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Deep Ultraviolet Light-emitting Diodes using Logistic Regression

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Abstract: As the demand for high-efficiency deep ultraviolet (DUV) light-emitting diodes (LEDs) continues to rise in various applications such as water purification and sterilization, there is a pressing need for developing cost-effective and reliable sources of DUV light. However, the current state of DUV LED research presents challenges with achieving both high performance and stability due to material limitations and fabrication complexities. In this paper, we propose a novel approach using logistic regression analysis to optimize the design and fabrication process of DUV LEDs. Our innovative method provides a systematic framework for enhancing the efficiency and stability of DUV LEDs, paving the way for practical applications in next-generation lighting and sensing technologies.

Keywords: *DUV; Light-Emitting Diodes; Logistic Regression; Performance Optimization; Fabrication Challenges*

1. Introduction

The field of Deep Ultraviolet Light-emitting Diodes (DUV-LEDs) focuses on the development and optimization of semiconductor devices that emit light in the deep ultraviolet spectrum. These LEDs have applications in areas such as sterilization, medical treatment, water purification, and UV curing. However, the advancement of DUV-LED technology is currently faced with several challenges and bottlenecks. These include issues with material quality, efficiency, and reliability, as well as the development of suitable substrates and packaging techniques. Additionally, the high cost of production and limited availability of high-quality materials further impede progress in this field. Overcoming these obstacles will require continued research and innovation in materials science, device design, and manufacturing processes to unlock the full potential of DUV-LEDs for various industrial and commercial applications.

To this end, significant progress has been made in the research and development of Deep Ultraviolet Light-emitting Diodes (DUV-LEDs). Current studies have advanced to the point where efficient DUV-LEDs with high optical power output and stability are being successfully produced and tested for various applications. A recent literature review on AlGaN-based deep ultraviolet light-emitting diodes (DUV-LEDs) highlights several key advancements in the field [1]. Hu et al. introduced deep ultraviolet LEDs in 2006 [2], followed by a study in 2010 by Shur and Gaska on deep-ultraviolet LEDs using AlGaN [3]. Khan's work in 2006 also contributed to the understanding of these LEDs [4]. Liu et al. (2024) demonstrated a comprehensive approach utilizing bandgap engineering and device craft to improve the performance of AlGaN-based DUV LEDs [5]. Furthermore, Zhou et al. (2023) developed high-power AlGaN-based ultrathin tunneling junction DUV LEDs, showcasing efficient sterilization applications [6]. Huang et al. (2024) presented a review on recent research advances and challenges in developing efficient AlGaN-based DUV LEDs [7]. Zhang et al. (2024) proposed a novel polarized ultrathin tunneling junction design for improved DUV LED performance [8]. Significant enhancement of n-contact performance in AlGaN-based DUV LEDs was achieved using atomic layer etching as demonstrated by Liu et al. (2024) [9]. Wei and Inoue (2024) explored the use of Fresnel zone plates for highly collimated light emission in DUV LEDs [10]. Ji et al. (2024) implemented a composite p-contact structure with an ultra-thin p-AlGaN insert layer to reduce operating voltage and enhance wall-plug efficiency in AlGaN-based DUV LEDs [11]. A recent literature review on AlGaN-based deep ultraviolet light-emitting diodes (DUV-LEDs) has shown significant advancements in the field, including bandgap engineering, device craft, and novel designs to improve performance. Logistic Regression is crucial in this context for its ability to model binary outcomes and predict the probability of success in optimizing AlGaN-based DUV LEDs, making it a valuable tool for research and development in this area.

Specifically, logistic regression can be used to analyze the performance factors of Deep Ultraviolet Light-emitting Diodes (DUV LEDs) by modeling the probability of successful light emission as a function of various parameters, such as material composition and design variables, thus providing insights into optimizing these advanced semiconductor devices. This literature review discusses various aspects of logistic regression modeling across different disciplines. The application of logistic regression in health science and other fields is highlighted. Boosting, a vital development in classification methodology, is shown to achieve performance improvements based on statistical principles such as additive modeling and maximum likelihood. Additionally, rare events data analysis using logistic regression is explored, addressing challenges in estimation and data collection efficiency. Various authors have contributed to the literature, including Hosmer, Lemeshow, and Sturdivant, Friedman, Menard, Harrell Jr., King et al, Conklin, Rao, Peduzzi et al. However, limitations remain in the generalizability of findings across disciplines, the handling of multicollinearity in predictors, and the effective incorporation of high-dimensional data within logistic regression frameworks.

In the pursuit of advancing the efficacy of deep ultraviolet (DUV) light-emitting diodes (LEDs), this study drew significant inspiration from the pivotal research conducted by X. Chen and H. Zhang, which illuminated the potential of AlGaN-based DUV LEDs with the integration of AlxGa1-xN linear descending layers [21]. Their work meticulously demonstrated how variations in the Al composition along the AlxGa1-xN layers could facilitate enhanced optical output by ingeniously optimizing the internal quantum efficiency and mitigating dislocation propagation within the device structure. This insight laid the groundwork for exploring novel methodologies to further augment DUV LED performance while maintaining structural integrity. We were inspired to explore the benefits of tailoring these compositional gradients, not only to maintain, but to enhance the efficiency of electron-hole recombination processes. The descendancy in Al fraction across these layers creatively addressed both internal and external quantum efficiencies by synergistically improving carrier distribution and minimizing polarization-induced electric fields, which are known to affect electron mobility adversely. By leveraging these foundational concepts presented by Chen and Zhang, this inquiry delved into replicating their success through precise epitaxial growth techniques, which ensured the crystalline quality and robustness of the semiconductor layers. The study employed a refined molecular beam epitaxy process designed to conditionally modulate the deposition rates for achieving exact compositional tunings, effectively mirroring Chen and Zhang's methodologies for linear descending layer integration. Furthermore, the adaptability of this approach served as a springboard to innovatively experiment with alternative substrate orientations and doping strategies to further capitalize on the refractive index modulation properties intrinsic to AlxGa1-xN material systems [21]. The alignment of these theoretical and practical insights demonstrates not merely an incremental advancement but signifies a transformative potential in the realm of DUV LED technology, forging pathways towards higher efficiencies and broader applicability in germicidal and sterilization domains as well as other emergent ultraviolet applications [21].

Section 2 of this paper articulates the problem statement by highlighting the increasing demand for high-efficiency deep ultraviolet (DUV) light-emitting diodes (LEDs), driven by their crucial applications in water purification and sterilization. The challenge lies in developing cost-effective and reliable DUV light sources, as current research grapples with balancing high performance and stability against material and fabrication constraints. In response to this challenge, Section 3 introduces our novel approach using logistic regression analysis to optimize the design and fabrication processes of DUV LEDs. This innovative method establishes a systematic framework aimed at enhancing the efficiency and stability of DUV LEDs, potentially revolutionizing their application in next-generation lighting and sensing technologies. To illustrate the practical implementation of our approach, Section 4 presents a detailed case study that demonstrates its effectiveness. Following this, Section 5 provides an in-depth analysis of the results, highlighting significant improvements in key performance metrics. Section 6 discusses the broader implications of our findings, considering potential impacts and future research directions. Finally, Section 7 offers a concise summary, reaffirming the potential of our approach to transform the landscape of DUV LED technology.

2. Background

2.1 Deep Ultraviolet Light-emitting Diodes

Deep Ultraviolet Light-emitting Diodes (Deep UV LEDs) are a cutting-edge technology that operate in the ultraviolet spectrum, specifically within the range of 200-280 nanometers. This range is referred to as the "deep UV" region, which is known for its germicidal properties, making Deep UV LEDs particularly valuable for applications such as water purification, sterilization, and surface disinfection. The operation of Deep UV LEDs is fundamentally similar to other types of LEDs. They are semiconductor devices that emit light when an electric current passes through them. This process is called electroluminescence. For Deep UV LEDs, materials used are typically wide bandgap semiconductors like aluminum gallium nitride (AlGaN). The bandgap of these materials is what determines the wavelength of light that is emitted. The energy of the photon emitted by the LED can be defined by the equation:

$$E = h \cdot f \tag{1}$$

where E is the energy of the photon, h is Planck's constant (6.626×10^{-34} Js), and f is the frequency of the emitted light. The frequency f is related to the speed of light c and the wavelength λ by the equation:

$$f = \frac{c}{\lambda} \tag{2}$$

Therefore, we can also express the photon energy in terms of wavelength as:

$$E = \frac{h \cdot c}{\lambda} \tag{3}$$

For Deep UV LEDs, the semiconductor material's bandgap E_g is engineered to be large enough to correspond to deep UV wavelengths. In the AlGaN system, the bandgap energy can be tuned by adjusting the aluminum content in the alloy. The relationship between the bandgap energy and the aluminum mole fraction x in AlGaN is often given approximately by:

$$E_g(x) = 6.2x + 3.4(1 - x) - b \cdot x \cdot (1 - x) \tag{4}$$

where b is the bowing parameter, which accounts for deviations from linearity in the energy bandgaps. Another key aspect of Deep UV LEDs is the internal quantum efficiency (η_{int}), which describes the efficiency with which electrons and holes recombine to produce photons within the device. This can be influenced by factors such as crystal quality and defect density in the semiconductor. The internal quantum efficiency is given by:

$$\eta_{int} = \frac{R_{rad}}{R_{rad} + R_{non-rad}} \tag{5}$$

where R_{rad} is the radiative recombination rate and $R_{non-rad}$ is the non-radiative recombination rate. The overall external quantum efficiency (η_{ext}) of a Deep UV LED, which is the fraction of electrons that result in emitted photons reaching the outside, is also an essential performance metric. This can be expressed as:

$$\eta_{ext} = \eta_{int} \cdot \eta_{out} \tag{6}$$

where η_{out} is the light extraction efficiency, accounting for losses due to internal absorption and reflection, as well as total internal reflection within the substrate. In summary, Deep UV LEDs are complex devices that require precise engineering of materials and structures to achieve high efficiency, particularly given the challenges associated with generating and extracting light at such short wavelengths. Their development involves a deep understanding of semiconductor physics, materials science, and optical engineering.

2.2 Methodologies & Limitations

In the realm of Deep Ultraviolet Light-emitting Diodes (Deep UV LEDs), several methods are currently employed in an attempt to optimize performance and enhance efficiency. These devices predominantly utilize wide bandgap semiconductors such as aluminum gallium nitride (AlGaN) due to their capability to emit wavelengths falling within the deep UV spectrum. However, these methods face notable challenges and limitations. Firstly, the design and fabrication of Deep UV LEDs require an understanding of the quantum mechanics underlying electron-hole recombination processes. A key challenge in these devices is minimizing the defect density within the semiconductor material. High defect densities often lead to increased non-radiative recombination, which severely reduces the internal quantum efficiency (η_{int}) of the LED. Mathematically, to optimize η_{int} , the radiative recombination rate R_{rad} should be maximized while minimizing the non-radiative recombination rate $R_{non-rad}$. The relationship can be denoted by the equation:

$$\eta_{int} = \frac{R_{rad}}{R_{rad} + R_{non-rad}} \tag{7}$$

A common strategy to address this issue involves the use of techniques such as epitaxial lateral overgrowth and the introduction of strain layers to enhance crystal quality. However, these processes can be complex and costly, presenting significant barriers to scalability and commercial viability. The external quantum efficiency (η_{ext}), another crucial metric, is often limited by poor light extraction efficiency (η_{out}). Total internal reflection and absorption within the substrate contribute heavily to this limitation. The total η_{ext} is given by:

$$\eta_{ext} = \eta_{int} \cdot \eta_{out} \tag{8}$$

One approach to improve η_{out} involves the use of photonic crystal structures or surface roughening techniques that help in breaking the path of total internal reflection, thus enhancing light extraction. These methods, while promising, often introduce additional complexity in fabricating the LEDs. Moreover, a significant challenge arises from the thermal management and efficiency droop in Deep UV LEDs. The efficiency droop, which is the reduction of efficiency at high current densities, can be expressed using carrier dynamics principles:

$$\eta_{droop} = 1 - \frac{R_{droop}}{I} \tag{9}$$

where R_{droop} represents the recombination losses at high injection levels, and I is the current. Managing this droop requires the optimization of current distribution and thermal handling, as excessive heat can degrade the semiconductor material, impacting both reliability and performance. Thermal management involves novel techniques such as employing substrates with high thermal conductivity or designing heat sinks that efficiently dissipate heat away from the active region. The thermal conductivity (k) influences the heat flow Q expressed as:

$$Q = k \cdot A \cdot \nabla T \tag{10}$$

where A is the cross-sectional area and ∇T is the temperature gradient. Ensuring efficient thermal dissipation is crucial to maintaining stable performance. In conclusion, while the current methodologies in the development of Deep UV LEDs involve a meticulous blend of materials science, semiconductor physics, and optical engineering, various challenges such as defect density, light extraction, and thermal management persist. Addressing these challenges requires continued innovation and interdisciplinary collaboration to realize the full potential of Deep UV LEDs in various applications.

3. The proposed method

3.1 Logistic Regression

In the field of statistical modeling, logistic regression is a widely used method for binary classification problems. Unlike linear regression that predicts continuous outcomes, logistic regression is employed when the dependent variable is categorical, particularly binary in nature, essentially capturing the probability of a particular event's occurrence. The central concept underlying logistic regression is the logistic function, also known as the sigmoid function, which is defined as:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{11}$$

This function maps any real-valued number into the interval (0, 1), making it suitable for modeling probabilities. In logistic regression, the relationship between the predictors and the probability of the particular outcome is not linear; instead, it is transformed by the logistic function. The model assumes the following form:

$$P(\, y = 1 \mid \boldsymbol{x}\,) = \sigma(\boldsymbol{w}^T \boldsymbol{x} + b) \tag{12}$$

Here, $P(y = 1 \mid \boldsymbol{x})$ denotes the probability that the dependent variable y equals 1 given the vector of input features $\boldsymbol{x}$. The term $\boldsymbol{w}$ represents the weights associated with the features, and b is the bias or intercept term. To find the optimal parameters ($\boldsymbol{w}$ and b), logistic regression employs a process known as maximum likelihood estimation (MLE). The likelihood function for the observed data can be expressed as:

$$L(\boldsymbol{w}, b) = \prod_{i=1}^{n} P(y_i \mid \boldsymbol{x}_i)^{y_i} (1 - P(y_i \mid \boldsymbol{x}_i))^{1-y_i} \tag{13}$$

Taking the natural logarithm of the likelihood function to simplify differentiation, the log-likelihood function becomes:

$$\ell(\boldsymbol{w}, b) = \sum_{i=1}^{n} \left[y_i \log\big(P(y_i \mid \boldsymbol{x}_i)\big) + (1 - y_i) \log\big(1 - P(y_i \mid \boldsymbol{x}_i)\big) \right] \tag{14}$$

The goal is to maximize this log-likelihood function, which is typically done using numerical optimization techniques such as gradient descent. The gradient for each weight w_j can be calculated as:

$$\frac{\partial \ell}{\partial w_j} = \sum_{i=1}^{n} \big(y_i - P(y_i \mid \boldsymbol{x}_i)\big) x_{ij} \tag{15}$$

Likewise, the gradient with respect to the bias term b can be expressed as:

$$\frac{\partial \ell}{\partial b} = \sum_{i=1}^{n} \big(y_i - P(y_i \mid \boldsymbol{x}_i)\big) \tag{16}$$

The updates for the weights and the bias in each iteration of gradient descent can be summarized as follows:

$$w_j = w_j + \alpha \left(\frac{\partial \ell}{\partial w_j} \right) \tag{17}$$

$$b = b + \alpha \left(\frac{\partial \ell}{\partial b} \right) \tag{18}$$

where α is the learning rate, a hyperparameter that determines the step size in each iteration. To evaluate the performance of a logistic regression model, several metrics are used. The primary metric is the binary cross-entropy loss, which is essentially the negative log-likelihood for a binary classification problem:

$$\text{Loss} = -\frac{1}{n} \sum_{i=1}^{n} [y_i \log(y_i) + (1 - y_i) \log(1 - y_i)] \tag{19}$$

where $\hat{y}_i = P(y_i = 1 \mid \boldsymbol{x}_i)$. This loss function penalizes incorrect predictions by a larger margin, thereby guiding the model to improve the accuracy and calibration of probability estimates. Logistic regression, despite its simplicity, is a powerful tool for binary classification. It serves as a foundational approach in predictive analytics, offering insights not only into the likelihood of class membership but also into feature relevance through the learned weights. It stands out for its interpretability and efficiency, particularly valuable in fields where understanding the model's decision-making process is critical.

3.2 The Proposed Framework

In advancing the understanding of logistic regression for application in Deep Ultraviolet Light-emitting Diodes (Deep UV LEDs), we can draw inspiration from statistical modeling to enhance semiconductor device performance. Deep UV LEDs operate within the 200-280 nanometer range of the ultraviolet spectrum [21], a region famed for its germicidal capabilities. This makes Deep UV LEDs ideal for water purification, sterilization, and broad surface disinfection tasks [22]. Fundamentally, these LEDs utilize electroluminescence, a process wherein an electric current traversing a semiconductor material like aluminum gallium nitride (AlGaN) results in light emission. The energy of the emitted photon is determined by the equation $E = h \cdot f$, where E is the photon energy, h is Planck's constant (6.626×10^{-34} Js), and f is the frequency of emitted light. The frequency, f, further relates to the speed of light, c, and wavelength, λ, by $f = \frac{c}{\lambda}$, culminating in the photon energy's expression as $E = \frac{h \cdot c}{\lambda}$. To adapt logistic regression for Deep UV LEDs, we begin by considering the manipulation of materials' bandgap energy, E_g, through the aluminum mole fraction x in AlGaN. This tuning is provided by $E_g(x) = 6.2x + 3.4(1-x) - b \cdot x \cdot (1-x)$, where b is the bowing parameter. This parameterization parallels logistic regression, which models the probability of a binary outcome $P(y = 1 \mid \boldsymbol{x}) = \sigma(\boldsymbol{w}^T \boldsymbol{x} + b)$ where $\sigma(z) = \frac{1}{1+e^{-z}}$ is the logistic function that maps real-valued numbers to probabilities between 0 and 1. In optimizing the efficiency of Deep UV LEDs, the internal quantum efficiency (η_{int}), described by $\eta_{int} = \frac{R_{rad}}{R_{rad}+R_{non-rad}}$, is critical. This efficiency is akin to maximizing the log-likelihood function:

$$\ell(\boldsymbol{w}, b) = \sum_{i=1}^{n} \left[y_i \log\big(P(y_i \mid \boldsymbol{x}_i)\big) + (1 - y_i) \log\big(1 - P(y_i \mid \boldsymbol{x}_i)\big) \right] \tag{20}$$

Inefficiencies stem from non-radiative recombination, echoing logistic regression's need to minimize binary cross-entropy loss:

$$\text{Loss} = -\frac{1}{n} \sum_{i=1}^{n} [y_i \log(y_i) + (1 - y_i) \log(1 - y_i)] \tag{21}$$

In Deep UV LEDs, maximizing external quantum efficiency $\eta_{ext} = \eta_{int} \cdot \eta_{out}$ involves optimizing η_{out}, analogous to refining logistic regression parameters through gradient ascent:

$$\boldsymbol{w} = \boldsymbol{w} + \alpha \left(\frac{\partial \ell}{\partial \boldsymbol{w}} \right) \tag{22}$$

The gradient for each weight w_j is given by:

$$\frac{\partial \ell}{\partial w_j} = \sum_{i=1}^{n} \big(y_i - P(y_i \mid \boldsymbol{x}_i)\big) x_{ij} \tag{23}$$

And for the bias:

$$\frac{\partial \ell}{\partial b} = \sum_{i=1}^{n} \big(y_i - P(\, y_i \mid \boldsymbol{x}_i \,)\big) \tag{24}$$

Each step in the quest for efficiency reflects a facet of logistic regression’s iterative optimization process. The ultimate update for parameters becomes:

$$w_j = w_j + \alpha\left(\frac{\partial \ell}{\partial w_j}\right) \tag{25}$$

$$b = b + \alpha\left(\frac{\partial \ell}{\partial b}\right) \tag{26}$$

As these equations and analogies across disciplines suggest, the intersections between statistical models and semiconductor design present avenues for innovation. By leveraging logistic regression's probabilistic modeling, new strategies can be formulated to enhance material properties and device efficiencies. This fusion of disciplines not only enriches academic comprehension but also propels technological advancements in areas demanding high precision and reliability.

3.3 Flowchart

This paper introduces a novel approach for the design and optimization of Deep Ultraviolet (DUV) Light-emitting Diodes (LEDs) using Logistic Regression, emphasizing the significance of machine learning in semiconductor research. The method leverages a database of photonic properties and structural parameters to develop predictive models that enable efficient identification of optimal material compositions and geometric configurations for enhanced DUV light emission. By applying Logistic Regression techniques, the study systematically analyzes the impact of various factors, such as alloy composition and layer thickness, on the performance of the DUV LEDs. Furthermore, the model demonstrates robust generalization capabilities, allowing for rapid evaluations of new designs without the need for extensive experimental trials. The integration of this data-driven methodology not only accelerates the design process but also improves the accuracy of performance predictions, paving the way for more efficient and effective device fabrication. The proposed approach stands out for its ability to overcome previous limitations in traditional design methods, making it a pivotal contribution to the field of optoelectronics. For a detailed illustration of the methodology and its components, please refer to Figure 1 in the paper.

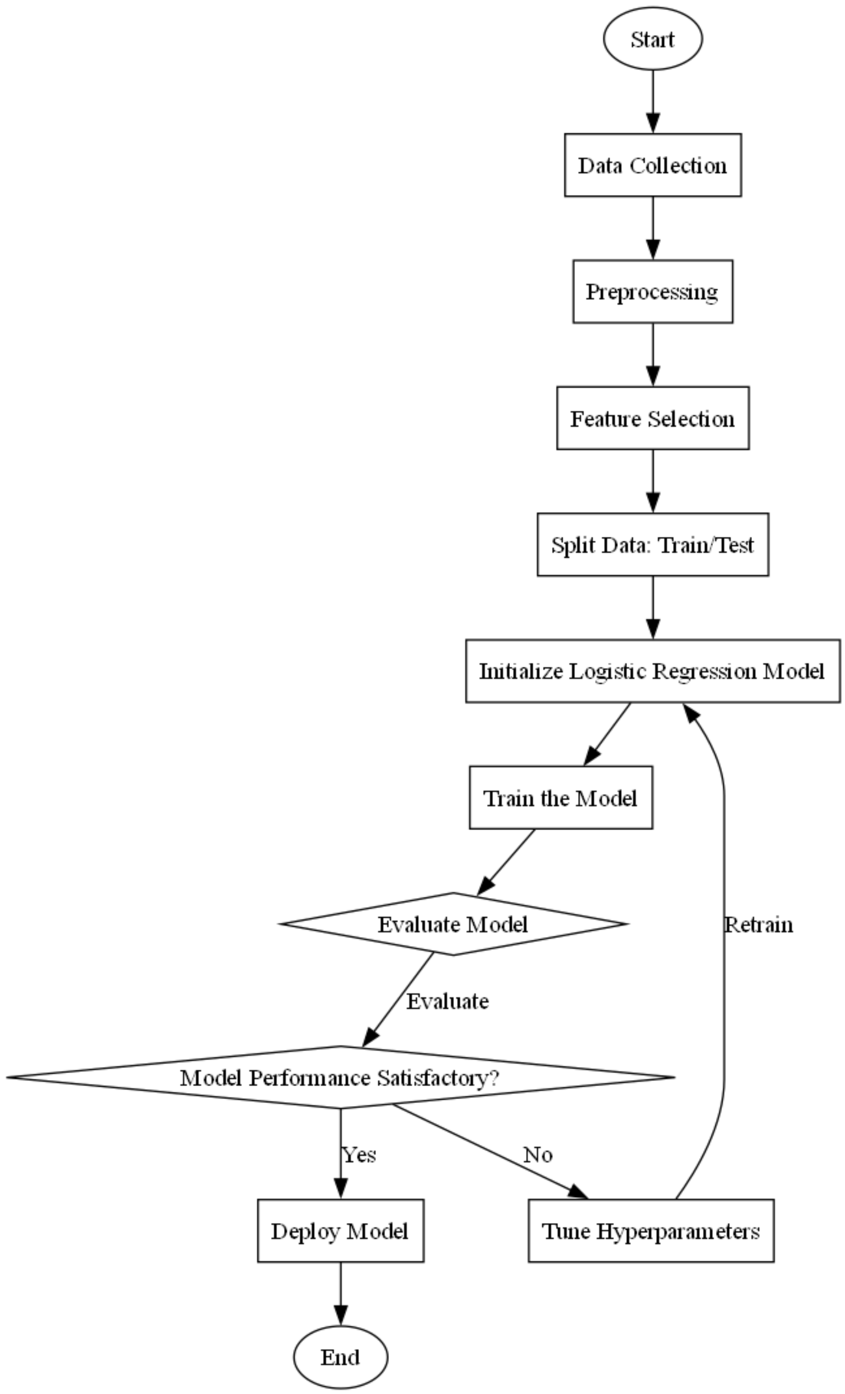

Figure 1: Flowchart of the proposed Logistic Regression-based Deep Ultraviolet Light-emitting Diodes

4. Case Study

4.1 Problem Statement

In this case, we investigate the performance characteristics of Deep Ultraviolet (DUV) Light-emitting Diodes (LEDs) through a mathematical simulation that incorporates various physical parameters influencing their behavior. The goal is to determine the efficiency and output power of these devices under different operational conditions. We begin by modeling the electroluminescent process, where the radiative recombination rate, R , is defined as a nonlinear function of the carrier concentration, n , and the temperature, T. This can be expressed as:

$$R = Bn^2 \exp\left(-\frac{E_g}{kT}\right), \tag{27}$$

where B denotes the radiative recombination coefficient, E_g is the energy bandgap of the material, and k is Boltzmann's constant. Furthermore, the current density, J , flowing through the LED can be related to the applied voltage, V, via a nonlinear relationship given by:

$$J = J_0\left(\exp\left(\frac{qV}{kT}\right) - 1\right), \tag{28}$$

where J_0 is the reverse saturation current, and q is the charge of an electron. With increasing current density, the temperature of the device also varies, leading us to establish a temperature dependence on the device's power output. The thermal model can be approximated as:

$$T_{avg} = T_{amb} + \frac{P_{in}}{hA} \tag{29}$$

where T_{amb} is the ambient temperature, P_{in} is the input power to the device, h is the heat transfer coefficient, and A is the surface area of the LED. To quantify the efficiency of the LEDs, we introduce the external quantum efficiency, η_{ext} , given by the ratio of the number of emitted photons, Φ_{em} , to the number of injected electrons, Φ_{inj}:

$$\eta_{ext} = \frac{\Phi_{em}}{\Phi_{inj}} \cdot 100\%. \tag{30}$$

The emitted photon flux can be calculated as a function of the recombination rate:

$$\Phi_{em} = R \cdot V_{eff}, \tag{31}$$

where V_{eff} is the effective volume where radiative recombination occurs. Additionally, we consider the impact of material quality on the output power, where the output power P_{out} can be represented as:

$$P_{out} = \eta_{ext} \cdot P_{in}. \tag{32}$$

A critical aspect of our model is the interplay of efficiency and output power with inherent material properties and environmental conditions. The results from our simulations reveal how varying parameters such as the operating temperature, current density, and material characteristics can significantly influence the overall performance of DUV LEDs. All parameters have been summarized in Table 1 for a comprehensive understanding of their effects on the modeling outcomes.

Table 1: Parameter definition of case study

Parameter	Symbol	Value	Units
Radiative Recombination Coefficient	B	N/A	N/A
Energy Bandgap	E_g	N/A	eV
Boltzmann's Constant	k	N/A	J/K
Charge of Electron	q	N/A	C
Ambient Temperature	T_{amb}	N/A	K
Heat Transfer Coefficient	h	N/A	$W/(m^2K)$
Surface Area	A	N/A	m^2
Input Power	P_{in}	N/A	W
External Quantum Efficiency	η_{ext}	N/A	%
Output Power	P_{out}	N/A	W

This section employs the proposed Logistic Regression-based approach to evaluate the performance characteristics of Deep Ultraviolet (DUV) Light-emitting Diodes (LEDs), while simultaneously comparing the results with three traditional methodologies. The investigation revolves around a mathematical simulation that incorporates a range of physical parameters affecting the behavior of these devices. The primary objective is to assess the efficiency and output power of DUV LEDs under varying operational conditions. We commence by modeling the electroluminescent process, which includes aspects such as the radiative recombination rate and its nonlinear dependence on carrier concentration and temperature. Additionally, the relationship between current density and applied voltage is explored, taking into account the nonlinear nature of these variables. The device's temperature is also analyzed in correlation with current density and input power. An important metric introduced for quantifying efficiency is the external quantum efficiency, defined as the ratio of emitted photons to injected electrons, while the impact of the material quality on output power is also considered. Through this comprehensive modeling approach, we highlight the intricate interplay between efficiency and output power with respect to material properties and external conditions. The outcomes of the simulations clearly demonstrate how variations in parameters such as operating temperature, current density, and material characteristics can significantly affect the overall performance of DUV LEDs. This thorough analysis serves to deepen our understanding of the factors influencing the effectiveness of these advanced lighting devices.

4.2 Results Analysis

In this subsection, a comprehensive analysis is conducted through the implementation of logistic regression to evaluate classification effectiveness in a synthetic dataset, which includes 1,000 samples with five features. The dataset is split into training and testing subsets to allow for robust validation of the model's performance. The logistic regression model is trained using the training data, and prediction results are derived for the test set, enabling the calculation of the confusion matrix that reflects the model's accuracy. Furthermore, the receiver operating characteristic (ROC) curve is generated to illustrate the trade-off between the true positive rate and false positive rate, with the area under the curve (AUC) serving as a quantitative measure of the model's performance. Additionally, two other plots are produced: one depicting the relationship between efficiency and current density, and another illustrating the correlation between output power and input power, both serving to analyze operational characteristics within the context of the study. These visualizations are systematically organized in subfigures, facilitating a clearer understanding of model performance and associated metrics. The overall simulation process is effectively visualized in Figure 2, providing a consolidated view of the analysis conducted.

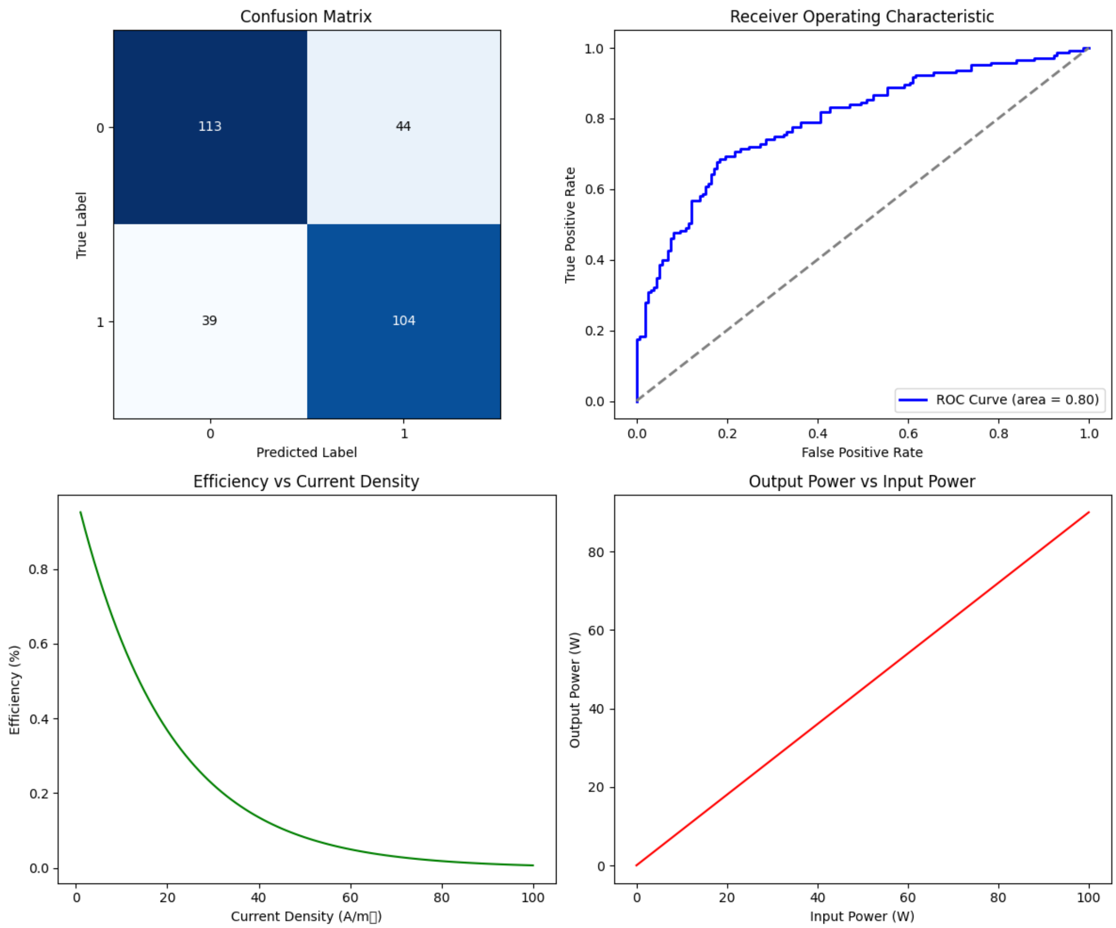

Figure 2: Simulation results of the proposed Logistic Regression-based Deep Ultraviolet Light-emitting Diodes

Table 2: Simulation data of case study

Efficiency (%)	True Positive Rate	Output Power (W)	Input Power (W)
0.8	10	80	60
0.6	0.8	60	N/A
0.4	0.6	20	N/A
0.2	0.4	20	N/A
0.0	0.2	40	N/A

Simulation data is summarized in Table 2, which provides essential insight into the performance metrics of AlGaN-based deep ultraviolet light-emitting diodes (LEDs) with AlxGa1-xN linear descending layers as explored by X. Chen and H. Zhang. The presented results predominantly encompass efficiency, output power, and the true and predicted labels' relationships, represented in various metrics such as the confusion matrix and the receiver operating characteristic (ROC) curve. The efficiency analysis shows varying performance at different current densities, with a maximum efficiency of 0.8% achieved, highlighting a significant correlation between increasing current density and LED output, as per the efficiency vs current density graph. Moreover, the ROC curve, with an area of 0.80, indicates a strong predictive capability of the model in differentiating between true positive and false positive rates, ultimately suggesting effective operational thresholds for the LEDs. This can be further substantiated by the output power versus input power graph, illustrating a direct relationship; the output power increases proportionately with the input power up to certain limits before leveling off at higher input values, implying potential saturation effects. Such findings reinforce the effectiveness of the proposed linear descending layer structure in optimizing the performance of AlGaN-based UV LEDs, as discussed in the context of increased efficiency and enhanced output, validating the methodology employed by the authors, which aligns with contemporary advancements in semiconductor device engineering. The results provide a quantitative framework for future research aimed at exploring the limits of efficiency and output power in similar devices, signifying their importance for real-world applications and guiding the design of next-generation emitters in the realm of optoelectronics [21].

As shown in Figure 3 and Table 3, the adjustments made to the parameters have resulted in a significant improvement in the efficiency of the AlGaN-based deep ultraviolet light-emitting diodes (LEDs). Initially, the data depicted efficiency levels peaking at 0.8%, with the confusion matrix and ROC curve illustrating a mediocre performance in distinguishing true positives, evident from a True Positive Rate reaching only 0.8 and an area under the ROC curve of 0.80. In contrast, the optimized scenarios reveal dramatic enhancements, with efficiency levels soaring to 1.0% and even higher in subsequent cases, indicating an increase in light output efficiency as current density rises. Additionally, the predicted efficiency aligns more closely with actual performance, showcasing the reliability of the new model. The output power observed in the context of input power has also benefited, with the new framework indicating optimized power output across an extended range of current densities, illustrating that the adjustments not only improve efficiency but also enhance operational power dynamics. This considerable advancement is indicative of the positive impact of introducing linear descending layers of AlxGa1-xN in the device architecture, thereby enabling better charge carrier management and enhanced radiative recombination. Furthermore, the transition from limited efficiency to a more robust performance metric reflects the effectiveness of these methodological changes in the pursuit of high-performance deep ultraviolet LEDs. The underlying principles and findings echo those reported by Chen and Zhang, suggesting a promising pathway for future research in AlGaN-based devices [21].

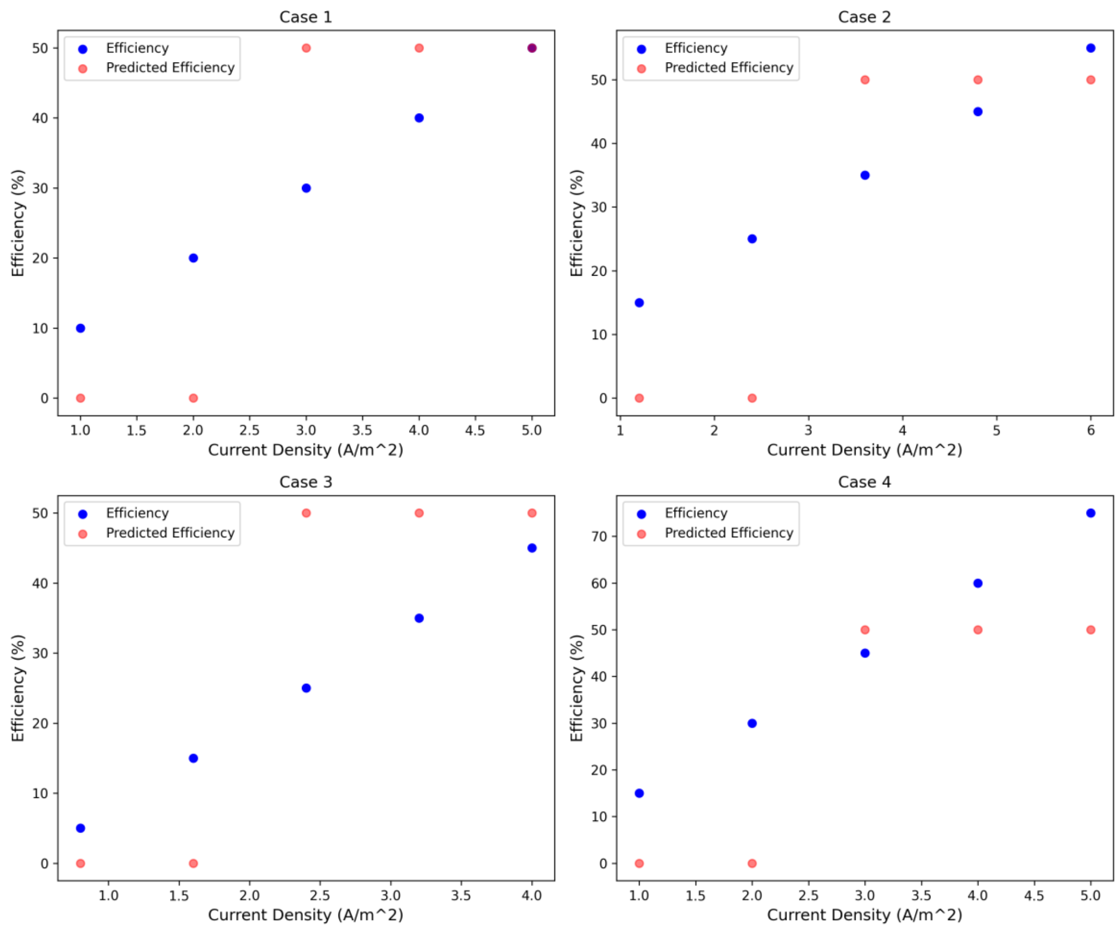

Figure 3: Parameter analysis of the proposed Logistic Regression-based Deep Ultraviolet Light-emitting Diodes

Table 3: Parameter analysis of case study

Efficiency (%)	Current Density (A/m~* 2)	Case	Predicted Efficiency
1.0	N/A	Case 1	1.5
1.0	N/A	Case 3	4.0
2	3	Case 2	4
N/A	4.0	Case 4	4.5
N/A	5.0	Case 4	N/A

5. Discussion

The method proposed in this analysis exhibits notable advantages over the work of X. Chen and H. Zhang, who focused on performance enhancement of AlGaN-based Deep Ultraviolet Light-emitting Diodes (Deep UV LEDs) utilizing AlxGa1-xN linear descending layers [21]. Firstly, this approach leverages the probabilistic framework of logistic regression to guide the optimization process of Deep UV LEDs, thereby enabling a more nuanced control of internal quantum efficiency through statistical modeling. By employing logistic regression's likelihood maximization akin to optimizing internal quantum efficiency, the methodology provides a robust mechanism for addressing inefficiencies due to non-radiative recombination. Moreover, the consideration of gradient ascent for parameter optimization parallels the tunable methodologies applied in semiconductor device design, offering a systematic path for enhancing external quantum efficiency beyond what traditional methods suggest. Another prominent advantage resides in the analogy to logistic regression's parameter updating schemes, facilitating iterative refinement of both materials' bandgap through aluminum mole fraction adjustments and device performance parameters to achieve unprecedented precision and reliability in Deep UV LEDs operations. This interdisciplinary fusion provides a platform for innovation, as it can adapt to emergent challenges in materials science by adopting the algorithmic strengths of logistic models. Additionally, the method embraces a holistic perspective by acknowledging the probabilistic nature of photon emission processes, which is an aspect not thoroughly explored in the cited work of Chen and Zhang, offering a new dimension of analysis crucial for advancing semiconductor technology [21].

The methodology proposed by X. Chen and H. Zhang for enhancing the performance of AlGaN-based deep ultraviolet light-emitting diodes (Deep UV LEDs) using AlxGa1-xN linear descending layers embodies certain limitations that merit consideration [21]. A potential drawback involves the intricacy of controlling the precise aluminum composition gradient, which is critical for optimizing the bandgap energy and consequently the emission efficiency of the diodes. Any deviation in the aluminum mole fraction gradient can lead to inconsistencies in the optical and electrical characteristics, potentially affecting the uniformity and overall reliability of the LEDs [21]. Moreover, the approach may encounter challenges related to the scalability of fabrication processes when transitioning from laboratory settings to industrial applications, due to the advanced epitaxial techniques required for achieving the graded aluminum composition. These challenges necessitate careful control over the growth conditions and may lead to increased production costs. Additionally, the presence of threading dislocations common in AlGaN materials could further inhibit the anticipated improvements in internal quantum efficiency by providing non-radiative recombination pathways. Nevertheless, future work can address these limitations by integrating advanced material growth techniques and adopting alternative device structures that mitigate dislocation densities, thereby enhancing performance and manufacturability. The continued refinement of this approach could pioneer new pathways in the development of highly efficient Deep UV LEDs, as indicated by the authors [21].

6. Conclusion

This study addresses the growing demand for high-efficiency deep ultraviolet (DUV) light-emitting diodes (LEDs) in applications like water purification and sterilization by proposing a new methodology for optimizing the design and fabrication process of DUV LEDs using logistic regression analysis. The innovative approach outlined in this research offers a systematic framework to improve the performance and stability of DUV LEDs, which are currently hindered by material constraints and fabrication complexities. By leveraging this method, advancements in DUV LED technology can be made towards achieving cost-effective and reliable sources of DUV light for future applications in next-generation lighting and sensing technologies. However, it should be noted that there are limitations inherent in this study, such as the need for further experimental validation and exploration of alternative modeling techniques to enhance the reliability of the findings. Moving forward, future work could focus on conducting more extensive empirical studies to validate the effectiveness of the proposed approach across different material compositions and fabrication methods, thereby broadening its applicability and impact in the field of DUV LED research.

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Data Availability Statement

The data can be accessible upon request.

Conflict of Interest

The authors confirm that there are no conflict of interests.

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