Analysis of the Influence of Pulse Width Modulation of Artificial Lighting Sources on the Human Body Using Artificial Intelligence Methods

Lyudmyla Kirichenko[1], Artur Zhadan[2] and Alla Selivanova[2]

[1] *Kharkiv National University of Radio Electronics, Nauky av., 14, Kharkiv, 61166, Ukraine*
[2] *Odesa National University of Technology, Odessa, Kanatnaya str., 65039, Ukraine*

Abstract

Poor-quality artificial light sources can be harmful to health and affect the productivity of workers in the workplace. This research focuses on the effects of pulse-width modulation (PWM) of artificial light sources such as displays or lamps on the human body. The main objective of the research is to make the process of checking the workplace for the presence of pulse-width modulation (PWM) more accessible and to minimize the negative impact of pulse-width modulation (PWM) on the human body. To achieve this goal, an alternative method of monitoring the pulse-width modulation (PWM) of artificial light sources has been developed using artificial intelligence (AI) methods that can even be used on a smartphone. The results of this research can be applied in the field of occupational safety and health (OSH).

Keywords

Pulse-width modulation, PWM, artificial intelligence, AI, artificial light sources, displays, lamps, Light-emitting diode, LED, organic light emitting Diodes, OLED, active-matrix organic light emitting diodes, AMOLED, complementary metal-oxide semiconductor, CMOS, rolling shutter, occupational safety and health, OSH

1. Introduction

With the advent of industrialization, most people began to work indoors. Artificial lighting sources are used to organize the work process on the premises. Artificial lighting sources include both external lighting sources and displays of computers, tablets, and smartphones with which the employee interacts [1]. The norms of artificial lighting sources acceptable for the work process are described in the sanitary and hygienic requirements for occupational safety and health (OSH) and European standards [2]. However, given the variety of artificial lighting sources on the market and the dishonesty of employers, they do not always meet acceptable standards. For example, an employer may purchase low-quality lighting sources to reduce the company's costs for them.

The main indicators of the quality of artificial lighting sources are the brightness of this source and the pulsation coefficient. Artificial lighting sources, made from cheap components, usually have low brightness and high ripple. The presence of a high pulsation coefficient indicates that the light source has a flicker that is invisible to the eye. This is because such artificial light sources use the pulse-width modulation (PWM) method to adjust the brightness [3]. These factors can cause increased worker fatigue, decreased visual performance, eye strain, headaches, and anxiety. In addition, it also negatively affects the power grid - it causes interference. High-quality artificial light sources do not have this flicker and, accordingly, the presence of pulse-width modulation (PWM), because they use a different method of dimming, namely a direct current regulation on the diodes. This type of dimming is called "DC Dimming" and is also known by the marketing name "Flicker Free" [4, 5, 6, 7]. Not all manufacturers of artificial light sources report this on their product packaging. To check artificial

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EMAIL: arthur.zhadan@gmail.com (A. 1); alikasalvano@gmail.com (A. 2)
ORCID: 0009-0008-3419-3396 (A. 1); 0000-0002-3395-1422 (A. 2)

lighting sources and place monitors for compliance with sanitary and hygienic requirements, the workplace is attested using special equipment, namely, lux meters. This equipment is not mass-produced, it is relatively expensive and, as a rule, only certification commissions have it.

Given the above, it is advisable to create an alternative to the described equipment, which would be devoid of the above disadvantages and solve the problem.

Thus, the objective of the presented research is to develop an alternative method for detecting pulse-width modulation (PWM), which would be more accessible and widespread.

To solve the problem, artificial intelligence (AI) methods will be used, which will allow the creation of a software-hardware implementation for checking artificial light sources for the presence of pulse-width modulation (PWM). Specifically, in this research, computer vision methods are used. The active development of artificial intelligence (AI) and its use in various fields of activity, which allows you to perform specific tasks more effectively, speaks of the feasibility of using this method [8]. For example, the resulting trained model can be embedded in an application on a smartphone or similar handheld device that has a camera. This will make the process of certification of the workplace for the presence of low-quality artificial lighting sources simpler and more widespread and will avoid low-quality artificial light sources and prevent a negative impact on the human body. For example, a person can use a smartphone camera to check the artificial light source at his workplace in live mode.

This also largely determines the scientific novelty of the research – artificial intelligence (AI) methods are used in this area for the first time, in addition, this research proposes a combination of various methods. The object of the research is the problem of the application of information technologies in the field of occupational safety and health (OSH). The subject of the research is the process of analyzing artificial lighting sources and displays at workplaces to improve the certification process for sanitary and hygienic requirements and avoid negative consequences for human health.

The results obtained in the course of this research can be used in the field of occupational safety and health (OSH). This research includes the following sections: title, authors, abstract, introduction, methodology, results, discussion, conclusion, acknowledgments, and references. These sections provide a framework for presenting the research process and contributing to the existing body of knowledge in the field.

2. Methodology

The methodology of this research includes mixed methods, such as methods using artificial intelligence (AI), and mathematical methods.

2.1. Detection using artificial intelligence (AI) methods

The use of artificial intelligence (AI) methods in various fields of activity is expedient due to its rapid development and increasing use throughout the world. Artificial intelligence (AI) methods allow you to perform specific tasks more subtly and efficiently [8]. The detection of pulse-width modulation (PWM) of artificial light sources using artificial intelligence (AI) methods is the main detection method presented in this research. To achieve this goal, computer vision methods are used, to be more precise, the detection of objects in images. The resulting trained model can be embedded in applications and accordingly used in portable devices such as smartphones. It also largely determines the scientific novelty of this research.

2.1.1. Data collection

The fact is that before training the image detection model, you need to have an array of data. Since the resulting image detection model must determine the pulse-width modulation (PWM) of artificial light sources, this imposes some limitations. Firstly, there is no ready-made data set date for this task at the moment, but it can be generated by yourself. Secondly, you need to understand what kind of training data is needed.

Based on already existing articles, it is known that you can see the pulse-width modulation (PWM) of artificial lighting sources using a camera that has a CMOS sensor. If you fix a flickering light source with such a camera, then black stripes will be displayed in the picture. This effect is also called a rolling shutter (RS). This is because pulse-width modulation (PWM) is a fast flicker of an artificial light source, and the CMOS sensor reads the image line by line, this allows you to display flicker in the pictures [2, 9, 10]. Rolling shutter (RS) mechanism is shown on Figure 1.

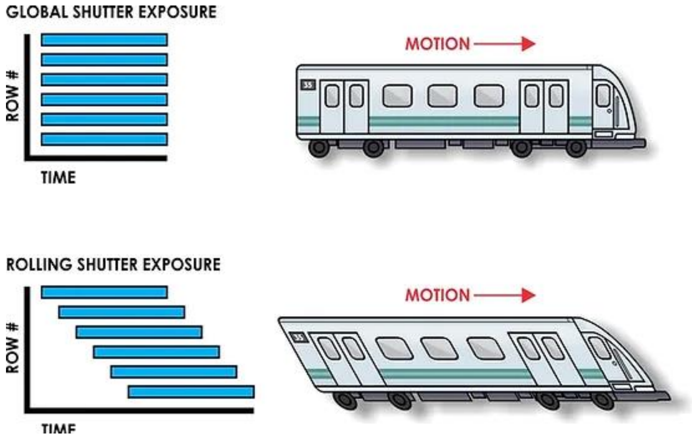

Figure 1: Rolling shutter (RS) mechanism

While the camera is taking a picture line by line, the artificial light source can flicker dozens of times. However, there are also some nuances here. To see the flicker more clearly, the camera shutter speed must be very fast. As practice has shown, flicker is already visible at a shutter speed of 1/1000. At shutter speeds of 1/4000, 1/8000 flicker is even more visible. However, extremely slow shutter speeds will result in incorrect exposure, and the viewfinder image will be very dark. In this case, it is necessary to increase the light sensitivity of the matrix, which leads to image distortions.

Based on this information, it was decided to use the maximum fast shutter speed and maximum sensor light sensitivity to fix low-quality artificial light sources in the laboratory. Also, since the training model needs a variety of data to get good training results, it was a nice decision to take data from the Internet, where flicker bands are fixed on the lights.

2.1.2. Data preprocessing and augmentation

It is necessary to take into account the current limitations, the smartphone camera is not an accurate sensor, so the classification into classes is subjective, however, it shows a trend. Based on mathematical measurements, the most popular flicker frequency values of pulse-width modulation (PWM) are:

1. less than 60 hertz (some incandescent lamps)
2. 250 hertz (common frequency for some LED/ AMOLED displays)
3. 480 hertz (common frequency for some AMOLED displays)
4. ~2000 hertz (common frequency for some new AMOLED displays)
5. ~ 25000 hertz (common frequency for some new laptops

It is important to note that OLED screens flicker more often than LED. This is due to the fact that when the current is dimmed at low brightness values, image artifacts appear [2].

However, it is important to keep in mind that this data only describes a trend and may vary from one artificial light source to another. In addition, the frequency may change when the brightness of the artificial light source changes. As practice shows, it is at the lowest brightness that the lowest flicker frequency of pulse-width modulation (PWM) is achieved and, accordingly, the harm to the human body increases. Some people, knowing that, for example, their LED monitor is flickering, may use a high screen brightness, which can also harm their eyes.

Answering the question of why a person does not notice this flicker, it can be noted that the human eye averages the flicker brightness when flickering is above 60 hertz. Flickering at 250 hertz can cause increased eye fatigue and headaches with prolonged contact and directly affect performance.

Flickering at 500 hertz can still be detected by some people, however, the effects of it are no longer so pronounced. Flickering over 2000 hertz is already relatively safe. Here, the brightness of an artificial light source is often directly proportional to its flicker frequency. True only if this artificial light source uses a pulse-width modulation method (PWM) to adjust the brightness. High-quality lighting sources use the method of direct current regulation on the diodes (DC Dimming) [3, 4, 5, 6, 7].

In other words, pulse width modulation (PWM) flicker can also be described as follows. If the brightness of the artificial light source is high, then the artificial light source will burn for a longer time. If the brightness of the artificial light source is low, then the artificial light source does not burn for a longer time. This can be seen in Figure 2.

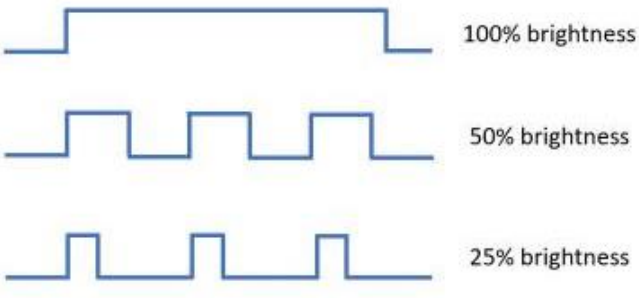

Figure 2: Pulse-width modulation (PWM) periods

Once the data has been collected, it needs to be processed. Firstly, the dataset must be divided into at least 2 samples - training and validation. Secondly, you need to classify the images [11, 12]. When testing in laboratory conditions, it was found that with the same exposure of the camera, sources with different frequencies of pulse-width modulation (PWM) have different widths of black bands. To change the frequency of the pulse-width modulation (PWM), it is enough to simply change the brightness of the light source, if possible. A larger black bar indicates that the pulse width modulation frequency is lower. This suggests that the test source of artificial lighting is the most harmful. A smaller black bar indicates that the pulse-width modulation (PWM) frequency is higher. This suggests that the test source of artificial lighting is less harmful. Thus, it was decided to classify the resulting dataset according to the degree of risk of harm to the human body:

1. acceptable
2. tolerable
3. unacceptable
4. no risk

Figure 3 shows the risk scale of the influence of pulse-width modulation (PWM) on the human body. Approximate data on the correspondence between health risk and qualitative amount of pulse-width modulation (PWM) are presented in Table 1.

Figure 3: Risk scale of the influence

Table 1
Correspondence between risk and frequency

Risk	Strip width
acceptable	narrow
tolerable	medium
unacceptable	wide

Let's look at example classes. They clearly show how the width of the black bars changes when the brightness of the AMOLED display changes. Figure 4 shows the class of risk "acceptable". Figure 5 shows the class of risk "tolerable". Figure 6 shows the class of risk "unacceptable". Figure 7 shows the class with no risk.

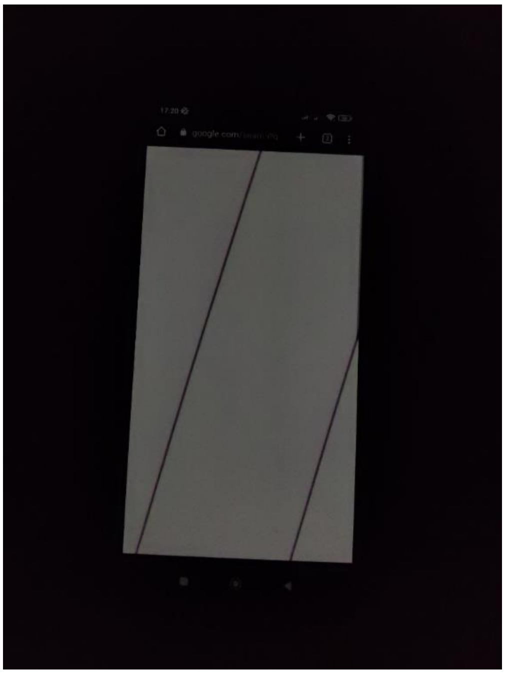

Figure 4: Example of acceptable class risk

Figure 5: Example of tolerable class risk

Figure 6: Example of unacceptable class risk

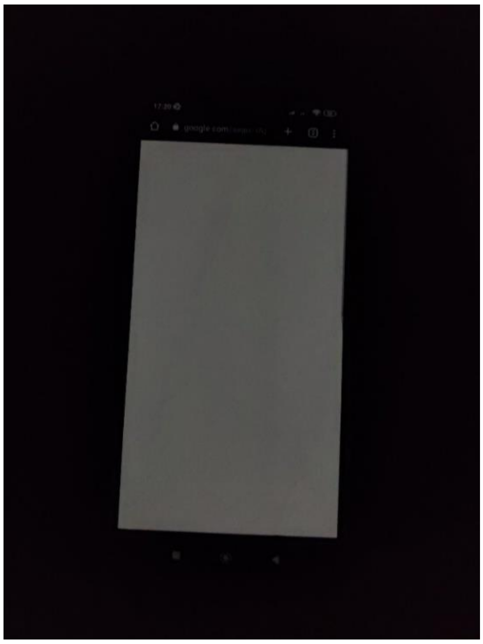

Figure 7: Example of class with no risk

In this case, we managed to collect 100 different images for training process and 10 for validation. Objectively, it's not much. Therefore, to increase the dataset size by several times, data augmentation should be applied. Augmentation is the process of mirroring images and rotating them by several degrees. It is also important to note that since object detection methods are used on images, and not image classification, to assign the above classes to the collected data set, you must manually specify labels with their names and areas on each image. This operation is shown in Figure 8.

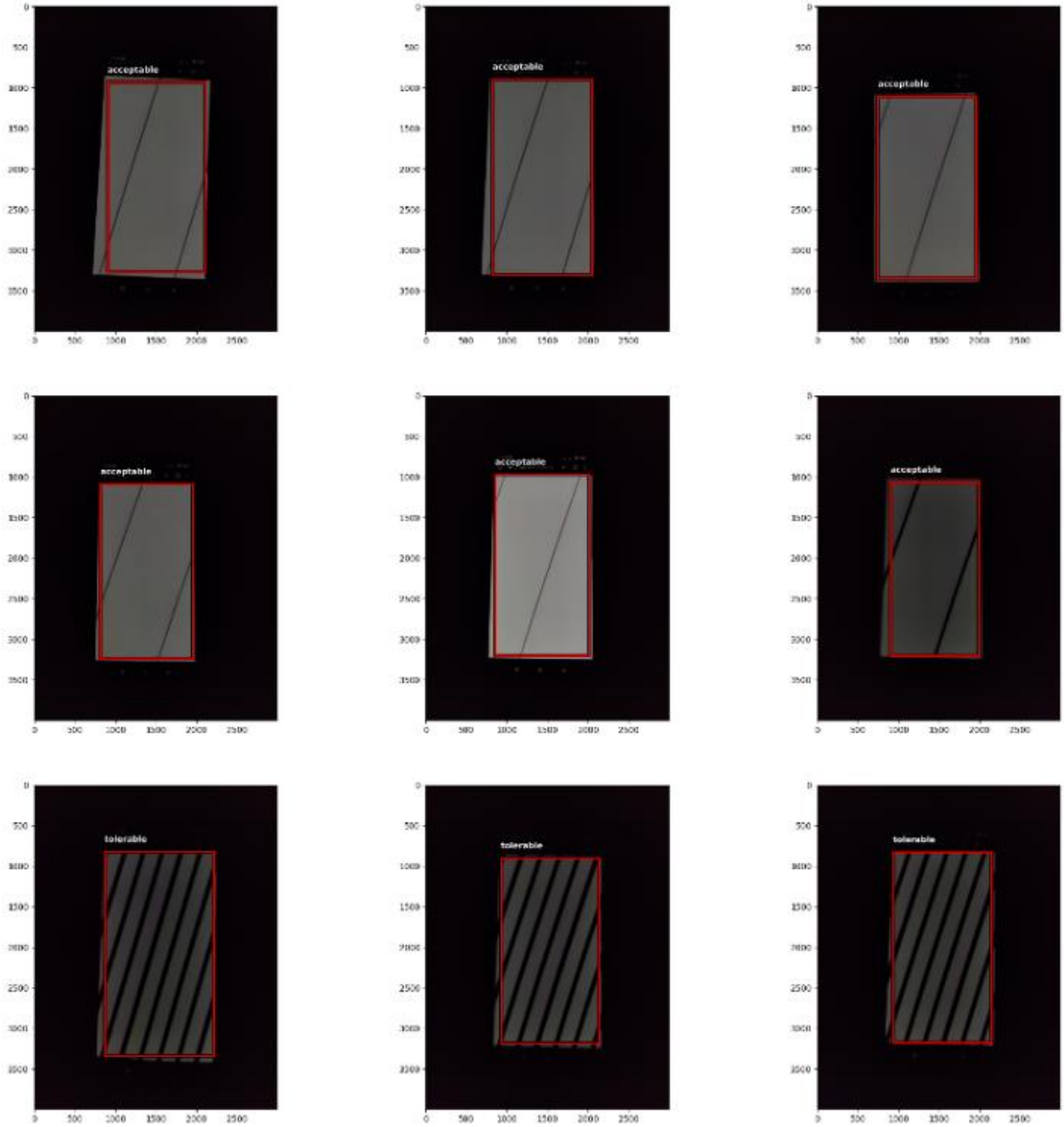

Figure 8: Data set labeling

2.1.3. Model architecture

This research uses a model RetinaNet model for object detection pulse-width modulation (PWM). RetinaNet is a model architecture that is commonly used for object detection tasks. It consists of two main components: a core network (for example, MobileNetV3 in this case) for extracting features from images, and a RetinaNet head for detecting objects based on these features [11, 12].

Model architecture is shown in Figure 9.

\ retina_net_model_7" model consists of several layers:

"mobile_net_6": This is the MobileNet layer that takes an input image and outputs feature maps with different development levels (64x64, 32x32, 16x16, 8x8 and 1x1). MobileNet is a convolutional neural network architecture with multiple layers that uses depth wise separable convolutions and ReLU activation functions.

"fpn_6": This is the Feature Pyramid Network (FPN) layer, which takes feature maps from the MobileNet layer and sequentially sets feature maps at different scales (8x8, 16x16, 32x32, 4x4 and 2x2).

"multilevel_detection_generator_7": This level is responsible for generating anchor fields at different scales and corresponding sides for each map object.

"retina_net_head_6": RetinaNet top layer that accepts feature maps from the FPN layer and performs feature detection. It outputs the coordinates of the turnover limit and probability classes for objects at different scales.

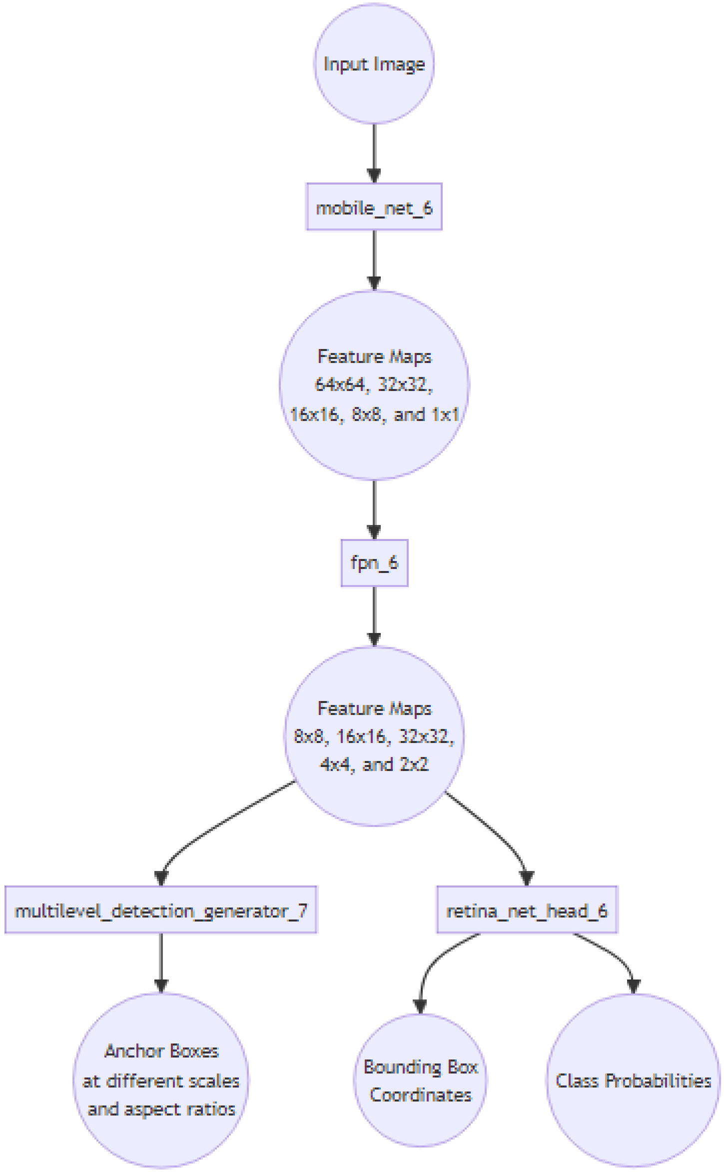

Figure 9: Model Architecture

MobileNetV3 includes pretraining on a large dataset called ImageNet, which comprises millions of labeled images from thousands of different classes. Through pretraining on ImageNet, MobileNet can learn to recognize diverse visual patterns and features, which can subsequently be transferred and fine-tuned for other computer vision tasks, including image classification, object detection, or semantic segmentation, using smaller and more specific datasets [11].

Also, MobileNetV3 includes average pooling as a method to reduce the complexity of feature mapping. Average pooling is a type of pooling operation that calculates the average value of a set of objects within a pooling window [13]. These techniques can improve the performance and accuracy of object detection, since a limited dataset was formed during this research.

The choice of these models is due to the fact that they are free, supported by large companies, have a balance of performance and accuracy. Thus, they are ideal for an our experimental setup.

2.1.4. Training and evaluation procedure

In this research, to retrain the model, the following procedure is used. First, the model is initialized with pre-trained weights on large datasets such as ImageNet. Then, the retraining phase is carried out, adjusting the model parameters on the generated specific image detection dataset.

The model training parameters used in this research are presented in Table 2.

Table 2
Model training parameters

Training parameter	Value
Number of epochs	20
Learning rate	1
Batch size	4

The selection of model training parameters is often individual and depends on specific goals and datasets. The parameters in Table 2 are often chosen empirically, but there are still some guidelines that drive the current values in this research. The main limitation here is a small dataset. With a small amount of data, the neural network can quickly remember all the examples, which can lead to overfitting. Limiting the number of epochs helps control overfitting and provides more robust model training. A higher learning rate can be chosen for faster model convergence. However, this parameter must be carefully selected to avoid convergence too fast or too slow. With a small amount of data, a smaller batch size can be chosen to improve the generalizing ability of the model and avoid overfitting. To achieve adequate accuracy of class determination, a detection accuracy of about 70% or more is required.

2.1.5. Experimental Setup

To form the dataset materials, a smartphone with a Sony IMX 586 CMOS and Snapdragon 765G was used. The shutter speed was set as short as possible – 1/11626, and the sensor light sensitivity (ISO) was as high as possible – 5699 [15].

To conduct experiments with retraining of the MobileNetV3 architecture for detecting images with the flickering of pulse-width modulation (PWM) of artificial light sources, Google Collaboratory was used as a platform for developing and executing code. Google Collaboratory provides access to graphics processing unit (GPU) computing resources, allowing you to effectively train deep learning models [16]. The high-level programming language Python was also used in conjunction with the MediaPipe framework to implement models and complete tasks. MediaPipe provides extensive functionality and tools for machine learning (ML) [17], and the Python language is often used in big data [18]. The matplotlib library in Python was used to analyze and obtain results. The labelImg program was used to create class labels on images.

During the experiments, data enhancement technologies were also applied to increase the selection of a sample data set and increase the generalizing power of the models. Extension techniques such as rotations, scaling, reflection, and adding a noise library have been applied using imgaug tools and features. Using this experimental setup, the results, estimated performance, and efficiency of the pre-trained architecture MobileNetV3 were obtained for the task of detecting images with the flickering pulse-width modulation (PWM) of artificial light sources.

2.2. Additional Math helper methods to improve the result accuracy

As mentioned above, the method for determining the pulse-width modulation (PWM) of artificial light sources using artificial intelligence (AI) methods is the main one in this research. However, to implement this method, you need to use a camera, for example, on a smartphone. Using the camera imposes some restrictions. The camera perfectly shows high-frequency ripples. For example, if the flicker frequency is extremely low, for example, about 30 hertz, then black bars may not form - the camera will track the flicker like a stroboscope.

2.2.1. Averaging the color of image pixels over time

This method consists in getting an image from the camera and then averaging the RGB colors. This will give the brightness of the color. This information should be added to the array over some time, such as 1 second. Compared to the first method, this method can be more accurate but still requires the use of a camera. You can then use a formula to calculate the relative deviation of the mean (the sum of the values divided by the number of values) of the data set (x) from the maximum value (max) as a percentage. An example of a mathematical formula that can represent this method is presented below

$$P = \frac{100 * (\frac{\sum x}{n})}{x_{max}}, \tag{1}$$

where P – is the percentage of flickering, $\sum x$ – is the total sum of average color values, n – is the total number of average color values, E_{max} – is the max value of average color value brightness.

Thus, the formula can show how much percent the light source flickers. If it turns out 100%, then this indicates that the light source does not flicker.

2.2.2. Averaging the luxes from the built-in light sensor over time

This method consists in getting an illumination of light from built-in hardware light sensor in luxes. However, keep in mind that installed light sensors in portable technology often have very low sensitivity and may be useless. To implement this method, you can use the principles and approaches described in section 2.2.1. Thus, it will be necessary to collect data from the built-in light sensor for some time and apply formula 1.

3. Results

This section presents the results of this research related to the detection of pulse-width modulation (PWM) of artificial light sources using artificial intelligence (AI) methods, namely computer vision to prevent their harm to human health. Here is the performance data for the object definition model.

The resulting model, based on the MobileNetV3 architecture and retraining, achieved a relatively average object detection accuracy on the test dataset. The results of validation on the test selection in COCO are shown in Table 3.

Table 3
Model validation in COCO metrics

Metric	IoU	Area	Max Dets	Value
Average Precision	0.50:0.95	all	100	0.703
Average Precision	0.5	all	100	0.914
Average Precision	0.75	all	100	0.889
Average Precision	0.50:0.95	small	100	-1
Average Precision	0.50:0.95	medium	100	-1
Average Precision	0.50:0.95	large	100	0.704
Average Recall	0.50:0.95	all	1	0.746
Average Recall	0.50:0.95	all	10	0.754
Average Recall	0.50:0.95	all	100	0.754
Average Recall	0.50:0.95	small	100	-1
Average Recall	0.50:0.95	medium	100	-1
Average Recall	0.50:0.95	large	100	0.754

The model training results show that the average accuracy (AP) at various IoU values ranges from 0.703 to 0.914. This means that the model accurately detects and classifies objects in the image.

However, the average accuracy for small and medium objects cannot be calculated, which may indicate difficulties in detecting such objects. In terms of recall (AR), the model achieves a value between 0.746 and 0.754 for various IoUs and maximum detections. This means that the model is able to detect most of the objects, but some may be missed.

The total validation loss is [0.8219069242477417, 0.5985177159309387, 0.003196648322045803, 0.758350133895874], indicating that the model converges and trains well enough. Given the relatively average detection accuracy of the resulting model, quantization was not applied to it.

The essence of quantization is rounding the values of the model. This allows to reduce the speed of detection, but reduce the accuracy of detection. Checking the model on random images from the public domain. Example of successful detecting tolerable class risk on LED lamp is shown in Figure 10 with 62% probability. Example of successful detecting acceptable and tolerable class risk on displays is shown in Figure 11 with 89% and 33% probability.

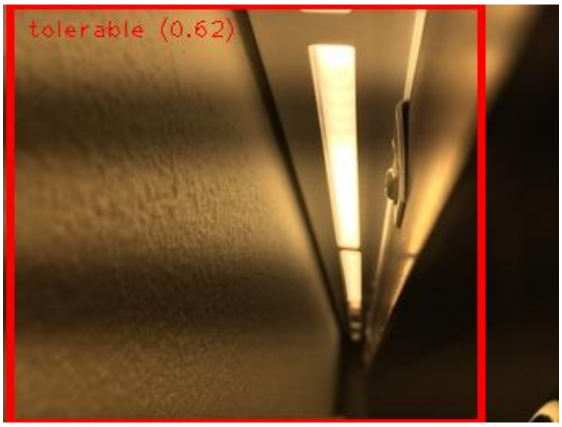

Figure 10: Example of detecting tolerable class risk on LED lamp

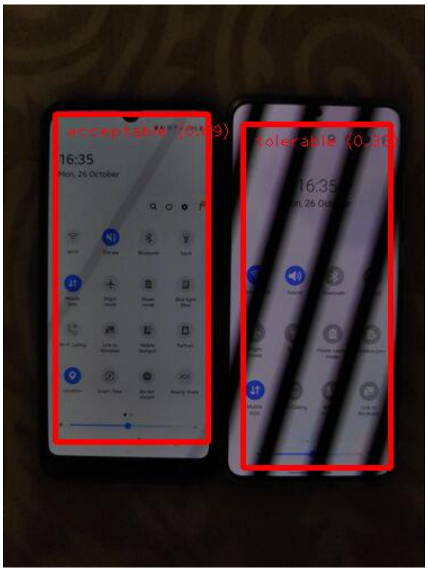

Figure 11: Example of detecting multiple classes of risk on displays

It is important to note that in the final implementation of this method on practical experience in the form of a native Android application, an auxiliary method for detecting pulse-width modulation (PWM) was also additionally used by determining the average pixel color of the resulting image.

Both of these methods allow you to work in real-time live mode. It takes about 0.1 second to get the result on mid-range smartphone with SoC Snapdragon 765G.

The native Android application works as an expert system (ES) and, after analyzing the artificial light source, shows recommendations that can positively affect human health and labor productivity.

Figure 12 shows an example of a native Android application that implements both of these methods and test model in real-time mode on LED lamp in room with probability 80%. This research confirms the effectiveness and applicability of the presented methodology within this field.

4. Discussion

This section analyzes the results of this research related to the detection of pulse-width modulation (PWM) of artificial light sources using artificial intelligence (AI) methods, namely computer vision to prevent their harm to human health.

The resulting image detection model, based on the MobileNetV3 architecture and retraining, showed relatively average accuracy and speed. The results obtained can be improved in next ways:

The very first and most important thing is to increase the size of the dataset. Instead of using square masks, masks of different shapes can be used to label the training data. All this will also entail a revision of the training parameters. The presented main method for detecting pulse-width modulation (PWM) of artificial light sources using artificial intelligence (AI) methods, namely computer vision may also have some limitations. First, the method is based on the rolling shutter (RS) effect of CMOS sensors. However, there are matrices of an older generation, namely CCD [9]. Most likely, this method will not work on matrices of this type. Secondly, the accuracy of determining objects is directly proportional to the quality of learning the object definition model.

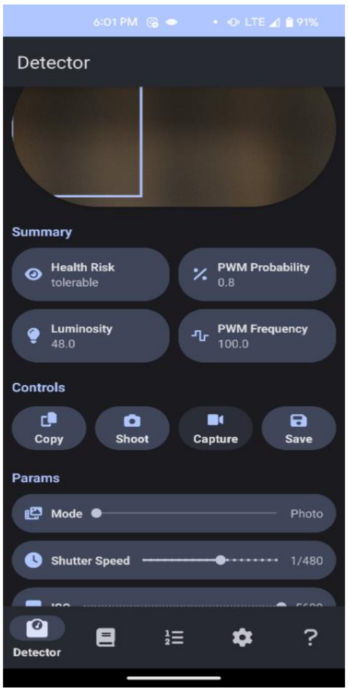

Figure 12: Android native application tests LED lamp in room with probability 80% in real-time mode.

In addition, a wide variety of CMOS sensors in portable devices also impose a limitation on the objectivity of the results obtained. For example, relatively new CMOS sensors, Sony IMX 586, have a shutter speed limit of more than 1/10000, and older ones, Sony IMX 363, have a shutter speed limit of 1/4000. This can directly affect the bar width [15]. However, given that this method was developed as a counterbalance to hardware implementations, we can make allowances for these points. Moreover, some of these points can be solved, for example, by introducing the minimum system requirements for the CMOS sensor. Although, even at a shutter speed of 1/1000, it is possible to detect the presence of pulse-width modulation (PWM) of artificial light sources.

5. Conclusion

This section summarizes the results of this research related to the detection of pulse-width modulation (PWM) of artificial light sources using artificial intelligence (AI) methods, namely computer vision to prevent their harm to human health and concludes its effectiveness, contribution, and opportunities for further development. As a result of experiments and analysis of this research, an alternative method for determining the pulse-width modulation (PWM) of artificial light sources using artificial intelligence (AI) methods, namely computer vision, was proposed and demonstrated. The effectiveness of the image detection model based on the MobileNetV3 architecture and additional training was shown, which confirms the applicability of the model under research in real scenarios.

In addition, to improve the results obtained, additional methods were also proposed and presented for the possible determination of the pulse-width modulation (PWM) of artificial light sources.

However, despite the results achieved, some limitations and room for improvement were also found. This includes improving the speed and accuracy of model definition.

For further development of this area of research, it is possible to consider proposals for developing a method for calculating the width of the black stripes of pulse-width modulation (PWM) in an image and comparing it with the real sizes obtained at different frequencies. Since the current solution represents a qualitative characteristic, and not a quantitative one in units of measurement.

In general, the results of this research confirm the significance and potential of the proposed methods. This work contributes to the development of the field of occupational safety and health (OSH), offering alternative available methods for attesting workplaces and preventing the negative impact of low-quality lighting sources.

6. Acknowledgments

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7. References

[1] Cascio, Wayne & Montealegre, Ramiro. (2016). How Technology Is Changing Work and Organizations. Annual Review of Organizational Psychology and Organizational Behavior. 3. 349-375. 10.1146/annurev-orgpsych-041015-062352.

[2] Boyce, Peter & Brandston, HM & Cuttle, Christopher. (2022). Indoor lighting standards and their role in lighting practice. Lighting Research & Technology. 54. 147715352211264. 10.1177/14771535221126413.

[3] Lehman, Brad & Wilkins, Arnold. (2014). Designing to Mitigate Effects of Flicker in LED Lighting: Reducing risks to health and safety. Power Electronics Magazine, IEEE. 1. 18-26. 10.1109/MPEL.2014.2330442.

[4] L. Anderson, Flicker, the display affliction - DXOMARK, 2021. URL: https://www.dxomark.com/flicker-the-display-affliction/.

[5] Özçelik, Mehmet. (2023). Investigation of the Effect of Light Pwm Frequency on the Object in Terms of Human Visual Comfort. 10.2139/ssrn.4475190.

[6] Cooper, Emily & Jiang, Haomiao & Vildavski, Vladimir & Farrell, Joyce & Norcia, Anthony. (2013). Assessment of OLED displays for vision research. Journal of vision. 13. 10.1167/13.12.16.

[7] Yoshimoto, Sanae & Garcia, Jesel & Jiang, Fang & Wilkins, Arnold & Takeuchi, Tatsuto & Webster, Michael. (2017). Visual discomfort and flicker. Vision research. 138. 10.1016/j.visres.2017.05.015.

[8] Xu, Yong-Jun & Wang, Qi & An, Zhulin & Wang, Fei & Zhang, Libo & Wu, Yanjun & Dong, Fengliang & Qiu, Cheng-Wei & Liu, Xin & Qiu, Junjun & Hua, Keqin & Su, Wentao & Xu, Huiyu & Han, Yong & Cao, Xin & Liu, Enke & Fu, Chenguang & Yin, Zhigang & Liu, Miao & Zhang, Jiabao. (2021). Artificial Intelligence: A Powerful Paradigm for Scientific Research. The Innovation. 2. 100179. 10.1016/j.xinn.2021.100179.

[9] Yizhen Lao. 3D Vision Geometry for Rolling Shutter Cameras. Robotics [cs.RO]. Université Clermont Auvergne, 2019. English. ffNNT : 2019CLFAC009ff. fftel-02276486f

[10] Oh, Wonseok & In, Chigak & Oh, Yongseung & Cho, Kyumin. (2019). Effects of PWM Dimming LED Illumination on Camera Images and Countermeasures. 1-7. 10.1109/RTUCON48111.2019.8982330.

[11] Howard, Andrew & Pang, Ruoming & Adam, Hartwig & Le, Quoc & Sandler, Mark & Chen, Bo & Wang, Weijun & Chen, Liang-Chieh & Tan, Mingxing & Chu, Grace & Vasudevan, Vijay & Zhu, Yukun. (2019). Searching for MobileNetV3. 1314-1324. 10.1109/ICCV.2019.00140.

[12] Al-Hasanat, Mohanad & Alsafasfeh, Moath & Alhasanat, Abdullah & Althunibat, Saud. (2021). RetinaNet-Based Approach for Object Detection and Distance Estimation in an Image. International Journal on Communications Antenna and Propagation (IRECAP). 11. 19. 10.15866/irecap.v11i1.19341.

[13] Bieder, Florentin & Sandkuehler, Robin & Cattin, Philippe. (2021). Comparison of Methods Generalizing Max- and Average-Pooling.

[14] Camera sensors ranking. URL: https://www.deviceranks.com/en/camera-sensor.

[15] Google Collaboratory. URL: https://colab.research.google.com/

[16] Quiñonez, Yadira & Lizarraga, Carmen & Aguayo, Raquel. (2022). Machine Learning solutions with MediaPipe. 212-215. 10.1109/CIMPS57786.2022.10035706.

[17] Jackeray, S., Doradla, A.S., Rane, R.L., & Colaco, B. (2020). A COMPARATIVE REVIEW BETWEEN PROGRAMMING TOOLS USED IN DATA SCIENCE.