Application of Machine Learning for Accurate Detection of Hemoglobin Concentrations Employing Defected 1D Photonic Crystal

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Abstract

Realizing the significance of precise detection of hemoglobin concentrations towards early diagnosis of several diseases, the present work addresses design and analysis of hemoglobin sensor based on the defective 1D photonic crystal (PhC). The alternating layers of Si and SiO₂ are used to design the proposed PhC with a central defect layer infiltrated with hemoglobin concentrations. The well-established transfer matrix method (TMM) is manipulated to study the transmission spectrum of the structure. The strong dependence of defect mode characteristics on the refractive index of the hemoglobin concentrations forms the backbone of this work. Numerous geometrical parameters such as thickness of defect layer, angle of incidence are meticulously optimized to realize high sensitivity. Additionally, the effect of temperature is thoroughly investigated on the sensing performance. It is perceived that at an incident angle of 30° and the defect layer thickness of 550 nm, the proposed structure bestows a maximum sensitivity of 1916.77 nm/RIU. Finally, we developed a machine learning model to predict different concentrations of hemoglobin in blood, where we found that the model output is closely matched with the output obtained through the TMM. Moreover, it is perceived that the developed machine learning model can predict hemoglobin concentrations with high accuracy and linearity.

Keywords 1D PhC • TMM • Transmission spectrum • Machine learning • Sensor • Sensitivity

1 Introduction

Human blood contains a fixed proportion of hemoglobin and plasma. Hemoglobin (Hb) is the most vital constituent of blood, which is mainly responsible for transporting oxygen from lungs to different tissues in the body and returning carbon dioxide from the tissues to lungs. [1, 2]. Any deviation in the hemoglobin concentrations in blood leads to deadly diseases like polycythemia, anaemia, diabetes, thyroid dysfunction [3, 4]. The conventional techniques for detecting the Hb concentrations lack accuracy, and require more money, skilled personnel, and well-equipped laboratories. To overcome such challenges, researchers are aiming to design real-time, label-free, cost-effective, and lab-on-chip sensing devices for the precise detection of Hb concentrations [5, 6]. In the recent decade, photonic biosensors have evolved as an excellent candidate for detecting various bio-analytes owing to their fabrication feasibility, miniature in size, low cost, design flexibility, and compatibility with other photonic devices [7–9]. Among various photonic structures, photonic crystals (PhC) are the most matured technology to envisage biosensors. PhC is comprised of periodically arranged unit cells in the order of two (binary) or three (ternary) alternate materials of different permittivity. The PhCs can be manufactured in one, two, and three dimensions [10–12]. 1D PhCs are the most researched structures compared to 2D and 3D PhC structures due to their simple design, easy analysis, and broad application domain. Besides this, 1D PhCs can be fabricated by the well-established techniques like thermal evaporation, sputtering, spin coating, electron beam evaporation, and photolithography [13–15]. Moreover, 1D PhCs are regarded as the best platform for lab-on-chip integration with microfluidics.
1D PhC is blessed with a special property known as photonic band gap (PBG), where light of certain wavelengths are obstructed to pass through the structure [16]. The appearance of PBG is described as the multiple Bragg scattering of the incidenting wave in the layered structure, where the optimum reflection can be perceived if the thickness of each layer is a quarter wavelength [17]. In order to utilize PhC as a biosensor, it is vital to modify its structural arrangement to produce a resonant mode in the transmission spectrum. The best way to form such resonant mode is introducing a defect in the structure. When the wavelength of incident light is matched with the resonant wavelength, a sharp distinct peak is observed within the PBG in the spectral characteristics. The position and intensity of the resonant mode is very sensitive to a small variation in the refractive index of the defect layer [18]. So, by infiltrating the defect layer with bio-analytes of different refractive index, it is possible to detect them precisely by measuring the shift in the defect mode wavelength. Over the last decade, 1D PhCs are widely used for detection of cancer cells, tuberculosis, waterborne bacteria, hormones, malaria pathogens, plasma, blood components, sucrose concentrations, creatinine concentrations, protein, gas, fat concentrations in milk [19–25].

In the recent decade, few works have been carried out on 1D PhC vis-à-vis hemoglobin detection. El-Khozondar et al. reported a ternary 1D PhC structure to measure hemoglobin concentrations in the range 0 g/L to 50 g/L, and the authors achieved a maximum sensitivity of 51.46 nm/RIU [26]. Recently, A.K. Goyal et al. investigated a Bloch surface wave-based defective PhC. By infiltrating the defect region with different concentrations of hemoglobin, the authors computed the angular shift and thereby obtained a sensitivity of 69 degree/RIU [27]. J. Hao and his team demonstrated superconductor-based 1D PhC refractive index sensor to measure various concentrations of hemoglobin in human blood, where the authors claimed a sensitivity of 6.85 μm/RIU and 6.48 μm/RIU at a temperature of 80 K and 134 K respectively [28]. Goyal et al. studied the reflectance spectrum of a 1D PhC with an inclusion of porous defect layer for the detection of hemoglobin concentrations. The authors concluded with an optimum sensitivity of 323 nm/RIU, and FOM of 517 1/RIU [29]. H.A. Elsayed et al. reported a binary 1D PhC hemoglobin sensor, where the authors employed TMM to measure the shift in the resonant peak with respect to different concentrations of hemoglobin, and achieved a sensitivity of 167 nm/RIU [22]. Recently, K. M. Abohassan and his team have extensively investigated 1D PhC structures by studying the reflectance characteristics through TMM for different biosensing applications [42–45].

In the recent years, the use of machine-learning algorithms in the field of photonics has become the hot research domain [47]. Due to their flexibility and efficiency, machine learning algorithms have been successfully applied to various domains of photonics and optoelectronics. Machine Learning is a subfield of artificial intelligence to build computer programs that automatically improve through the past experiences and takes decisions [48]. In order to forecast new output values, machine learning algorithms use previous data as input. Machine learning algorithms normally require two factors: training data and objective function. The training data constitute the input vectors with their label values. Herein, the machine employs the training data to create an input-output mapping that proficiently produces the desired result. In the training data, the label value may be discrete or continuous. For discrete labels, machine learning employs the classification algorithms, whereas, for continuous labels, machine learning employs a regression algorithms. Linear regression is the most preferred algorithm, which establishes a relation between dependent and independent variables by fitting a best line.

Machine learning algorithms can greatly enhance the prediction accuracy of photonic devices, especially photonic sensors. F. N. Khan et al. applied machine learning to optical fiber, for effective monitoring of the fiber non-linearity [30]. Y. Khan et al. studied the spectral response of an optical fiber by applying a machine learning based mathematical model [31]. A. Ghosh et al. reported a 1D PhC gas sensor, where the authors applied machine learning algorithms to identify the greenhouse gases like CO₂, CH₄, and SF₆ [32]. H. Zhang et al. demonstrated a photonic ring resonator, where the authors used machine learning algorithm to predict different chemical components [33]. S.K. Roy et al. employed machine learning to a PhC to detect different concentrations of salinity in the drinking water [34]. A. Venkateswaran and his team reported a detailed review on the application of machine learning in the design of numerous fiber optic sensors [35]. Recently K.P. Swain and his team reported hemoglobin sensors using 2D and 3D PhC, where they applied machine learning algorithm to predict the Hb concentrations [49–51]. However, they have not computed the sensitivity of the sensor.

The present research has a considerable amount of newness compared to the similar works listed in the literature. Herein, we propose a defect-based 1D PhC to detect different Hb concentrations by assaying its transmission spectrum. The incident angle and layer thickness are judiciously optimized to envisage high sensing performance. The effect of temperature on the spectral characteristics is explored, which boosts the novelty of this work. On top of that, a machine learning model is developed through regression algorithm to predict different Hb concentrations, which has not been addressed in any earlier works. The developed machine learning model can detect the Hb concentrations with high accuracy and high linearity and high stability.
2 Proposed Structure and Formalism

For effective measurement of hemoglobin, we have considered a defect-based 1D PhC structure, which is shown in Fig. 1. The entire configuration of the designed structure is Air/(A/B)^N/Defect/(A/B)^N/Air. Here, A and B are the high and low indexed dielectric materials of Si and SiO_2 respectively. The central region is the intentionally created defect layer, where blood samples containing different concentrations of hemoglobin are infiltrated by using suitable techniques [36]. The thickness of Si, SiO_2, and defect layer are denoted as \(d_A\), \(d_B\), and \(d_D\) respectively. N signifies the number of period of the PhC in each side of the defect layer. Different layers of the PhC are arranged along the x-z plane and y-direction is the normal to the interface of each layer. A He-Ne laser source is used to generate the TE polarized light of central wavelength 633.2 nm, which incident onto the designed structure. Depending upon the geometrical parameters such as refractive index contrast of adjacent layers, and layer thicknesses, some part of the incident light is reflected at each interface of the layers, which forms the PBG. The mechanism of interaction of the incidenting light with the proposed layered structure can be explained by employing the transfer matrix method (TMM). The electric field \(E_s(y)\) and magnetic field \(H_s(y)\) components in the \(s^{th}\) layer can be mathematically expressed as [22],

\[
\begin{pmatrix}
E_s \\
H_s
\end{pmatrix} = \frac{1}{2} \begin{pmatrix}
\exp(iq_s \alpha_s) + \exp(-i \alpha_s) \\
-\gamma_s [\exp(iq_s \alpha_s) - \exp(-i \alpha_s)]
\end{pmatrix} \begin{pmatrix}
\frac{1}{2}[\exp(iq_s \alpha_s) - \exp(-i \alpha_s)] \\
\gamma_s [\exp(iq_s \alpha_s) + \exp(-i \alpha_s)]
\end{pmatrix} \begin{pmatrix}
E_{s+1} \\
H_{s+1}
\end{pmatrix}
\]

(2)

Where, \(\alpha_s = d_s \cos \theta_s\). Here, \(d_s\) is the thickness of the layer \(s\), and \(\theta_s\) is the incident angle through the \(s^{th}\) layer.

Equation (2) can be written in simplified form as follows,

\[
\begin{pmatrix}
E_s \\
H_s
\end{pmatrix} = \begin{pmatrix}
\cos(q_s \alpha_s) & -i/\gamma_s \\
-i/\gamma_s \sin(q_s \alpha_s) & \cos(q_s \alpha_s)
\end{pmatrix} \begin{pmatrix}
E_{s+1} \\
H_{s+1}
\end{pmatrix} = M_s \begin{pmatrix}
E_{s+1} \\
H_{s+1}
\end{pmatrix}
\]

(3)

Where, \(M_s\) represent the characteristics matrix. The matrix \(M_s\) relates the field components at the interface of two successive layers i.e. \(s^{th}\) layer and \((s + 1)^{th}\) layer. The characteristics matrix for the complete configuration is stated as [37],

\[
M = (M_A M_B)^N M_{\text{Defect}} (M_A M_B)^N = \begin{pmatrix}
M(1,1) & M(1,2) \\
M(2,1) & M(2,2)
\end{pmatrix}
\]

(4)

The terms \(M_A\), \(M_B\), and \(M_{\text{Defect}}\) denote the transfer matrix of layer A, layer B, and the defect layer respectively. The transmission can be computed using the elements of the transfer matrix \(M\), which is stated as [37].

Fig. 1 Schematic representation of the proposed 1D defective PhC
\[ t = \frac{2\gamma_0}{(M(1,1) + M(1,2)\gamma_{\text{sub}})\gamma_0 + (M(2,1) + M(2,2)\gamma_{\text{sub}})} \]

In Eq. (5), \( \gamma_0 \) and \( \gamma_{\text{sub}} \) are the parameters for initial medium (air) and final medium (air) respectively, which can be expressed as \( \gamma_{0,\text{sub}} = \sqrt{\varepsilon_{0,\text{sub}}\varepsilon_0\cos\theta_{0,\text{sub}}} \).

Lastly, transmittance \( (T) \) of the proposed structure can be numerically expressed as [37],

\[ T = \frac{\gamma_{\text{sub}}}{\gamma_0} |r|^2 \]

Owing to the thermo-optic effect, the refractive index of each dielectric layer of the PhC changes with variation in temperature. The variation in the refractive index can be stated as [38],

\[ n(T) = n_0[1 + \gamma(T-298)] \]

Where, \( n_0 \) represents the refractive index of the dielectric layers at the room temperature, and \( \gamma \) denotes the thermo-optic coefficient of the dielectric layers, which is stated in the Table 1.

### 3 Results and Discussions

The refractive index of hemoglobin (Hb) is temperature dependent. The variation in the refractive index of different Hb concentrations (g/L) with respect to the temperature can be measured through Abbemat Refractometer technique [46], and it is plotted in Fig. 2. From this fig. it can be observed that the refractive index (RI) increases with increase in Hb concentrations, whereas RI decreases with increase in the temperature. A Hb concentration of below 130 g/L is regarded as low Hb concentration, which leads to anemia diseases, whereas Hb concentration of below 165 g/L is regarded as high Hb concentration, which leads to diseases like emphysema, heart failure, kidney failure etc. So, it is very essential to accurately detect the Hb concentration in blood for the early stage detection of various diseases. In this research, we have considered the Hb concentrations on the range 0 g/L to 150 g/L.

In this work, all the simulations are carried out in MATLAB 9.5 R2018b software package. Initially, we enquired the effect of incident angle \( (\theta_{\text{in}}) \) on the shift in the position of the defect mode (formed within the transmission spectrum) between 0 g/L and 150 g/L concentrations of Hb at \( d_A = 47.96 \text{ nm}, d_D = 109.17 \text{ nm}, d_D = 550 \text{ nm}, N = 7, \) and temperature \( (T) = 293.15 \text{ K}, \) which is delineated in Fig. 3. The incident angle is varied from \( 0^\circ \) to \( 30^\circ \) to \( 60^\circ \). It is observed that for \( \theta_{\text{in}} = 0^\circ \), the defect mode wavelength \( (\lambda_{\text{res}}) \) shifts from 729.3 nm to 769.4 nm with a total shift in the defect mode wavelength \( (\Delta\lambda_{\text{res}}) \) of 40.1 nm. Similarly, for \( \theta_{\text{in}} = 30^\circ \) and \( 60^\circ \), the \( \lambda_{\text{res}} \) shifts from 712.1 nm to 764.5 nm, and 713.2 nm to 752.7 nm respectively. It is seen that with an increase in \( \theta_{\text{in}} \), the position (wavelength) of the defect mode is blue-shifted (i.e. moves to lower wavelength). The principal cause for such blue-shift nature of the \( \lambda_{\text{res}} \) can be described by the Bragg condition, which is stated as [40],

\[ m\lambda_{\text{res}} = 2N\sqrt{n_{\text{eff}}^2 - \sin^2 \theta_{\text{in}}} \]

Here, \( \lambda_{\text{res}} \) indicates the resonant mode wavelength, \( m \) represents the constructive diffraction order, \( N \) implies the period of the PhC, \( \theta_{\text{in}} \) signifies the angle of incidence, \( n_{\text{eff}} \) denotes the effective refractive index.

Further, we computed sensitivity using the equation \( S_\lambda = \Delta\lambda_{\text{res}}/\Delta n \) [42], where \( \Delta\lambda_{\text{res}} \) represents the change in the defect mode wavelength and \( \Delta n \) denotes the change in refractive index of the Hb concentrations. The sensitivity of the sensor is evaluated as 1775.12 nm/RIU, 1916.77 nm/RIU, and 1748.56 nm/RIU for the incident angle \( 0^\circ, 30^\circ, \) and \( 60^\circ \) respectively. So, it is concluded that at \( \theta_{\text{in}} = 30^\circ \), the proposed 1D PhC sensor bestows maximum sensitivity, therefore we select \( \theta_{\text{in}} = 30^\circ \) in the subsequent analysis.

By infiltrating the defect layer with different Hb concentrations (0 g/L to 150 g/L), we investigated the shift in the wavelength and intensity of the defect mode for each concentration, which is shown in Fig. 4. It is noticed that with increase in the concentration, the wavelength of the defect mode is moved to higher wavelength values within the PBG. The cause of such nature of shift is that the refractive index of

Table 1. The properties of the considered dielectric materials [39]

| Dielectric materials | Refractive index at room temperature | Thermo-optic coefficient |
|----------------------|------------------------------------|-------------------------|
| Si                   | 3.3                                | \( 1.86 \times 10^{-4} \) |
| SiO₂                 | 1.45                               | \( 1 \times 10^{-5} \)   |
the defect layer increases with increase in the Hb concentrations, which eventually modifies the transfer matrix of the entire structure.

Afterwards, we evaluated the sensitivity of different concentrations of hemoglobin by considering 0 g/L as the reference concentration, which is illustrated in Fig. 5. From this figure, it is perceived that sensitivity increases with increase in the hemoglobin concentrations. A maximum sensitivity of 1916.77 nm/RIU is obtained for 150 g/L. The variation in sensitivity is nicely fitted to 3rd order polynomial equation, which can be mathematically expressed as,

\[ S_\lambda = -0.0004 \times C^3 + 0.0457 \times C^2 + 5.5254 \times C + 1283.8 \quad (9) \]

Figure 6a demonstrates the transmission spectrum of the proposed structure at different thicknesses of the defect layer \( d_D \) by keeping \( \theta_{in} = 30^\circ \), and \( T = 293.15 \) K. The value of \( d_D \) is varied in the range 550 nm to 670 nm with an interval of 30 nm. It is apparent that the defect mode wavelength is red-shifted with an increase in \( d_D \). The prime reason for the aforementioned shift in resonant wavelength can be understood from standing wave condition [41].

\[ \delta = p\lambda = n_{eff} \tau \quad (10) \]

Where, \( \delta \) and \( \tau \) represent the optical and geometrical path difference respectively. \( n_{eff} \) is the effective refractive index, \( p \) is an integer and \( \lambda \) denotes the wavelength. When the thickness of the defect layer increases, the value of \( \tau \) is increased, which results in shift in \( \lambda \) towards higher value in order to keep \( \delta \) fixed.

Further, we investigated the optimum sensitivity of the sensor at different \( d_D \), which is represented in Fig. 6b. It is observed that the sensitivity is maximum at \( d_D = 550 \) nm. For higher values of \( d_D \), the sensitivity goes on decreasing. So, we select \( d_D = 550 \) nm as the optimized value.

From the aforementioned discussions, the optimized geometrical parameters are summarized in Table 2.

We studied the effect of temperature on the position of the defect mode in the transmission spectrum of the proposed structure at the hemoglobin concentration of 0 g/L, \( d_D = 550 \) nm, and \( \theta_{in} = 30^\circ \), which is shown in Fig. 7. The temperature is varied from 293.15 K to 318.15 K. It is seen that with an increase in temperature, the \( \lambda_{res} \) is shifted to lower wavelength and the FWHM (full width at half maximum) increases. In particular, \( \lambda_{res} \) decreases from 721.2 nm to 720.1 nm to 718.8 nm to 715.8 nm to 714.4 nm as the temperature increases from 293.15 K to 298.15 K to 303.15 K to 308.15 K to 313.15 K to 318.15 K. A total wavelength shift of 6.8 nm is perceived for a temperature change of 25 K. The main reason for this nature of shift in \( \lambda_{res} \) is due to the increase in refractive index of hemoglobin with increase in the
temperature as studied in Fig. 2. So, temperature can have a significant impact on sensing performance.

We have also repeated the above-mentioned analysis for other hemoglobin concentrations, but the results are not shown in the manuscript in order to simplify the same. Figure 8 demonstrates the variation in the maximum sensitivity with respect to the change in the temperature. From this figure, it is concluded that the maximum sensitivity of the proposed structure decreases with increase in the temperature. The maximum sensitivity decreases from 1916.77 nm/RIU to 1833.19 nm/RIU as the temperature increases from 293.15 K to 318.15 K.

Eventually, we applied the regression algorithm of the machine learning to the dataset obtained from the TMM computational technique. We computed the corresponding energy (eV) associated with different defect mode wavelengths as depicted in Fig. 4 by using the equation: 
\[ \text{Energy (eV)} = \frac{hc}{\lambda_{\text{res}}} \]
where \( h \) denotes the planks constant, \( c \) is the speed of light in vacuum, and \( \lambda_{\text{res}} \) is the defect mode wavelength. The variation in energy with respect to different hemoglobin concentrations is represented in Fig. 9. Here, it is seen that with an increase in hemoglobin concentration, there is a decline trend in the energy. The linearity index of such variation is found to be \( R^2 = 0.9760 \). The linearity index can be improved by applying machine learning algorithm to the data set.

We selected the energy data (as presented in Fig. 9) as the training data set of the designed machine learning model, and applied the regression algorithm to predict the hemoglobin concentrations as presented in Table 3. In this table, energy is the independent variable and concentration is the dependent variable, which is predicted by the linear equation formed by the patterns found in the training data. Training set refers to the data found from the computational method (TMM), whereas the testing set refers to the data obtained through regression algorithm of machine learning. The energy values of the

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### Table 2  Optimized structure parameters

| Parameters | Optimized value |
|------------|----------------|
| \( d_A \)  | 47.96 nm       |
| \( d_B \)  | 109.17 nm      |
| \( d_D \)  | 550 nm         |
| \( N \)    | 7              |
| \( \theta_{\text{in}} \) | 30°           |
| Reference wavelength | 633.2 nm     |

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![Fig. 6](image1)  
**Fig. 6**  
a Analysis of transmission spectrum at different values of \( d_D \)  
b Sensitivity at different values of \( d_D \)

![Fig. 7](image2)  
**Fig. 7**  
Transmission spectrum at different temperature

![Fig. 8](image3)  
**Fig. 8**  
Variation in the optimum sensitivity of the structure with respect to temperature

![Fig. 9](image4)  
**Fig. 9**  
Variation in output energy with respect to different concentrations through TMM
testing set are selected randomly and it is perceived that the predicted concentrations are matched closely with that of the training set (obtained through TMM). Finally, we computed different errors like mean square error (MSE), root mean square error (RMSE), and mean absolute error (MAE) which are found to be 0.180625, 0.425, and 0.418 respectively.

The complete process of evaluating the testing data set is explained through the flowchart diagram as illustrated in Fig. 10.

Lastly, we plot the testing data set (concentration vs energy) as shown in Fig. 11. Interestingly, it is noticed that the variation between energy and hemoglobin concentration is excellently fitted with the linear trend line with $R^2 = 0.9968$. So, the linearity is greatly enhanced from $R^2 = 0.9760$ to $R^2 = 0.9968$ with the application of machine learning approach, which makes the proposed sensor more stable.

Eventually, sensitivity of the designed 1D PhC sensor is compared with recently published similar types of works and

| Training Set (obtained from TMM) | Testing Set (obtained from machine learning) |
|----------------------------------|---------------------------------------------|
| Concentration (g/L) | Energy (eV) | Energy (eV) | Predicted Concentration (g/L) |
|-----------------|--------|--------|---------------------|
| 10 | 1.715875 | 1.715881 | 9.521165 |
| 20 | 1.710875 | 1.710065 | 18.501936 |
| 30 | 1.707625 | 1.703190 | 29.117973 |
| 40 | 1.697562 | 1.697009 | 38.662368 |
| 50 | 1.697875 | 1.697800 | 47.440945 |
| 60 | 1.685812 | 1.685100 | 57.050888 |
| 70 | 1.676000 | 1.6766 | 70.176941 |
| 80 | 1.665187 | 1.668999 | 81.912502 |
| 90 | 1.660750 | 1.66275 | 91.563429 |
| 100 | 1.654562 | 1.655662 | 102.507597 |
| 110 | 1.650625 | 1.650736 | 110.114856 |
| 120 | 1.643812 | 1.643823 | 120.788644 |
| 130 | 1.637312 | 1.637413 | 130.686804 |
| 140 | 1.633875 | 1.634886 | 134.589646 |
| 150 | 1.628062 | 1.628063 | 145.124614 |

**Fig. 10** Flowchart of testing dataset formation through linear regression algorithm
a comparative analysis is presented in Table 4. From this table, it can be perceived that the proposed sensor delivers maximum sensitivity, which proves the worth of the present work in the research domain of biosensors and biophotonics.

4 Conclusion

A Si/SiO$_2$-based 1D defective PhC is designed for bioanalytes (hemoglobin concentrations) sensing application. Blood containing different concentrations of hemoglobin is infiltrated into the defect layer. The TMM has been employed to investigate the transmission spectrum of the designed structure. The mainstay of this work is based on analysis of the positional shift of the defect mode, which is appeared in the transmission spectrum. At the optimized incident angle of 30° and the defect layer thickness of 550 nm, the proposed structure gives a maximum sensitivity of 1916.77 nm/RIU. Besides this, a detailed assay is carried out to explore the effect of temperature on the sensor performance. On top of that, a machine learning algorithm is successfully applied to a predefined data set which is computed from the TMM technique. A linear regression algorithm is used to predict the hemoglobin concentrations. The outcomes of the model indicate that the presented approach can be helpful in the design of precision hemoglobin sensor employing a simple 1D PhC structure.

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Data Availability The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Competing Interests The authors have no relevant financial or non-financial interests to disclose.

Ethics Approval Not applicable.

Consent to Participate Not applicable.

Consent for Publication Not applicable.

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Table 4 Comparative analysis of sensitivity

| Sensing analyte     | Sensitivity (nm/RIU) | Reference |
|---------------------|----------------------|-----------|
| Waterborne bacteria | 387.5                | [11]      |
| Alcohol             | 873                  | [23]      |
| Soybean biodiesel   | 277.7                | [20]      |
| Hemoglobin          | 167                  | [22]      |
| Sucrose             | 1016.35              | [16]      |
| Hemoglobin          | 1916.77              | This work |
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