Neural Networks for Classification and Regression Applied to Public Lighting Project

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This paper explores using neural networks to evaluate public lighting projects according to Brazilian Standard 5101/2018. Employing Multilayer Perceptron (MLP) models, the study performs regression to predict illuminance, uniformity, and classification to assess compliance with the standard. The regression model achieved a mean squared error (MSE) of 0.002. The classification model attained an accuracy of 97.26%, with a precision of 97.0%, a recall of 96.5%, and an F1-score of 96.7%. These results underscore the effectiveness of MLP networks in improving compliance evaluation and optimizing public lighting projects.
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Recent estimates indicate that Brazil has over 18 million public lighting points, representing 4% of the nation's electricity consumption and 3% to 4% of municipal budgets [1]. These data highlight the urgent need to ensure the effective implementation and quality of public lighting across all municipalities. Enhancements in quality, focusing on efficacy, efficiency, and effectiveness, can be significantly enhanced through innovations such as advanced project planning [1].

Ensuring quality in public lighting in Brazil involves municipalities, energy concessionaires, the National Electric Energy Agency (ANEEL), the National Institute of Metrology Quality and Technology (INMETRO), and the Brazilian Association of Technical Standards (ABNT). ABNT's Brazilian Standard (NBR) 5101/2018 provides recommended guidelines for public lighting implementations throughout the country. Adequate public lighting reduces nighttime accidents, improves traffic conditions, and enhances public safety by deterring crime [2].

However, traditional methods for evaluating compliance with standards like NBR 5101/2018 are often prone to errors and time-consuming (e.g., specialized software needs to process both calculations for predictions and rendering graphics). This study is justified by applying neural networks to improve the accuracy and efficiency of compliance evaluations in public lighting projects.

Several studies have explored the application of neural networks in public lighting. One study developed an Extreme Learning Machine (ELM) model for simulating public lighting projects, focusing on reducing simulation time, enhancing energy efficiency, and maintaining a low error rate [3]. The ELM-based model achieved an error rate of less than 6% compared to DIALux (lighting design software) simulations and processed 1,000 different typologies in 10 seconds, showcasing the potential of neural networks to optimize public lighting design and evaluation [3].

This study develops and evaluates two distinct Multilayer Perceptron (MLP) neural network models [4, 5] for assessing compliance with NBR 5101/2018. The newer NBR 5101/2024 standard is not applied in this study due to the absence of approved LED luminaires in the Brazilian market by INMETRO that meet the new standard [6] and because simulation software has not yet been adapted. The first model is a regression-based MLP, which predicts illuminance and light uniformity in a pathway. The second model is a classification-based MLP that uses these predicted parameters and classifications of roads and sidewalks to assess compliance with the NBR

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5101/2018. A thorough review of the guidelines in Brazilian Standard 5101/2018 is essential to identify the relevant parameters for evaluation. The study involves analyzing and preprocessing data from real-world public lighting projects to ensure its suitability for training neural network models. This process includes evaluating the models' precision, recall, and F1-score for classification tasks and the mean squared error (MSE) for regression tasks. The goal is to demonstrate the feasibility and effectiveness of using neural networks to optimize public lighting systems, ultimately contributing to safer and more efficient urban environments.

Theoretical Background

Brazilian Public Lighting Standards

Brazilian Standard 5101/2018 establishes comprehensive guidelines for public lighting systems in Brazil. These guidelines ensure safety, visibility, and efficiency in public spaces, particularly in urban areas. The standard specifies requirements for several critical parameters, including illuminance and its uniformity, to ensure that lighting systems meet the necessary criteria for safety and functionality. [2].

Illuminance is the total luminous flux incident on a surface per unit area, measured in lux (lx). It is a fundamental metric for assessing the adequacy of lighting in each region. The standard sets minimum and recommended illuminance levels for different classes of public roads and areas (e.g., high-traffic urban roads and highways require higher illuminance levels than residential streets or pedestrian pathways. This differentiation is vital to provide appropriate visibility for drivers and pedestrians, reducing the likelihood of accidents and enhancing overall safety [7].

Illuminance uniformity, now referred to as uniformity, measures the evenness of light distribution across a surface. It is expressed as a minimum-to-average illuminance ratio and is crucial for preventing areas of excessive brightness or darkness, which can cause visual discomfort or hazards. NBR 5101/2018 outlines specific uniformity ratios that must be achieved to ensure a consistent and comfortable visual experience for road users and pedestrians [7].

According to NBR 5101/2018, roads are classified due to their pedestrian and vehicle traffic intensity. Different classes of roads require specific illuminance and uniformity levels to ensure safety and visibility and enhance efficiency [7]. Table 1 summarizes these requirements, indicating the minimum and average illuminance values and uniformity ratios for various road categories.

Neural Networks

Artificial Neural Networks (ANNs) are machine learning algorithms inspired by the human nervous system. They consist of interconnected neurons called perceptrons that propagate information. ANNs optimize functions to either maximize or minimize an objective function. In supervised learning, the goal is to minimize an error function that measures the difference between predicted outputs and actual values. This optimization enables the network to learn from data and improve its performance over time, making ANNs powerful tools for various applications, including public lighting project evaluation and improvement [4,5].

Multilayer Perceptrons (MLPs), a type of ANN, consist of several interconnected neurons: an input layer, one or more hidden layers, and an output layer. Information is fed forward from the input layer through the hidden (intermediate) layers to the output layer. Each neuron in a layer is connected to neurons in the previous and subsequent layers, with links having weights and biases that are adjusted during training to optimize network performance. The input layer receives raw data processed by hidden layers using activation functions. Common activation functions include the Rectified Linear Unit (ReLU), which introduces non-linearity to capture

Table 1. Minimum average illuminance and uniformity for Road / Sidewalk classes [7].

Road Lighting class	Illuminance (lux)	Uniformity (dimensionless)	Sidewalk Lighting class	Illuminance (lux)	Uniformity dimensionless)
V1	30	0.4	P1	20	0.3
V2	20	0.3	P2	10	0.25
V3	15	0.2	P3	5	0.2
V4	10	0.2	P4	3	0.2
V5	5	0.2			

complex data patterns, and the Sigmoid function, which maps input values between 0 and 1 and is valid for binary classification tasks [4, 5].

Training MLPs involves adjusting the weights to minimize the error between predicted and actual targets using a backpropagation algorithm. This algorithm calculates the error gradient for each weight and updates the weights in the opposite direction of the gradient. This process repeats over many iterations, known as epochs, until the network converges to a solution that minimizes error [4, 5].

Due to the backpropagation algorithm and interconnected perceptrons (which suit non-linear situations), MLPs can handle large datasets and complex relationships [4,5]. This implies they are well-suited for applications beyond public lighting, including image and speech recognition, financial forecasting, and medical diagnosis. Based on input parameters such as road width, mounting height, installation angle, and lamp power, MLPs can predict illuminance and uniformity in public lighting. They can also classify whether a lighting project complies with Brazilian Standard 5101/2018.

Materials and Methods

Data

The first step of this project was to collect comprehensive data from public lighting projects. This data was provided by a company specializing in public lighting, 42LUX, allowing us to gather a substantial dataset containing over 250,000 projects. Each project includes the following parameters: power, installation angle, mounting height, recoil, projection, road width, adjacent and opposite sidewalk width, and distance between poles. Additionally, the dataset contains road and sidewalk classes and output parameters such as illuminance and uniformity, which are critical for assessing compliance with Brazilian Standard 5101/2018 and validating the accuracy of both the classification and the regression models.

We performed several preprocessing steps to ensure the dataset was adequate for training our neural network models. Initially, we removed incomplete or erroneous records to guarantee the dataset's integrity and prevent potential bias. Next, we divided the dataset into training and test sets. As the literature suggests, the train-test ratio was 70%—30% to have enough data to train the network and tune hyperparameters, minimizing overfitting [4,5].

Normalization techniques were applied to address the different scales of the input parameters. Determining the most suitable data format for processing the dataset was essential. This understanding justified the construction of a specific feedforward classification network with backpropagation to examine the different loss graphs per epoch during training. The most suitable was standardization (removing the mean and dividing by the standard deviation of the values set) [4].

Proposed Models

Two types of Multilayer Perceptron (MLP) models were developed for this study: one for regression and the other for classification. The regression model aims to predict the illuminance and uniformity values based on the project input parameters (reflecting the lighting devices and their spatial settings). In contrast, analyzing its illuminance and uniformity, the classification model determines whether a public lighting project complies with Brazilian Standard 5101/2018.

The regression model has an input layer with nine neurons, each corresponding to one of the parameters (power, installation angle, mounting height, recoil, projection, road width, adjacent and opposite sidewalk width, and distance between poles). The model includes one hidden layer with 100 neurons using the Rectified Linear Unit (ReLU) activation function and an output layer with six neurons, representing the illuminance and uniformity of the road and both sidewalks. The Adam optimizer minimizes the mean squared error (MSE) between predicted and actual values. The model was trained for 250 epochs.

The classification model uses the six output neurons from the regression model as inputs, sidewalks, and road classes. It has a hidden layer of the same dimension as the regression model but features a single neuron in the output layer with a sigmoid activation function. This neuron outputs a probability between 0 and 1, indicating whether the project complies with NBR 5101/2018. The Adam optimizer was used with the same learning rate and early stopping criteria as the regression model, and the model was trained for 250 epochs. Performance was evaluated using accuracy, precision, recall, and the F1-score.

Evaluation

After training, the models were evaluated using the test set. The mean squared error (MSE) and the coefficient of determination (R^2) were calculated for the regression model to assess prediction accuracy. For the classification model, accuracy, precision, recall, and the F1-score were used to evaluate performance [4,5].

The Receiver Operating Characteristic (ROC) curve was plotted, and the area under the curve (AUC) was calculated to assess discriminative ability. The ROC curve plots the valid positive rate against the false positive rate at various thresholds, and the AUC represents the probability that the model ranks a randomly chosen positive instance higher than a randomly chosen negative instance.

Results and Discussion

The regression model achieved an MSE of 0.002 and an R^2 of 0.047, contrasting the proposed model's evaluation. The very low MSE indicates that the predictions are very close to the actual values within the data context, implying high precision in individual predictions. However, the low R^2 value suggests that the model does not adequately capture the overall variability in the data, indicating limited explanatory power regarding the data's variance. This discrepancy is likely related to the data imbalance and the scale difference between the regression model outputs.

To improve the R^2, addressing data balancing issues and applying more effective normalization or standardization techniques are recommended.

Figure 1 illustrates the ROC curve for the classification model. The training process resulted in a loss of 0.08, suggesting a well-trained model with potential overfitting. However, as the confusion matrix analysis suggests, this was not observed in practice. The confusion matrix provides a detailed breakdown of the classification model, showing the number of true positives, true negatives, false positives, and false negatives. As shown in Table 2, the model accurately classified 31,125 compliant projects and 43,171 non-compliant projects. However, it misclassified 1,124 compliant projects as non-compliant and 967 non-compliant projects as compliant. This detailed

Figure 1. ROC curve and AUC of the classification MLP.

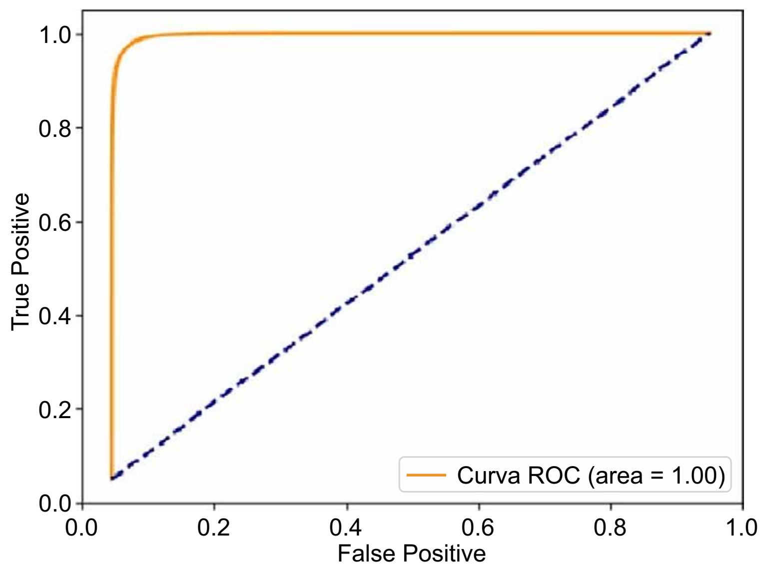

Table 2. Confusion matrix of classification model.

	Predicted Positive Class	Predicted Negative Class
Real Positive Class	31,125	1,124
Real Negative Class	967	43,171

analysis highlights the model's high accuracy and effectiveness in distinguishing between compliant and non-compliant public lighting projects.

As demonstrated in Table 2, the model achieved an accuracy of 97.26%, precision of 97% (indicating that most projects classified as compliant were correctly identified), recall of 96.5% (showing that most truly compliant projects were correctly detected), and F1-score of 96.7% (reflecting a strong balance between precision and recall), along with the ROC curve (showing an area under the curve (AUC) of approximately 1). The metrics confirm the effectiveness of the classification model in the public lighting context since it efficiently determines whether a set of illuminance and uniformity parameters meets the NBR 5101 standard.

In summary, the results show the potential of neural networks, particularly MLPs, to enhance the evaluation and implementation of public lighting projects. These models offer valuable tools for urban planners and engineers, helping them design and maintain lighting systems that comply with standards and improve public safety and efficiency.

Conclusion

This study demonstrated the feasibility of using MLP neural networks to evaluate the compliance of public lighting projects with Brazilian Standard 5101/2018. The obtained results are promising, indicating that this approach can help optimize the implementation of public lighting systems. We successfully implemented, trained, and evaluated the MLP neural network models. The regression model achieved an MSE of 0.002, demonstrating high precision in individual predictions. The classification model attained an accuracy of

97.26%, with a precision of approximately 97.0%, a recall of about 96.5%, and an F1-score of around 96.7%. These metrics indicate that the classification model is highly effective in identifying compliant projects and minimizing misclassification. Future research can explore the inclusion of additional variables or the application of other neural network architectures to enhance model performance and accuracy further.

Potential extensions of this work include experimenting with various hyperparameters, such as using variable or adaptive learning rates that adjust based on the loss function's convergence. Another possibility for future research could involve modifying the problem to identify the closest configuration for parameters that do not initially comply with NBR 5101/2018 but could be adjusted to meet the standards.

Additionally, a comparative analysis with commercial software designed for public lighting scenario simulations could be conducted, evaluating their accuracy and processing times against the neural network models used in this study. Finally, an update to the study could involve applying the proposed models by the new NBR 5101/2024 standards once approved LEDs and suitable simulation software become available, providing deeper insights and further advancements in applying neural networks to public lighting projects.

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