.57	92.86	92.86	64.29
	4	71.43	64.29	71.43	64.29	85.71	57.14
	5	50.00	71.43	78.57	78.57	78.57	57.14
	6	71.43	64.29	71.43	71.43	71.43	64.29
	7	57.14	57.14	64.29	78.57	85.71	71.43
	8	57.14	71.43	78.57	78.57	85.71	64.29
	9	71.43	50.00	78.57	78.57	71.43	57.14
Statistics	Average	65.71	63.57	75.71	77.86	81.43	66.43
	Standard Deviation	9.99	7.10	6.02	7.86	6.90	9.55
	MAX	85.71	71.43	85.71	92.86	92.86	85.71
	MIN	50.00	50.00	64.29	64.29	71.43	57.14

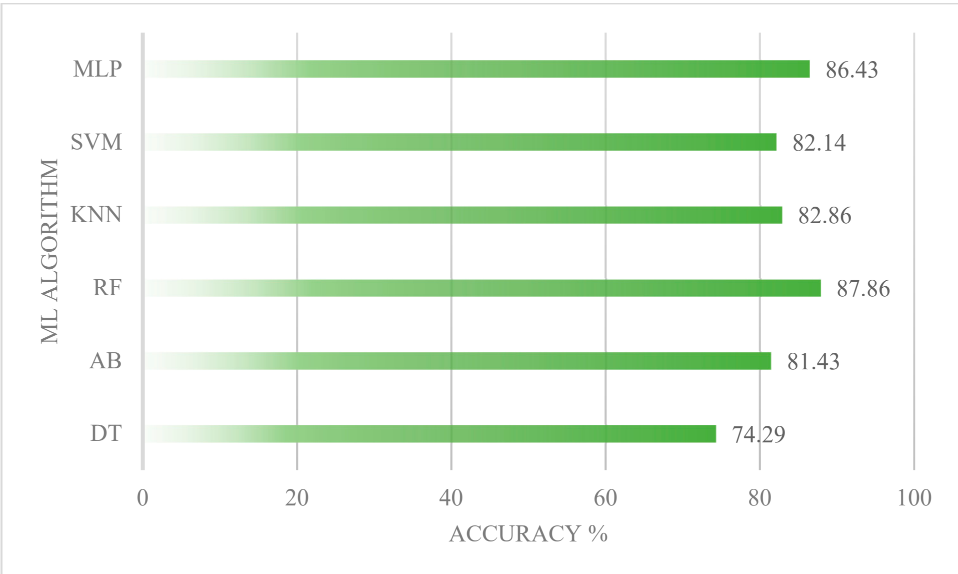

Figure 1. Average classification accuracies for variable V5.

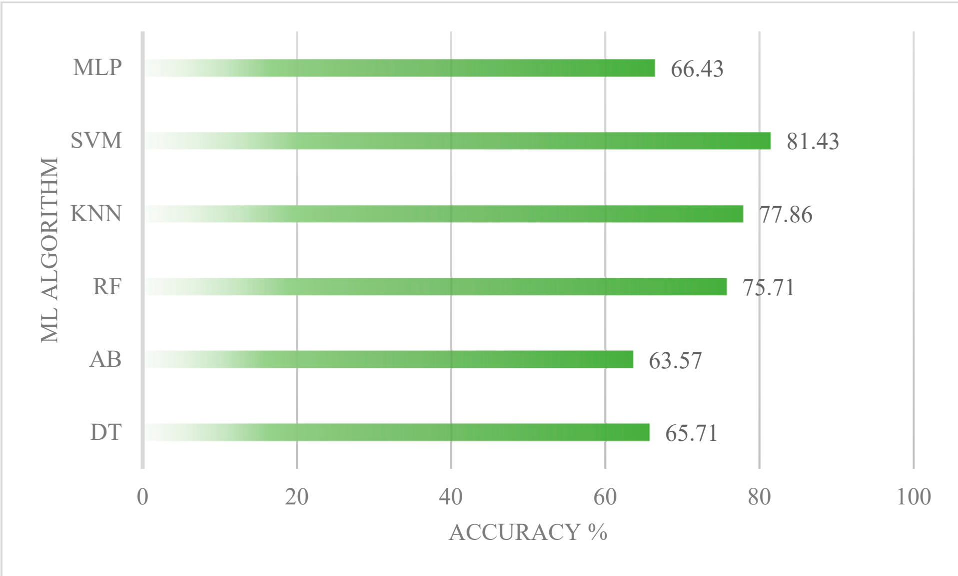

Figure 2. Average classification accuracies for variable V28.

4. Discussion

4.1. Comparative Analysis Discussion

From the results, it is clear that the process of studying lighting design as an element to increase employee satisfaction and productivity is not an easy task. A lot of factors can affect the accuracy of the results, and many setbacks can limit the research reliability starting with the lower number of participants in the survey. Only fifty-two out of one hundred employees participated in the study, which resulted in a lower number than expected. Having said that, the limited results in this study are still an indication of the increase in satisfaction that correlated with an increase in light exposure and the availability of natural views or windows in the office. However, the percentage of the correlation is not clearly identified and might not be relevant due to the number of participants. Another factor to be discussed is the age of the participants and the nature of their tasks inside the office.

4.2. Lighting Design Prediction Discussion

As can be observed in Section 3.2, the prediction results for all studied seeds across machine-learning algorithms are stated in Table 3 for variable V5. It should be noted that the classification accuracy for variable V5 was significantly higher than the accuracy of variable V28. In fact, the average of averages was 82.5% for variable V5 and 71.8% for variable V28. On average, the machine-learning algorithms used in this paper were more capable of accurately classifying the existence of direct sunlight when compared to the classification of the importance of manually controlling light intensity in the office.

For the purposes of enhancing the visual presentation and allowing for a clear comparison, classification accuracy figures were constructed. The average accuracy scores for each of the studied machine-learning algorithms are plotted for variables V5 and V28 in Figures 1 and 2, respectively. One of the major factors affecting the accuracy of the classification was the class imbalance that existed in the responses for variable V28. In binary classifications, it is estimated that roughly 50% of the class labels should belong to class 0, and the other 50% should belong to class 1. However, in variable V28, 23% of the responses belonged to class 0. It is worth mentioning that future research is needed in order to balance the dataset to possibly obtain a more accurate classification scheme.

In relation to the machine-learning algorithms under investigation in this paper, Table 5 provides a ranking of said algorithms based on the classification accuracies. For example, the best algorithm to classify the label of variable V5, direct sunlight, was random forest.

In addition, random forest and k-nearest neighbor seemed to consistently appear in the top three algorithms for classifying both predicted variables' labels. Additional studies are needed to improve the classification performance of the algorithms. Possible methods to do so would be optimizing the algorithms for the best selection of hyperparameters. The optimization might be more effective if a dataset of larger dimensions were used. It is worth mentioning that highest performing classifiers as per Table 5 are also used in a variety of other applications in the literature [32–35]

Table 5. Ranking of algorithms' classification accuracies per predicted variable.

	Predicted Variable	
Rank	**V5**	**V28**
1	RF	SVM
2	MLP	KNN
3	KNN	RF
4	SVM	MLP
5	AB	DT
6	DT	AB

The studied algorithms provide insight into the possibility of depending on machine-learning algorithms for office design considerations. The current results are considered satisfactory given the dataset dimensions and class labels' imbalance. Future research is needed to further optimize the algorithms and to increase the classification accuracy for a more sustainable office design as it relates to direct sunlight and manual control of light intensity. In addition, the predicted results can be used as a guideline for lighting design in office spaces. The two predicted variables, direct sunlight and manual control of light intensity, were mapped to the preferences as well as the current lighting design conditions of office employees in the studied dataset. As a result, the obtained relationship may be used for future design considerations of office spaces without the need for further data collection related to direct sunlight and manual control of light intensity. This paper demonstrates the accuracy of utilizing this relationship in terms of using independent variables to predict the two dependent variables mentioned above.

Additionally, to enhance the discussion of the obtained results as it relates to the utilized methods, Table 6 shows a comparison among a few of the cited studies from the introductory section of this paper in terms of the machine-learning techniques they utilized.

Table 6. Utilized machine-learning techniques in the literature.

Cited Literature	**Use of Machine Learning**	**Specific Algorithm Used**
[17]	No *	N/A
[18]	Yes	Q-learning/reinforcement learning
[19]	Yes	MLP
[20]	Yes	LR, DT, PR
[21]	Yes	KNN, SVM, MLP
[22]	Yes	KNN
This paper	Yes	DT, AB, RF, KNN, SVM, MLP

* State-of-the-art review.

Some of the cited articles did not utilize machine-learning techniques specifically for lighting design considerations. However, it has been shown that the use of machine learning can have a significant positive impact to ease the process of lighting design selection and building design considerations in general. In addition, this paper used a systematic approach of applying six different algorithms and determining the best algorithm in terms of the overall classification accuracy with respect to lighting design considerations. Optimizing the machine-learning algorithms to achieve higher accuracies is considered one of the crucial next steps in future research. When higher classification accuracies are achieved, the existing relationship between independent variables and the two dependent variables can be utilized for future design considerations. To elaborate, future data collection as it relates to the dependent variables, i.e., direct sunlight and manual control of light intensity, may not be necessary, which was one of the purposes of this research. For example, knowing the current conditions of office employees in terms of the independent variables studied in this paper will help to provide insight into the existence of direct sunlight in employees' offices and their perspective on the importance of manually controlling the light intensity. This insight will guide future office designs without the need for data collection as it relates to these two dependent variables.

5. Conclusions

Different light sources and exposures can have multiple effects on the users of any space. More research needs to be conducted on the workspace in Saudi Arabia, as the market is booming with new businesses. By 2030, massive growth in construction is expected, as up to SAR 5 trillion of private sector investment should result from the cooperative government framework according to the Saudi Vision 2030 (more information on the Saudi Vision 2030 can be found on the web: https://www.vision2030.gov.sa/thekingdom/explore/economy/ (accessed on 26 December 2022)). Therefore, studying the influence of design on the users of the work environment will be vital in the coming years. A follow-up study discussing some of the design recommendations and limitations presented here will be the second step for this paper, including an in-depth analysis on the lumens, color selection, and size of the office room, which can then lead to a longitudinal study that follows the employees of Ensan Charity after they move to a new building.

Additionally, as seen in the work performed in this paper, it is beneficial to achieve an accurate classification accuracy for the purposes of lighting design considerations. Two variables, direct sunlight and manual control of light intensity, were predicted with reasonable accuracy. The predicted variables may be used for future design considerations without the need for further data collection. As mentioned in the discussion, the relationship between current office space conditions and lighting design considerations as per employees' preferences are mapped. The machine-learning-based prediction schemes provide insight on this relationship to aid in future design considerations. The more accurate the classification accuracy, the more confidence can be put into utilizing the prediction results for future designs. For this reason, it is recommended to further optimize the machine-learning algorithms to achieve higher classification accuracies. When higher classification accuracies are achieved in future research, direct sunlight and manual control of light intensity can be easily determined for any given inputs of office conditions. Nonetheless, these two dependent variables can now be determined with reasonable accuracy, as shown in this paper by means of predicting the test sets.

One of the implications that can be drawn from this paper is the fact that more research is needed to improve prediction accuracy. Another implication is the issue of the dataset size and the need for implementing resampling techniques to augment the dataset. A third and final implication of the study highlights the importance of lighting design as it relates to employees' productivity, as shown in this paper.

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