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Prediction of Bending Loss in Photonic Crystal Fibres: A Machine Learning Approach Using Low-Computing-Cost Algorithm

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Abstract: This study explores the potential of using low-computing-cost machine learning models for predicting Bending Loss in Photonic Crystal Fibers (PCFs). Algorithms for machine learning that utilise historical data and trends can be utilized to provide a potent tool for predicting Bending Loss. The bending loss data and the other associated parameters of the bent PCF were obtained using the Finite Element Method-based modal solution technique (FEM). The PCF has 3 ring air-holes in the cladding with a pitch length (Λ) of 2.6μm a wavelength (λ) of 1.55μm and a silica refractive index (n) of 1.445. The bending radius was varied from of 10000μm to 230μm and the calculations were done in the Transverse Electric (TE) mode. The Bending Loss Dataset was used to train and evaluate five different low-computing-cost regression Algorithms such as Linear Regression, Random Forest Regressor, Gradient Boosting Regressor, Support Vector Machine Regressor, and Gaussian Process Regression are utilized. The Linear Regression model was found to be the most accurate and reliable predictor of Bending Loss in Photonic Crystal Fibres (PCFs) achieving a Mean Square Error (MSE) of 0.0002 and an R-squared (R^2) score of 0.9999. The findings of this work show how machine learning models can be used to forecast crucial PCF parameters, which could progress the field of photonics even utilizing Low-Computing-Cost computers. The use of machine learning models have the potential to greatly increase efficiency and accuracy of predicting important parameters in PCFs by improving the design and optimisation of PCFs for diverse optical applications.

Keywords: Machine Learning, Photonic Crystal Fibre, PCF, Bending Loss, Low-Computing-Cost.

Research Paper

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1.0 INTRODUCTION

Because of their special characteristics, Photonic Crystal Fibres (PCFs) have completely changed photonics including in the areas of optical communication [1] and sensing [2]. For the design and optimisation of PCFs, accurate parameter prediction, including Bending Loss [3, 4] is essential. The bending radius, propagation constants, effective index and mode characteristics are important variables that affect bending loss [3, 5]. The application of machine learning techniques, which leverage historical data and patterns, can yield a powerful tool for Bending Loss prediction [3]. Recently, there has been a growing interest in utilizing machine learning methods in the photonics field [3, 6]. Machine learning, a subset of artificial intelligence, refers to the development of techniques that allow computers to learn from data, make predictions based on that data, and do so without explicit programming [7-10]. The development of metamaterials [11], photonic crystals [12], sensors [13], power splitters [14], and multimode fibres [15] are just a few of the photonics fields that can benefit from this. The use of machine learning models has also improved PCF design and optimisation [6, 16, 17]. These models could greatly improve the effectiveness and precision of predicting crucial factors, including Bending Loss in PCFs [18]. When designing and optimising PCFs for different optical applications, the prediction of Bending Loss is vital. When a Photonic Crystal Fibre is bent, there is an attenuation or loss of signal that occurs which is also known as bending loss [19, 20]. The guided optical mode's interaction with the fibre's structural elements and the air-holes would result in this bending loss. Since Bending Loss affects the functioning and overall performance of PCFs, accurate Bending Loss prediction is essential. Macrobending loss [21] in particular has been the subject of research due to its effect on the bending sensitivity of PCFs. Table 1 shows the bending radius, propagation constants, effective index, and mode characteristics which all performance a significant part in deciding the Bending Loss of PCFs.

Table 1: Description of Independent Features

Feature	Description
Rbend	Bending radius
Br	Real part of propagation constant
Bi	Imaginary part of propagation constant
ne	Effective index
Hx	Transverse magnetic mode (TM)
Hy	Transverse electric mode (TE)
spotsize	Spot Size

To forecast Bending Loss in PCFs, a thorough comparison examination of numerous low-computing-cost machine learning models was carried out in this study. The study compared the performance of five distinct regression algorithms, that is; Gaussian Process Regression, Gradient Boosting Regression, Support Vector Machine Regression and Random Forest Regression. These algorithms were chosen because they require less computational power and are suitable for locations with limited resources. Finding the best model for predicting Bending Loss in PCFs was the main goal of this investigation. Standard assessment measures such as Mean Squared Error (MSE) [22] and R-squared (R^2) [23] were used to evaluate each machine learning model's performance. The most accurate and trustworthy predictor of Bending Loss in PCFs was determined to be the Linear Regression model, proving the potential of machine learning models to enhance the efficiency and accuracy of predicting important parameters in PCFs.

2.0 MACHINE LEARNING MODELS

2.1. Linear Regression

For predicting continuous target variables, linear regression is a popular machine learning model that is easy to understand and apply [24, 25]. It seeks the optimal line that minimizes the total squared errors between the predicted and observed values, presuming a linear relationship between the independent features and the target variable.

$$y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \varepsilon \; \ldots\ldots\ldots\ldots\ldots\ldots \; 1$$

Where y = dependent variable, x_i = independent variable, β_i = parameter, ε = error

When it comes to predicting Bending Loss in PCFs, Linear Regression emerged as the top-notch performer in terms of accuracy and dependability. The Linear Regression model delivered outstanding results with an MSE of 0.0002 and an R^2 score of 0.9999, underscoring its exceptional precision in forecasting Bending Loss, as indicated in Table 2. Linear Regression boasts several advantages compared to other machine learning models. It's a straightforward and interpretable model that can be seamlessly put into action even in settings where computing resources are limited. Additionally, it offers valuable insights into how the independent factors relate to the target variable, enabling a deeper grasp of the underlying principles governing the system. However, Linear Regression also has its limitations, as pointed out in reference [26]. The assumption is a linear connection in between the independent factors and the objective variable, which may not always be the case in real-world scenarios. Furthermore, it presupposes that errors follow a normal distribution and maintain a consistent variance, which may not necessarily align with the real-world conditions in all cases [26].

2.2. Random Forest Regressor

The Random Forest Regressor, a machine learning model, employs multiple decision trees to produce predictions [27, 28]. It's a versatile and robust model capable of handling both simple and intricate connections between the input factors and the objective outcome. With the specific task of predicting Bending Loss in PCFs, the Random Forest Regressor did not perform as accurately as Linear Regression. It yielded an MSE of 22029.46 and an R^2 score of 0.95, which is less than the precision achieved by Linear Regression. However, it outperformed the other models assessed in this study as can be seen in Table 2. Random Forest Regressor brings several advantages compared to some other machine learning models. It is adaptable enough to manage both linear and nonlinear connections between the input variables and the target output, making it a versatile choice for various applications [29]. Also, it is less prone to overfitting than some other models because it combines multiple decision trees for its predictions although it did not work so well for us in this particular study. Random Forest Regressor also has some certain limitations. It can be computationally demanding and may require more computational resources than other models [30]. Additionally, it is less interpretable due to its ensemble nature of combining the insights from multiple decision trees to make its predictions [30].

2.3. Gradient Boosting Regressor

The Gradient Boosting Regressor is a machine learning model that sequentially constructs an ensemble of decision trees to make predictions [31, 32]. The Gradient Boosting Regressor is a robust and versatile machine learning model capable of handling a wide range of applications and handling both straightforward and complex relationships between the input factors and the desired outcome. When it comes to predicting Bending Loss in PCFs, the Gradient Boosting Regressor was found to be less precise than Linear Regression. It achieved an MSE of 8365.56 and an R^2 score of 0.98, which fell short of the accuracy achieved by Linear Regression. Nevertheless, it outperformed most of the other models assessed in this study, except for the Random Forest Regressor, as shown in Table 2. The Gradient Boosting Regressor offers numerous advantages over alternative machine learning models [33]. It's proficient at handling both linear and nonlinear connections between the input variables and the objective outcome, making it a flexible choice for various applications [34]. Furthermore, it's relatively less prone to overfitting compared to some other models, thanks to its sequential ensemble approach although it did not work as well for us in this particular study. Gradient Boosting Regressor does have its limitations [35]. It can demand significant computational resources and be computationally expensive compared to some other low-computing-cost models considered. Additionally, it is less straightforward to interpret due to its sequential ensemble construction.

2.4. Support Vector Machine Regressor

The Support Vector Machine (SVM) Regressor, a machine learning model, seeks a hyperplane that effectively fits the data points [36, 37]. It's a potent and adaptable model capable of dealing with both simple and intricate connections between the input factors and the objective outcome. In the specific context of predicting Bending Loss in Photonic Crystal Fibers (PCFs) which this study is all about, the SVM Regressor proved to be less accurate than both Linear Regression and Gradient Boosting Regressor. It achieved an MSE of 26770.52 and an R^2 score of 0.94, as indicated in Table 2. Nonetheless, the SVM Regressor provides a number of benefits compared to alternative models for machine learning [38, 39]. The Support Vector Machine (SVM) Regressor is a model that seeks a hyperplane to effectively fit the data, capable of handling both linear and nonlinear relationships among the input variables and the desired output, making it a versatile choice for a wide range of applications although it did not work out well for us in this study. Additionally, it is relatively less susceptible to overfitting, thanks to its focus on finding a hyperplane that best suits the data [40]. However, the SVM Regressor does have its limitations. It can be computationally intensive and may require more computing resources compared to some other models which this study is trying to minimize [41]. Moreover, it tends to be less intuitive to interpret due to its primary goal of discovering the optimal hyperplane for the data [41]. The SVM Regressor, therefore, stands as a powerful and adaptable machine learning model capable of handling both linear and nonlinear relationships between variables connections between the target and the input features outcome [41]. While it may not have been as accurate as Linear Regression and Gradient Boosting Regressor in predicting Bending Loss in PCFs in this particular study, it still holds potential for numerous applications within the realms of photonics and optics.

2.5. Gaussian Process Regression

A novel approach to machine learning is taken by the Gaussian Process Regression model by modeling the distribution of the target variable [42]. It is a robust and adaptable model capable of accommodating both linear and nonlinear relationships between the input factors and the target outcome [43]. It has also found utility in various applications, spanning materials science [44], chemistry [45], and battery health estimation [46]. Gaussian Process Regression provides a number of benefits over alternative machine learning algorithms. It excels in modeling the distribution of the target variable, which allows it to provide uncertainty estimates for its predictions [41]. Additionally, it's a non parametric model, that is, it does not assume anything on the distribution of the underlying data [47]. However, Gaussian Process Regression does come with its own set of limitations. It can be computationally demanding [43] and may require more computational resources compared to some other models and this study is all about minimizing that. It also tends to be less straightforward to interpret because it focuses on modeling the distribution of the target variable rather than providing a simple equation [42]. Gaussian Process Regression stands as a potent and adaptable machine learning model capable of addressing both linear and nonlinear relationships between input characteristics and the intended outcome [42].

To put it briefly, this study underscores how machine learning models hold great promise in predicting Bending Loss in PCFs. The findings from this research offer valuable insights that can be harnessed to improve PCF design and optimisation for various optical applications. By leveraging the low-computing-cost machine learning models, we can markedly boost the precision and efficiency of forecasting crucial parameters in PCFs, ultimately driving advancements in the field of photonics. As can be deduced from the discussions, Linear Regression stands out as a low-computing-cost and formidable tool for forecasting continuous target variables, such as Bending Loss in PCFs. Its simplicity and interpretability would make it a well-liked option for many applications, such as photonics and optics.

3.0 METHODOLOGY

The bending loss data and the other associated parameters of the bent PCF were obtained using the modal solution approach based on the Finite Element Method (FEM) [48]. The PCF has 3 ring air-holes in the TE mode with a pitch of 2.6 μm a wavelength of 1.55 μm and a silica refractive index of 1.445 and the bending radius was varied from of 10000 to 230 μm. In the FEM, the elaborate cross-sectional area of the PCF including the core is broken down and represented into various triangular shapes and sizes [49]. This approach is much more robust and flexible contrasted with the Finite Difference Method (FDM) that utilizes inefficiently regularly spaced and also does not represent curved and slanted dielectric surfaces well hence, the FEM is preferable. Due to the high index contrast PCF, the two-dimensional optical modes in the confinement are also hybrid in nature, with all six components of the **E** and **H** fields being present. Moreover, confinement is hybrid in character, containing all six elements of the **E** and **H** fields. Moreover, the inclusion of inclined or curved dielectric interfaces enhances modal hybridity. Therefore, an appropriate depiction of these interfaces is as crucial as a vectorial formulation for precisely calculating their modal solutions. The current method analyses the performance of PCFs with air holes placed in a triangular lattice in the silica cladding using an H-field-based rigorous full vectorial FEM [49]. A viable method for microwave and optical guided-wave devices, covering the intermediate THz frequency range, is the previously developed H-field formulation. The following is the H-field formulation using the increased penalty function technique:

$$\omega^2 = \frac{\left(\int (\nabla\times\vec{H})*\cdot\hat{\varepsilon}^{-1}(\nabla\times\vec{H})d\Omega\right)+\left(\int (\alpha/\varepsilon_o)(\nabla\cdot\vec{H})*(\nabla\cdot\vec{H})d\Omega\right.}{\int \vec{H}*\cdot\hat{\mu}\vec{H}d\Omega} \;\ldots\ldots\; 2$$

Where $\vec{\boldsymbol{H}}$ denotes the comprehensive vector description of the intricate magnetic field [50]; $\boldsymbol{\varepsilon}$ and $\boldsymbol{\mu}$ refer to the permittivity and permeability of the waveguide, respectively [50]; $\boldsymbol{\varepsilon_o}$ refers to the permittivity of the vacuum [50]; $\boldsymbol{\omega^2}$ is the eigenvalue (where $\boldsymbol{\omega}$ is the angular frequency of the wave) [50]; and $\boldsymbol{\alpha}$ is a unitless factor employed to enforce the divergence-free condition of the magnetic field in a manner that minimizes errors through least squares [50]. In this formulation, both the $\hat{\boldsymbol{\varepsilon}}$ and $\hat{\boldsymbol{\mu}}$ parameters can be arbitrary complex tensors with possible off diagonal coefficients, suitable to characterize electro-optic, acousto-optic, and elasto-optic devices [50]. Perfectly Matched Layers (PMLs) were added around the computational window since we also required to compute the leakage and bending losses in the bent PCF. This resulted in a complex eigenvalue equation for the final formulation [49]. The dataset obtained and used in this study, which is referred to as the "Bending Loss Dataset" consists of 25 samples and 8 features. The target variable is the "Bending Loss" representing the amount of optical loss induced by bending the PCF. The independent features include: Bending radius (Rbend), Real part of propagation constant (Br), Imaginary part of propagation constant (Bi), Effective index (ne), Transverse magnetic mode (TM) component (Hx), Transverse electric mode (TE) component (Hy), Spot Size (spotsize) as can been seen in Figure 2.

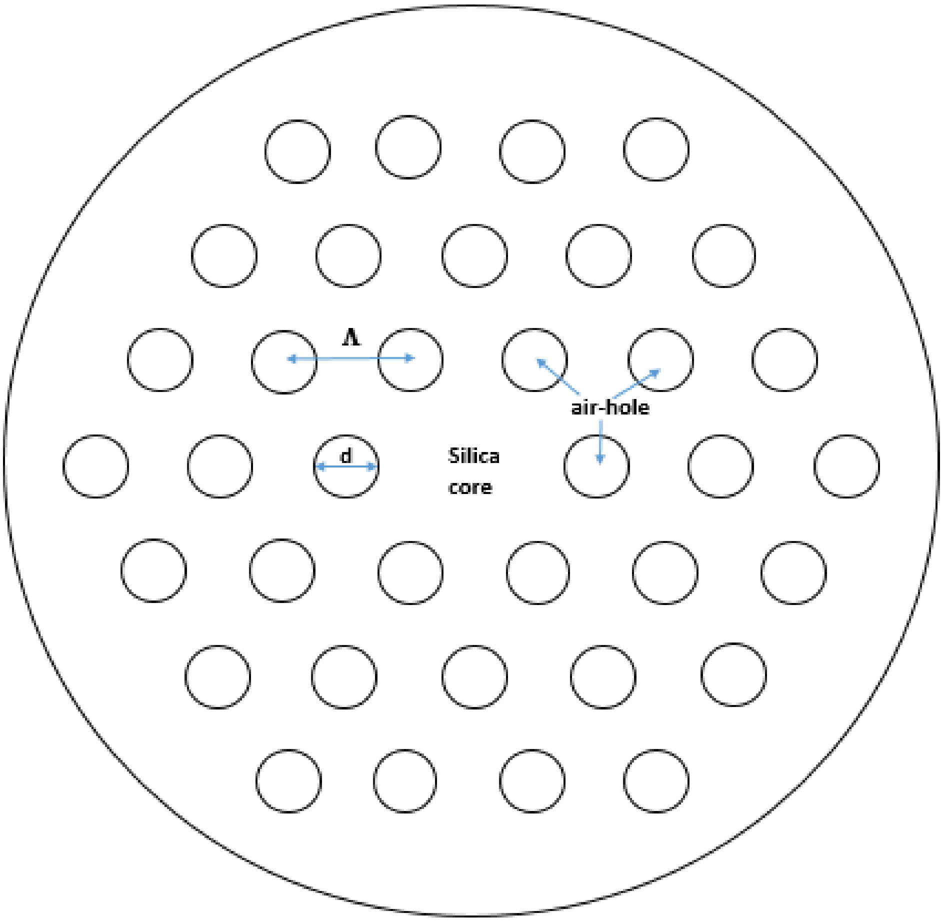

Figure 1: Schematic depiction of the cross-section of 3 ring air-holes PCF

Figure 1 depicts the cross-sectional area of the Photonic Crystal Fiber (PCF) having 3 rings of air-holes around the silica core. The pitch length (Λ) is 2.6μm, the diameter to pitch ratio (d/Λ) is 0.5 and the diameter (d) is 1.3μm. The wavelength (λ) of operation is 1.55μm refractive index (n) of the silica material of the PCF is 1.445 and that of air is 1.000. The calculations were carried out for the Transverse Electric (TE) mode.

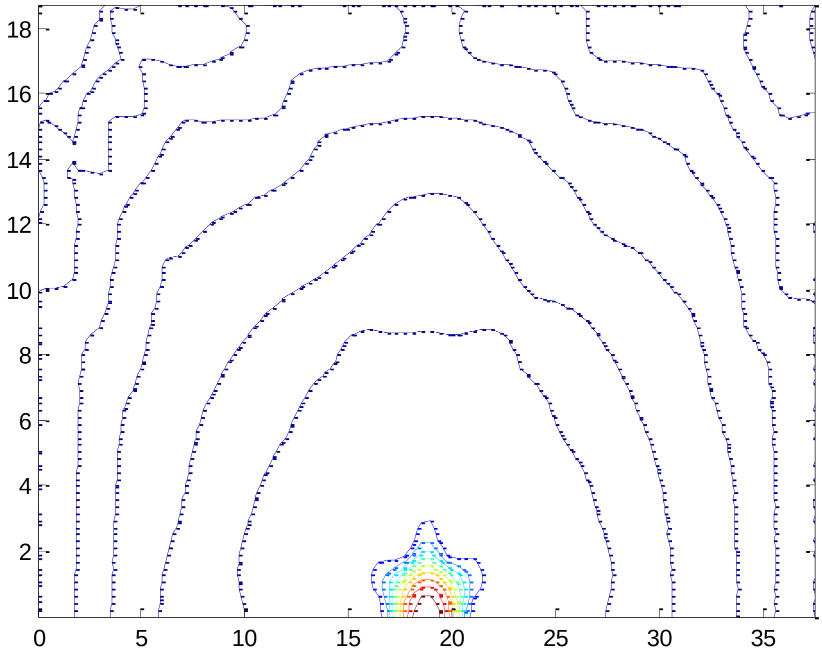

Figure 2: Half-structure field profile for Rbend = 10000μm, the half structure field contour of the 3 ring air-holes PCF in the TE mode PCF, Pitch = 2.6μm, d = 1.3μm, d by pitch = 0.5, λ = 1.55μm, silica of n = 1.445

Figure 2 shows the half structure field contour of the 3 ring air-holes PCF with Rbend of 10000μm in the TE mode, with a pitch of 2.6 μm a wavelength of 1.55 μm and a silica refractive index of 1.445. It is assumed that the PCF is straight and not bent and this high value of bending radius and that is depicted in contours of the field profile.

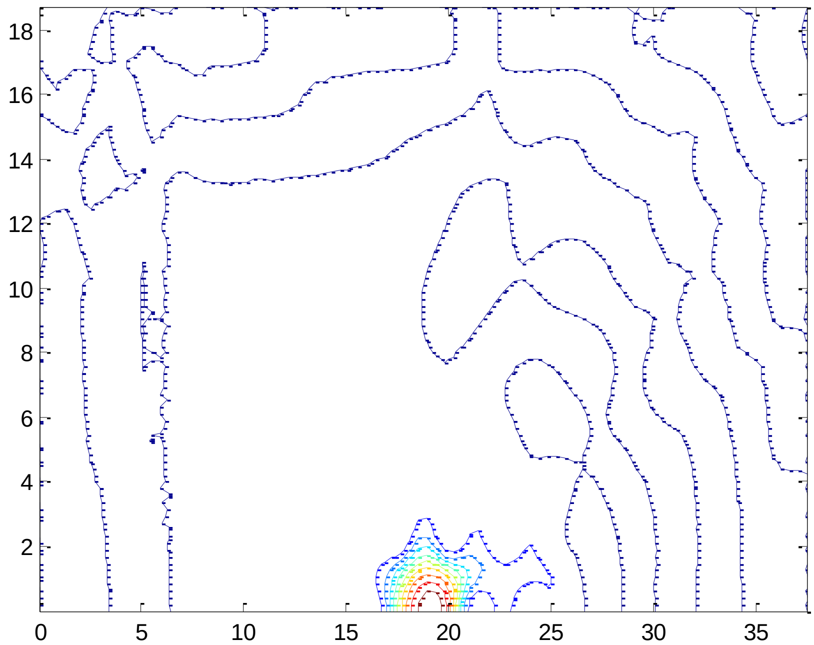

Figure 3: Half-structure field profile for Rbend = 300μm, the half structure field contour of the 3 ring air-holes PCF in the TE mode PCF, Pitch = 2.6μm, d = 1.3μm, d by pitch = 0.5, λ = 1.55μm, silica of n = 1.445

The half structure field contour of the 3 ring air-holes PCF with Rbend of 300μm in the TE mode for is shown in Figure 3, with a pitch of 2.6 μm a wavelength of 1.55 μm and a silica refractive index. It is observed that the PCF is significantly bent at this low value of bending radius and that is depicted in contours of the field profile as it leaks more into the cladding region.

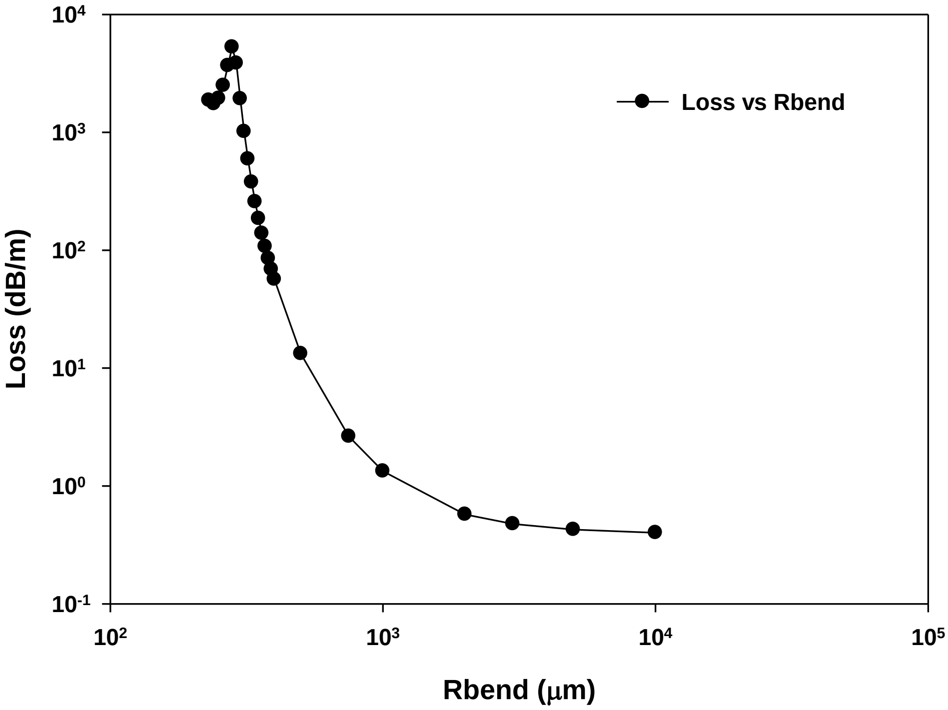

Figure 4: Plot of Bending Loss against bending Radius (Rbend) for a pitch length of 2.6μm, Transverse Electric (TE) mode

Figure 4 in the study displays a graph illustrating the relationship between Bending Loss and bending radius (Rbend) for a pitch length of 2.6μm, specifically in the Transverse Electric (TE) mode. This graph represents a portion of the data that was utilized in our low-cost machine learning algorithms. The methodology employed in our research consisted of several key steps. Initially, we performed Data Preprocessing, which involved preparing the dataset used in our study. This dataset comprised 25 samples and 8 features. During preprocessing, we addressed missing values, standardized the features, and separated the dataset using an 80/20 split into training and testing sets. Following data preprocessing, we moved on to Model Training. In this phase, we selected and implemented five different regression algorithms aimed at predicting Bending Loss within the Bending Loss dataset. These algorithms encompassed Linear Regression, Random Forest Regressor, Gradient Boosting Regressor, Support Vector Machine Regressor and Gaussian Process Regression. Each algorithm was trained using the designated training dataset. The subsequent step was Model Evaluation. We evaluated the performance of these models using the testing dataset and recorded pertinent performance metrics, such as Mean Squared Error (MSE) and R-squared (R^2). These metrics allowed us to gauge the accuracy and reliability of each machine learning model. Lastly, Model Selection was performed. Based on the outcomes of our comparative analysis, we identified the Linear Regression model as the most precise and dependable predictor of Bending Loss in PCFs.

To summarize, our research methodology encompass preprocessing the dataset, training and evaluating five distinct regression algorithms, and ultimately selecting the Linear Regression model as the most accurate and reliable choice for predicting Bending Loss in PCFs.

4.0 DISCUSSION

The results of this research demonstrate the possibility of low-computing-cost machine learning models in predicting Bending Loss in PCFs. The Linear Regression model was found to be the most accurate and reliable predictor of Bending Loss in PCFs, demonstrating the potential of machine learning models to enhance the efficiency and accuracy of predicting important parameters in PCFs. The use of machine learning models can significantly improve the design and optimization of PCFs for various optical applications.

Table 2: Performance Metrics of Machine Learning Models

Model	Mean Squared Error (MSE)	R-squared (R^2)
Linear Regression	0.0002	1.00
Random Forest Regressor	22029.46	0.95
Gradient Boosting Regressor	8365.56	0.98
SVM Regressor	26770.52	0.94
Gaussian Process Regression	0.00	1.00

The Linear Regression model achieved an MSE of 0.0002 and an R^2 score of 0.9999, while the other models achieved higher MSE and lower R^2 scores. The ability of the Linear Regression model to capture the linear connection between the independent characteristics and the target variable accounts for its higher performance. The linear regression model is an easy-to-implement, straightforward, and interpretable model that works well in contexts with limited resources.

The results of this study are consistent with previous studies that have demonstrated the potential of machine learning models in predicting important parameters in PCFs. The use of machine learning models have the potential to greatly improve accuracy and efficiency of predicting important parameters in PCFs, leading to advancements in the field of photonics. The Bending Loss Dataset used in this study consists of 25 samples and 8 features. The preprocessed dataset was divided into training and test sets, with missing values handled and features normalised and testing sets using an 80/20 split. The testing set was employed to evaluate the performance of the machine learning models following their training using the training set. The results of this study can be used to improve the design and optimization of PCFs for various optical applications. The use of machine learning models can greatly improve the accuracy and efficiency of predicting important parameters in PCFs, leading to advancements in the field of photonics as can be seen in Table 2.

5.0 CONCLUSIONS

In this study, we delved into the exciting potential of low-computing-cost machine learning models for predicting Bending Loss in PCFs. Using the Finite Element Method (FEM)-based modal solution approach, the PCF has 3 ring air-holes in the Transverse Electric (TE) mode with a pitch length (Λ) of 2.6μm and a wavelength (λ) of 1.55 μm and a silica refractive index (n) of 1.445 and the bending radius was varied from of 10000 to 230 μm and the analysis of the Bending Loss Dataset. Five distinct regression algorithms were rigorously evaluated, namely Linear Regression, Random Forest Regressor, Gradient Boosting Regressor, Support Vector Machine Regressor and Gaussian Process Regression using the Bending Loss Dataset. Importantly, we chose algorithms suitable for situations with limited computational resources. The standout performer among these models was the Linear Regression model, which proved to be the most accurate and dependable predictor of Bending Loss in PCFs. It achieved remarkably low values for both Mean Squared Error (MSE) at 0.0002 and an impressively high R-squared (R^2) score of 0.9999. These findings highlight the immense potential of machine learning models in predicting vital parameters within PCFs, paving the way for notable advancements in the field of photonics. The application of these models can significantly enhance the precision and efficiency of predicting crucial PCF parameters, ultimately contributing to the optimization and design of PCFs for various optical applications. The integration of machine learning models promises to revolutionize the design and optimization of PCFs for various optical applications, enhancing their performance and reliability.

In future studies, we hope to further explore the use of more intricate machine learning models and larger datasets to elevate the accuracy of predicting essential parameters in PCFs. The knowledge gained from this study can be used to continue to inform the refinement and optimization of PCFs for other diverse optical applications, thus driving further progress in the realm of photonics.

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