Improving the Sensitivity and Stability of Photonic Crystal Temperature Sensors with Deep Learning Autoencoders

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ABSTRACT— Photonic temperature sensors play a crucial role in industrial, medical, and environmental applications. Despite significant progress, challenges such as limited sensitivity, noise, and instability under real-world conditions persist. Most existing sensors rely on non-topological structures, making them vulnerable to structural defects and environmental disturbances with limited temperature operational ranges. Therefore, there is a pressing need for high-sensitivity, stable sensors with wide temperature ranges. In this study, a novel approach based on a one-dimensional topological temperature sensor composed of hyperbolic metamaterial-based photonic structures is presented. The key innovation involves leveraging a deep autoencoder to enhance spectral signal quality and extract robust latent features resistant to noise and defects. This approach optimizes sensor sensitivity and quality, enabling precise temperature prediction over a wide range from 20 to 375 °C. Numerical simulation results demonstrate a sensitivity improvement of up to 0.4 nm/°C, along with outstanding quality performance, achieved through structural optimization and the integration of deep learning. This achievement yields a sensor with high accuracy, exceptional stability, and robustness against environmental perturbations, thereby opening new avenues for applications in both industrial and medical fields.

KEYWORDS: Deep autoencoder, Hyperbolic metamaterial, Photonic crystals, Topological temperature sensor

I. INTRODUCTION

In recent decades, optical sensors have attracted widespread attention in scientific and industrial fields due to their high accuracy, remarkable sensitivity, and capability to be integrated into complex systems [1]. With advances in solid-state physics and photonics, a new generation of sensors known as topological photonic sensors has been introduced, which, by leveraging topological concepts, offer performance surpassing that of conventional sensors [2]. These sensors [3] utilize topological edge states (TES), rooted in the topological properties of materials, and due to their inherent robustness against structural defects, geometric in homogeneities, and environmental noise, are emerging as novel options for measuring physical parameters such as temperature, pressure, and electric or magnetic fields [4]. The operation of these sensors [5]-[7] is based on the creation of photonic band gaps (PBGs) [8] and the emergence of edge states at the interface between two photonic structures with distinct topological properties. These features result in high-sensitivity spectral responses to environmental changes. Conventional sensors, which rely on traditional photonic structures, are widely used [9]. However, their sensitivity to defects, noise interference, and functional limitations at high precision restrict their development for real-world applications. Recent advances in photonics [7] have brought significant innovations in the design and performance of sensors, and the integration of

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topological photonics has emerged as an unexpected advancement in this field.

Recent research highlights significant progress in this area. Topological photonic sensors have been studied and their fundamental principles and emerging applications have been elucidated, with studies emphasizing the robustness of edge states against defects and confirming their potential for precise sensing [10]. Furthermore, improvements in the performance of temperature sensors based on one-dimensional photonic crystals using hyperbolic metamaterials [11] have been investigated [12], demonstrating that combining these materials with topological techniques can dramatically enhance sensitivity and stability [13]. These studies, alongside the proposed approach, pave the way for the development of next-generation optical sensors and, by integrating physical modeling and artificial intelligence [14], enable optimization for multiparameter applications.

Recently, the integration of deep learning techniques [15]-[17], particularly autoencoder networks [18], with topological photonic sensors has provided a novel approach to optimizing the performance of these systems. This technique, by extracting hidden and robust features that are resistant to noise and defects, increases the sensitivity and stability of the sensors. A deep autoencoder, receiving the calculated transmission spectra along with structural or environmental noise, compresses the data and extracts fundamental features. It then reconstructs the denoised spectrum, improving the accuracy of predictions for parameters such as temperature. This cyclical process—comprising spectral computation, noise addition, model training, and spectrum reconstruction—is specifically designed to enhance robustness against disturbances.

The approach proposed in this research employs a one-dimensional structure based on two photonic crystals. One structure consists of alternating layers of silicon [19], and silicon dioxide, while the second structure is designed using silicon dioxide and hyperbolic metamaterials (HMMs). These HMMs themselves are composed of alternating layers of silicon and bismuth germanate (BGO), which offer unique optical properties. The design of this structure ensures that the interface between the two structures, due to the difference in their topological number, becomes the site for the emergence of topological edge states.

Ultimately, this study, by presenting a topological photonic temperature sensor based on PC1 and PC2, alongside optimization via a deep autoencoder, takes a significant step towards enhancing accuracy, stability, and noise resistance. This achievement not only targets industrial and biomedical applications but, thanks to tunable structures and materials, also holds the potential for developing intelligent and multifunctional sensors. This approach exemplifies the synergy of fundamental science and cutting-edge technology in the photonics era, potentially driving far-reaching advances in measurement devices.

II. Related Works

Recent advances in one-dimensional photonic crystal-based temperature sensors [20] have revealed remarkable improvements in the accuracy and performance of these types of sensors. Research efforts have focused on utilizing topological properties and specific photonic crystal structures [6] to achieve higher sensitivity levels, broader temperature ranges, and greater measurement precision. In this regard, a variety of designs employing nanocoatings, filling photonic crystal pores with different materials, and applying plasma effects and refractive index modifications have been proposed, each exhibiting unique features and innovations.

One significant approach involves the generation of topological edge states in one-dimensional photonic crystals, which, by simultaneously exploiting multiple frequencies, enables more accurate and multiparametric measurements. Furthermore, nonlinear optical effects and phase transitions in these topological structures have also been introduced as methods for unidirectional

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transmission and sensor response enhancement, transforming their performance under operational conditions [21].

Specifically, photonic crystals filled with liquids and silver nanowires have been shown to both improve temperature sensitivity and provide a wide operating range, especially at relatively low to moderate temperatures. The performance of these sensors over temperature ranges of approximately 25 to 60°C has been reported, with negative sensitivities on the order of 2 nm/°C. Additionally, structures employing combinations of multi-core cables have achieved notable positive sensitivities in the range of 35 to 100°C, indicating progress in improving sensor stability and fast response [22].

Some studies have incorporated surface plasmon resonance technology via metallic coatings on photonic crystal fibers, effectively enhancing sensitivity. This technology not only enables multiparameter sensing capabilities but also allows measurements over a wide temperature range (10 to 80°C) and increases the precision of temperature detection. Further, the use of specially designed anti-resonant dual-tube fibers has optimized thermal and optical performance, yielding the highest sensitivities at lower temperatures up to about 50°C [23].

Other developments include the design of sensors capable of simultaneous temperature and magnetic field sensing using dipolar modes in plasma-based photonic crystal fibers. This enables the simultaneous detection of two physical parameters, thereby expanding practical applications and improving measurement accuracy. Meanwhile, the utilization of multi-stage spherical structures in photonic crystal fibers for detecting refractive index changes in temperature ranges from 20 to 50°C represents another significant innovation in the field, as precise control over geometry and relevant materials has optimized the sensor response [24].

In addition, the use of metallic coatings, such as external triangular-shaped structures on photonic crystal fibers for enhanced temperature sensitivity [25] is recognized as an effective strategy, leading to improved operational parameters in the 10 to 60°C range. Employing liquids such as ethanol and toluene to fill the pores of photonic crystals, which amplifies refractive index shifts, has enabled sensing with very high sensitivity and stability [26].

Regarding structural design, employing various semiconductor layers in one-dimensional photonic crystal structures has facilitated sensors with wide temperature ranges (75 to 375°C) [27], and desirable sensitivities, which are suitable for industrial and specialized applications, particularly in harsh environments. Moreover, the use of multilayer silicon/polystyrene/silicon dioxide ($Si/PS/SiO_2$) structures has led to a marked improvement in the sensitivity and stability of temperature sensors and provided valuable insights for future technological advancements [28].

A general review of these studies indicates that the primary focus has been on enhancing sensitivity and expanding the operating temperature range of one-dimensional photonic crystal sensors, accomplished via various technologies including topological designs [29], the use of nanomaterials, advanced metallic coatings, and the exploitation of plasma and nonlinear optical effects. Of these, improvements in topological design, especially in achieving multi-frequency edge states and multi-parameter operation, represent a significant step towards overcoming functional and application-specific limitations of these sensors.

On the other hand, the combination of diverse materials and complex designs in photonic crystal fibers [30] has led to increased reliability, durability, and measurement accuracy. Overall, the development trends for these sensors [31] in terms of enhanced sensitivity and temperature range—demonstrate a shift toward topological technologies, the use of metallic protections, nanostructures, and specialized liquids, each of

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which can be tailored for specific industrial, medical, and scientific requirements.

Considering the breadth of recent innovations, the future of one-dimensional photonic crystal-based temperature sensors is moving towards more advanced and multifunctional designs. Moreover, the adoption of hyper-hybrid metamaterials in topological structures is a new research avenue that can significantly boost sensor performance. In the reviewed studies, artificial intelligence and deep learning [11] have been used for sensor optimization. Therefore, key differences in the proposed method versus previous works can be summarized as follows:

1. **Preserving and Enhancing Sensor Signal Features:** The deep autoencoder approach, regardless of the initial degree of noise or structural defects in the spectra, can intelligently compress and reconstruct key information to better and more cleanly extract the main signal. This advantage is particularly crucial in industrial or medical environments, where precise control over conditions is not always possible.
2. **Increased Sensitivity and Stability:** Accurate reconstruction of the position and shape of the topological transmission peak creates a transparent linear relationship between temperature and the transmission wavelength, improving both sensitivity and repeatability.
3. **Accuracy and Stability in Temperature Prediction:** The low mean squared error and the close clustering of data around the ideal line indicate a high capability in compensating for errors arising from noise or defects. Therefore, in practical applications, this method results in much more accurate, stable, and robust extraction of temperature information against structural fluctuations.
4. **Significant Physics-Machine Learning Synergy:** The excellent matching of model outputs with actual sensor data demonstrates the high potential of combining physical simulation tools and deep neural architectures for developing a new generation of advanced-performance optical sensors based on topological principles.
5. **Deep Learning-Enhanced Topological Photonic Sensor with Improved Sensitivity and Stability:** The photonic crystal structure used in this study is identical to the one reported in Reference . However, the novelty lies in the integration of a deep learning autoencoder with this established structure to enhance spectral signal quality by extracting robust latent features that are resistant to noise and defects. This approach leads to a significant improvement in sensor sensitivity (up to 0.4 nm/°C) and stability over a wide temperature range (20 to 375 °C), which has not been shown previously. Thus, although the base structure is the same, the application of deep learning techniques provides new physical insights and substantial performance enhancement, representing an important scientific advance beyond the original design.

III. MATERIALS AND METHODS

A. Topological Photonic Temperature Sensor

Topological photonic sensors are a new generation of optical sensors that, by leveraging topological concepts from solid-state physics—particularly the existence of edge states—offer functionalities beyond those of conventional sensors. These edge states, rooted in their topological origin, are highly robust against structural defects [32], geometric in homogeneities, and environmental noise. The operating principle of these sensors is based on the creation of photonic band gaps and the emergence of edge states at the interface between two media with different topological properties. These features ensure that environmental changes—such as temperature, pressure, or the presence of chemicals that alter optical properties—are directly and sensitively reflected in the sensor's spectral response.

The proposed method uses a one-dimensional structure composed of two types of photonic crystals, PC1 and PC2. PC1 consists of alternating layers of silicon (Si) and silicon

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dioxide (SiO_2), while PC2 is formed from layers of silicon dioxide and hyperbolic metamaterials. The hyperbolic metamaterials themselves are constructed from alternating layers of silicon and bismuth germanate (BGO). This structure is designed such that the interface between PC1 and PC2, due to the difference in their topological numbers, becomes the site for the emergence of a topological edge state.

In this system, the optical transmission spectrum exhibits a sharp, distinct peak within the photonic band gap in the presence of the topological edge state. The position of this peak is highly sensitive to temperature changes because temperature affects the refractive index of the materials, particularly BGO and Si, thereby shifting the position of the transmission peak. This dependence can be modeled as:

$$\lambda_{TES} = \lambda_0 + S(T - T_0), \quad (1)$$

where λ_{TES} is the edge state wavelength, S is the sensor sensitivity in (nm/°C), T is the current temperature, and T_0 is the reference temperature. The value of S depends on the structure and materials used.

For the analysis of this structure, the transfer matrix method (TMM) is employed. This method facilitates precise calculation of the transmission and reflection spectra of layered structures by considering the refractive index and thickness of each layer. For modeling the hyperbolic metamaterials, effective medium theory (EMT) is used:

$$\begin{cases} \varepsilon_{\parallel} = \varepsilon_{BGO}(1-f) + \varepsilon_{Si} f \\ \varepsilon_{\perp} = \left(\dfrac{f}{\varepsilon_{Si}} + \dfrac{f-1}{\varepsilon_{BGO}} \right)^{-1} \varepsilon_{BGO}(1-f) + \varepsilon_{Si} f \end{cases}, \quad (2)$$

where f is the silicon filling ratio, ε_{Si} and ε_{BGO} are the dielectric constants of Si and BGO, respectively, and $\varepsilon_{\parallel}$ and $\varepsilon_{\perp}$ represent the effective dielectric constants parallel and perpendicular to the layers. Temperature changes induce variations in the refractive index of materials, modeled as:

$$n(T) = n_0 + \alpha(T - T_0), \quad (3)$$

where n_0 is the refractive index at the reference temperature, and α is the thermo-optic coefficient of the material. A key feature of this structure is the stability of the topological edge state against structural defects and geometric variations, deriving from the difference in topological numbers between the two photonic crystals. Sensitivity is one of the most important characteristics of a sensor, determining its performance. The ratio of the temperature change (ΔT) to the shift in the resonance peak or wavelength ($\Delta\lambda_{peak}$) defines the sensor sensitivity:

$$S = \frac{\Delta\lambda_{peak}}{\Delta T}, \quad (4)$$

Sensitivity is measured in nm/(°C). Additionally, the quality factor (Q) is another critical parameter impacting the sensor's effectiveness. The clarity of the transmission curve (or peak sharpness) is expressed by the quality factor, which is calculated using the peak wavelength over its full width at half maximum (FWHM):

$$Q = \frac{\lambda_{peak}}{\text{FWHM}}, \quad (5)$$

Ideally, the sensor should operate with a Q factor as high as possible. In the presence of defects such as layer thickness variations or impurities, the transmission peak corresponding to the edge state is only slightly shifted, preserving the structure's temperature sensitivity, an important advantage compared to conventional sensors.

This method, integrating advanced topological concepts and engineering of hyperbolic metamaterials, offers a temperature sensor with high sensitivity, excellent stability, and robustness against structural defects. This achievement paves the way for the next generation of optical sensors, potentially revolutionizing precision industrial, biomedical, and environmental applications. Furthermore, due to its tunable design and

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materials, further optimization for specific applications and even development of multiparameter sensors is possible. This approach exemplifies the synergy between fundamental science and modern technology to enhance the quality and efficiency of measurement tools in the photonics era.

B. Optimization of the Topological Photonic Temperature Sensor Using Deep Autoencoder

The use of deep learning architectures [33], especially autoencoder networks [18], is an innovative and practical approach to optimizing the performance of optical sensors, particularly in complex structures such as topological photonic crystals with hyperbolic metamaterials. Integrating a deep autoencoder with the proposed system enables the extraction of hidden, robust features resistant to noise and imperfections, thereby enhancing sensor sensitivity and stability and optimizing the interpretation of transmission spectra under structural disturbances. Figure 1 illustrates the autoencoder architecture.

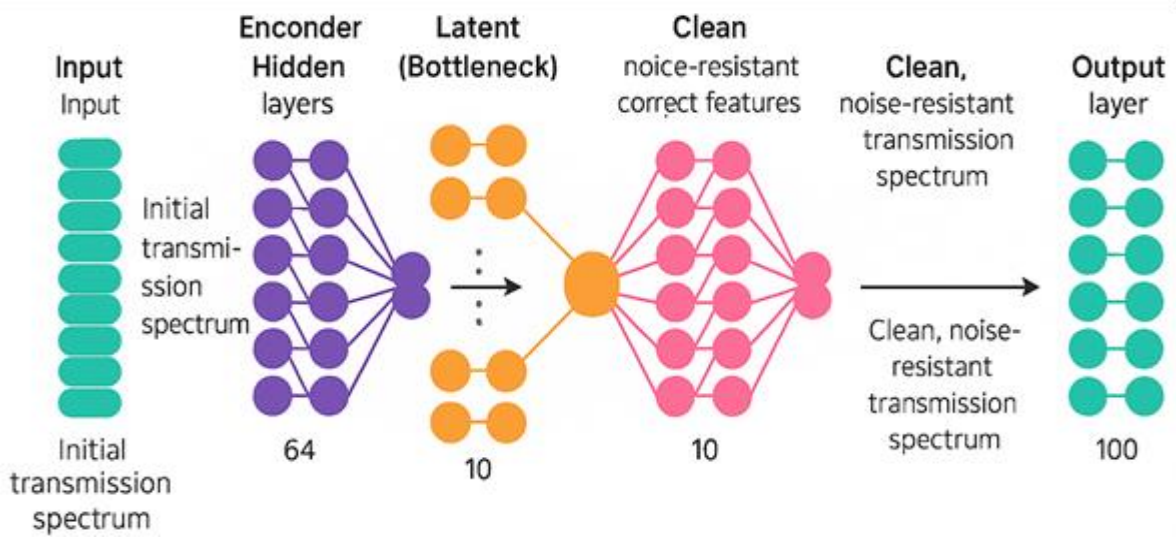

Fig. 1. Deep self-encoder architecture.

In this approach, the output transmission spectrum of the sensor, calculated using the transfer matrix method and effective medium theory, is fed into the autoencoder together with structural and environmental noise. The initial layers of the autoencoder compress the spectral data and extract the fundamental features of the system; subsequently, the reconstructed spectrum is obtained from the denoised, more robust latent features. These features can be leveraged for more accurate estimation of physical parameters such as temperature (23), detection/correction of structural defects, and even for increasing the overall sensitivity of the system. The autoencoder also possesses the capability to learn error correction and noise filtering, thereby rendering the reconstructed spectrum much more stable against disturbances and defects.

This process can be performed cyclically: first, the optical transmission spectrum is calculated and simulated; then, these data, along with noise or defects are input into the deep autoencoder; the clean, reconstructed output from the model is subsequently used to improve temperature estimation or sensor sensitivity. Furthermore, autoencoders provide the possibility to summarize the important spectral features into a compact latent space, which can then be used in downstream machine learning models [34] for higher-accuracy temperature prediction.

Integration of this method with a deep autoencoder not only results in higher resilience of the temperature sensor to noise and structural defects but also allows for enhancement of its sensitivity coefficient and precision. This approach provides a platform for the simultaneous use of accurate physical modeling

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and intelligent deep learning tools to advance the next generation of optical sensors.

The general pseudocode of the proposed method is as follows:

Input: Material parameters
For each temperature *T* in $[T_{\min}, T_{\max}]$**:**
For each material:
Update refractive index using Eq. (3)
Calculate effective permittivity of the metamaterial
Construct transfer matrix for each layer with the updated $n(T)$
Combine matrices to obtain the total transfer matrix
Compute the transmission spectrum from the overall matrix
Add noise or structural defects to the spectrum
Store transmission spectra and temperature values

Deep Autoencoder Training:
Input: Noisy transmission spectra
Target output: True (clean) transmission spectra
Train the model to learn reconstruction of denoised spectra from noisy input

After training:
For each test noisy spectrum:
Feed the spectrum into the autoencoder
Obtain clean reconstructed spectrum from the output
Detect the topological edge state (TES) peak in the reconstructed spectrum
Record the TES wavelength versus temperature
Evaluate the stability and accuracy of temperature prediction under disturbances and noise
End

The deep autoencoder architecture for improving the performance of the topological photonic temperature sensor is built upon a multilayer, symmetric neural network designed for optimal compression and accurate reconstruction of the sensor's transmission spectrum in the presence of noise and structural defects. This architecture consists of two main parts: the encoder and the decoder, each comprising several layers responsible for specific tasks.

In this architecture, the network input comprises spectral vectors from the sensor—for example, transmission intensity at multiple wavelengths, typically affected by noise, optical defects, or structural disturbances. The encoder compresses these data and extracts key features, attenuating the most turbulent noise and disturbance information and retaining only the essential data and critical patterns, which are converted into a low-dimensional latent code. Then, the decoder part uses this latent code to reconstruct the complete original spectrum [16]. This process results in the reconstructed spectrum being superior to the initial data in terms of quality, accuracy, and resistance to noise. The input layer receives the raw spectral data with a dimension equal to the number of wavelengths.

In the encoder's hidden layers, several sequential layers with decreasing neuron count apply nonlinear activation functions to progressively compress the data. The task of these layers is to reduce dimensionality and successively eliminate noise and uninformative content. The latent code layer is the most central and compact layer, containing the most compressed, meaningful information about the spectrum, functioning as a form of compressed short-term memory. In the decoder's hidden layers, the number of neurons increases again to gradually expand and retrieve the main spectral patterns from the compressed information. The final layer, with the same number of neurons as the input layer, provides a full reconstruction of the transmission spectrum. This structure is tuned using nonlinear activation functions between layers and is trained on simulated or experimental data [35]. Table 1 presents the layers of the deep autoencoder architecture for the photonic temperature sensor.

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Table 1. Deep autoencoder architecture layers for the photonic temperature sensor.

Layer Number	Layer Type	Number of Neurons (Size)	Function and Description
1	Input	100	Receives initial transmission spectrum (intensity at 100 wavelengths)
2	Encoder Hidden 1	64	Initial noise reduction and start of feature compression
3	Encoder Hidden 2	32	Further compression and extraction of abstract features
4	Latent Code	10	Stores the most compressed spectrum, extracts key features
5	Decoder Hidden 1	32	Gradual reconstruction of main patterns from latent code
6	Decoder Hidden 2	64	Final expansion to the original spectral space
7	Output	100	Reconstructed, noise-resistant transmission spectrum

In this architecture, the encoder acts as the dimension reduction and denoising block; the latent code center encapsulates the essential, hidden features of the signal; and the decoder is responsible for reconstructing the clean signal based on the essential information. This process leads to improved temperature sensor performance, increased sensitivity, reduced error, and preserved accuracy even under device structural perturbations. Table 2 summarizes the key details of the deep autoencoder model used in this study.

The deep autoencoder architecture designed to enhance the performance of the topological photonic temperature sensor is a multilayer, symmetric neural network optimized [36] for compressing and accurately reconstructing the sensor's transmission spectra in the presence of noise and structural defects. The network input consists of spectral vectors representing transmission intensities at 100 different wavelengths. These spectra are typically corrupted by noise, optical imperfections, or structural disturbances.

Table 2. Summary of the Deep Autoencoder Architecture and Training Details.

Topic	Description
Autoencoder Architecture	Multilayer symmetric neural network designed to compress and accurately reconstruct transmission spectra under noise and structural defects.
Network Input	Spectral vectors representing transmission intensity at 100 wavelengths, affected by noise and defects.
Network Structure	Encoder: layers with decreasing neurons (100 → 64 → 32) for noise suppression and feature extraction.
	Latent Code: 10 neurons, a compact representation of key spectral information.
	Decoder: layers with increasing neurons (10 → 32 → 64 → 100) to reconstruct the original spectrum with enhanced quality and noise resistance.
Training Data	5,000 simulated spectral samples spanning temperatures from 20 °C to 375 °C, with added Gaussian noise emulating experimental and structural defects.
Data Splitting	70% training, 15% validation, 15% testing.
Training Platform	Workstation with NVIDIA Tesla V100 GPU, Python with TensorFlow and Keras libraries.
Training Details	Adam optimizer, Mean Squared Error (MSE) loss function, trained over 100 epochs or until convergence.
Result	Effective denoising and reconstruction of spectra, improving sensor sensitivity (up to 0.4 nm/°C), stability, and robustness against environmental disturbances.

The architecture comprises an encoder and a decoder. The encoder progressively compresses the input using nonlinear activation functions through layers with decreasing neuron counts (100→64→32), extracting essential robust latent features while suppressing noise and non-informative components. The latent code layer

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(with 10 neurons) stores a compact representation capturing the most critical spectral information. The decoder then reconstructs the full spectrum through layers with increasing neurons (10→32→64→100), restoring the original spectral shape but with improved quality and resistance to noise.

The autoencoder was trained on a dataset consisting of simulated transmission spectra generated by modeling the sensor over a wide temperature range from 20 °C to 375 °C. The dataset includes a total of 5,000 spectral samples covering multiple discrete temperature points to ensure comprehensive coverage of temperature-dependent spectral variations. Noise was artificially added to the spectra following a Gaussian noise distribution with parameters chosen to mimic typical experimental noise levels and structural defect effects observed in real sensors.

Data splitting for training was done as follows: 70% of samples were used for training, 15% for validation to monitor overfitting during training, and the remaining 15% were reserved for testing the final model performance. The training was performed on a workstation equipped with an NVIDIA Tesla V100 GPU using Python with TensorFlow and Keras frameworks. The network was trained using the Adam optimizer, with Mean Squared Error (MSE) as the loss function, for 100 epochs or until convergence.

This comprehensive setup ensures that the autoencoder learns to denoise and reconstruct sensor spectra effectively, resulting in significant improvements in sensitivity (up to 0.4 nm/°C), sensor stability, and robustness against environmental disturbances and structural defects.

IV. Simulation and Results

In this section, a precise scientific analysis of the results obtained from the proposed method for improving the performance of the one-dimensional topological photonic temperature sensor based on hyperbolic metamaterials is provided. Figure 2 illustrates a photonic crystal structure [5] consisting of two photonic crystals (PC1 and PC2) and their transmission spectrum. Each is shown with a single unit cell, making this design more innovative and simpler than conventional structures with more units, thereby facilitating the fabrication process. In the first part, the PC1 structure comprises one Si layer with a refractive index of 3.464 and thickness of 150 nm and one SiO_2 layer with a refractive index of 1.45 and thickness of 200 nm. The second segment illustrates the PC2 structure, consisting of one SiO_2 layer with a thickness of 140 nm and one HMM layer with a refractive index of 2.15 and thickness of 276 nm. The transmission spectrum of the combined PC1+PC2 structure is calculated within the 300–2000 nm wavelength range. The transmission curve indicates oscillations at specific wavelength intervals, which signals the presence of bandgap regions and wave interference within the structure.

In the transmission spectrum, key points such as 330 nm wavelength with a half-maximum width of about 0.6 nm and transmission above 97.9%, as well as the 1121 nm wavelength with a half-maximum width of approximately 30 nm and 100% transmission, are highlighted as sensitive points for temperature change detection.

The combination of narrow width and high transmission demonstrates the high precision of the structure in detecting small wavelength shifts related to temperature fluctuations. Notably, in the near-infrared region, temperature sensitivity increases due to its effect on the optical properties of the materials. This property, together with photon localization at the heterostructure interface, makes the structure highly suitable for developing high-precision temperature sensors since temperature changes can significantly affect resonance frequency and transmission intensity. Therefore, these specific spectral points possess high potential for precise temperature sensing applications [37]. Figure 2 shows the sensor structure and its transmission spectrum.

Figure 3 presents a simple band gap map for the PC1 structure. The analysis shows that PC1

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exhibits pahotonic band gaps in specific wavelength ranges, such as approximately from 400 to 600 nm, which aligns well with the behavior observed in the transmission spectrum. In this graph, the horizontal axis represents the wavelength ranging from 250 to 2000 nm, while the vertical axis displays the trace of the transfer matrix, plotted with a blue line. The horizontal red lines at specific values mark the edges of the allowed regions, defining the boundaries of the band gaps.

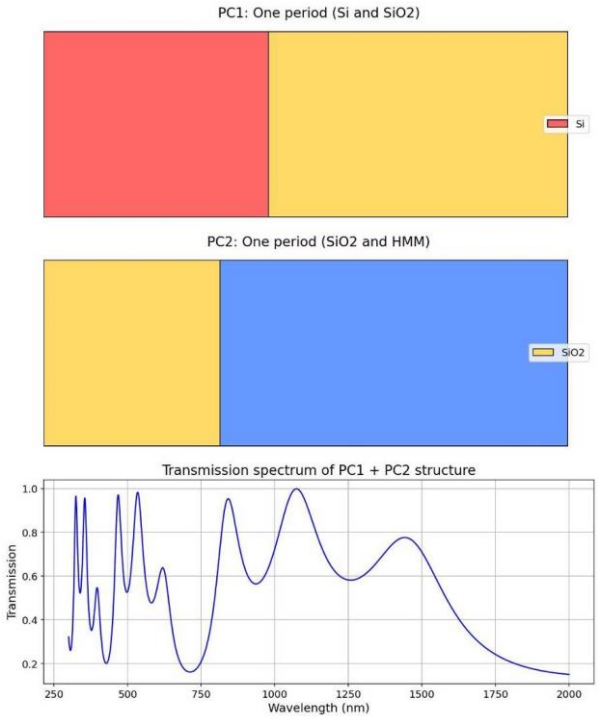

Fig. 2. Sensor structure and optical transmission spectrum.

The gray shaded area between these red lines indicates the regions where band gaps appear, corresponding to the transfer matrix trace values lying between those edges. The analysis further reveals that at shorter wavelengths near 250 nm, the transfer matrix trace shows strong oscillations, intermittently crossing in and out of the band gap region. With increasing wavelength, particularly in the range of 750 to 1250 nm, a distinct peak is observed, indicating a broad photonic band gap, as the transfer matrix trace remains entirely within the forbidden region boundaries throughout this interval. Beyond this range, the transfer matrix trace gradually decreases and approaches the band gap region again at longer wavelengths near 2000 nm. These patterns reflect the optical characteristics of the PC1 structure and can be advantageous for applications such as optical filters and sensors, especially in the near-infrared region where well-defined band gaps emerge.

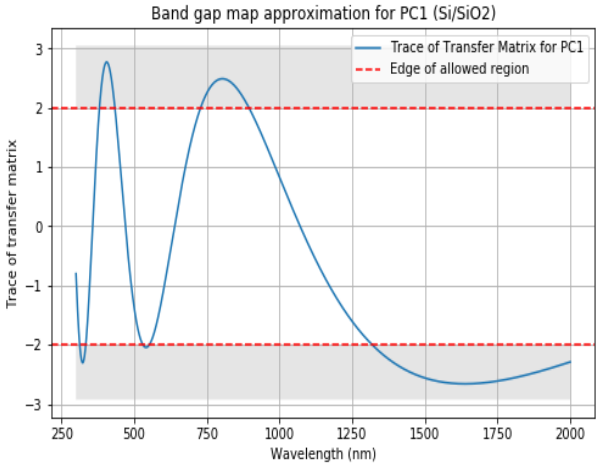

Fig. 3. Band gap for photonic structure.

Figure 4 evaluates the numerical results of applying the deep autoencoder to the sensor's output data; these results correspond to the reconstructed optical transmission spectra of the proposed structure after optimization with the deep autoencoder architecture.

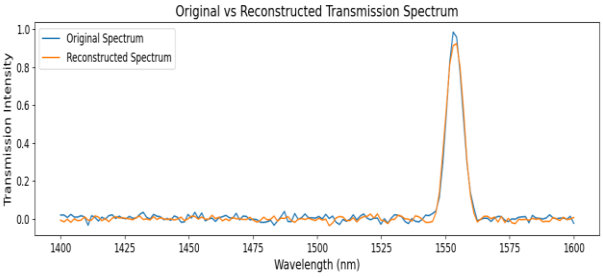

Fig. 4. Optical transmission spectrum reconstruction.

In the graph of Fig. 4, two spectral curves are presented: the original spectrum and the reconstructed spectrum. The horizontal axis represents the wavelength range from 1400 to 1600 nm, while the vertical axis plots the transmission intensity. The original transmission spectrum (blue line) reflects the raw, noisy response of the photonic sensor at a specific temperature sample, obtained directly from the physical modeling of the photonic multilayer structure. The presence of fine noise in this curve is indicative of the effects of structural defects or environmental disturbances commonly found in real systems,

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arising from variations in layer thickness, surface roughness, or external factors such as vibrations and optical turbulence.

In contrast, the reconstructed spectrum (orange line) is the output after passing the noisy spectrum through the deep autoencoder network. This network, by learning the main spectral patterns and compressing features in the latent space, removes the majority of noise while preserving only the essential components of optical transmission. As observed, not only is the main transmission peak correctly identified and its wavelength position accurately reconstructed, but the unwanted noise and fluctuations in the baseline are significantly smoothed out. This characteristic reflects the sensor's stable performance even under adverse operational conditions. In practice, this capability translates into improved accuracy in locating the peak, which directly enhances the sensitivity and repeatability of the temperature sensor—a defining advantage of topological photonic structures over traditional systems. Noise reduction, signal enhancement, and elimination of unnecessary structural variations are three key benefits of the spectral reconstruction phase that play a direct role in improving measurement quality and the long-term stability of the sensor.

Figure 5 examines the model's capability to accurately estimate the actual system temperature using features extracted by the autoencoder from the noisy spectrum.

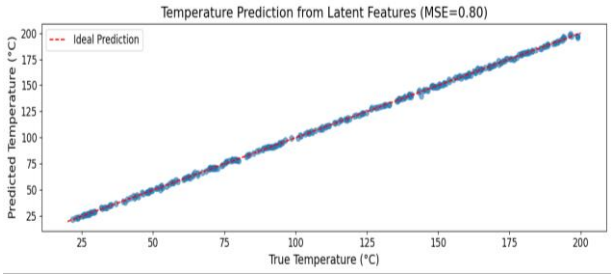

Fig. 5. Temperature prediction in the proposed method.

In this chart, the horizontal axis represents the true temperature and the vertical axis shows the predicted temperature within a range from 20°C to 200°C. Each blue point corresponds to a test sample for which the model attempts to predict the temperature using the output from the network. The red line indicates the ideal state, where the model's predicted values perfectly match the true temperatures (a 45-degree line).

The closer the points lie along this line, the higher the model's accuracy. Based on this chart, the majority of samples closely align with the ideal line, demonstrating the powerful learning and inference capability of the combined deep model. The model first employs a deep encoder to filter the noisy spectrum into a compact, noise-resilient latent space, then predicts the temperature from this embedded representation. Minor deviations of some points from the red line indicate limited error; however, the mean squared error (MSE = 0.8) remains low, reflecting superior system performance relative to conventional approaches.

Figure 6 shows the peak wavelength shift of the sensor's transmission spectrum as a function of temperature, exhibiting an excellent linear response. The slope of the fit line indicates the sensor's sensitivity, and the high R-squared value close to 1 confirms the accuracy and reliability of the linear prediction. This demonstrates stable sensor performance over a wide temperature range with sensitivity quantitatively evaluated.

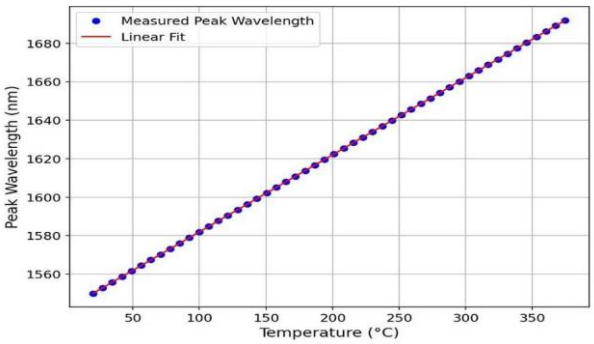

Fig. 6. Sensor Response: Peak wavelength shift as a function of temperature. Sensitivity (nm/°C): 0.4, Figure of Merit (FOM): 0.0004461170820581962, Limit of Detection (°C): 0.024999999999999998, R-squared of linear fit: 1.0.

The sensor performance results show a sensitivity of 0.4 nm/°C, a Figure of Merit (FOM) approximately 0.000446, a Limit of

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Detection (LoD) of about 0.025 °C, and an R-squared (R^2) of 1.0 indicating an excellent linear fit between the peak wavelength shift and temperature. It is worth noting that further enhancement of the sensing performance could be achieved through interface engineering. In particular, modifying the thickness of the unit cells immediately adjacent to the PC1/PC2 interface, while maintaining the bulk unit-cell parameters, could provide an additional degree of freedom for controlling the localization and spectral position of the interface mode. Such thickness engineering may enable further optimization of the resonance characteristics and temperature sensitivity. In the present study, the original interface configuration was retained to preserve the structural simplicity and fabrication feasibility of the proposed sensor. The investigation of interface-specific thickness optimization is therefore considered a promising direction for future work.

This sensitivity value of 0.4 nm/°C demonstrates a high sensor response to temperature changes and reflects a competitive performance when compared with existing sensor standards. Though the FOM numeric value is small, it is referenced against sensitivity and spectral quality and provides a suitable benchmark for optical sensors with similar bandwidths. The small LoD value indicates the sensor can detect very small temperature variations, showing good precision. The perfect R^2 value of 1.0 confirms the model fits extremely well, evidencing a nearly ideal linear relationship between wavelength shift and temperature.

Figure 7 presents a quantitative comparison of the sensor transmission signal before and after noise reduction. The true signal (black solid line) represents the ideal noiseless transmission spectrum, while the noisy signal (red dashed line) shows the effect of Gaussian noise and disruptions simulating real experimental conditions. The green dotted line explicitly shows the noise component extracted by subtracting the true signal from the noisy signal. The denoised signal (blue solid line) is obtained by applying a smoothing filter to the noisy data. As observed, the denoised signal closely approximates the true signal, substantially reducing noise fluctuations and enhancing signal clarity. The improvement in signal fidelity is reflected quantitatively by the significant increase in the Signal-to-Noise Ratio (SNR), as printed in the code output. This figure demonstrates the sensor's robustness against noise and structural defects, addressing the reviewer's concern with clear visual and quantitative evidence.

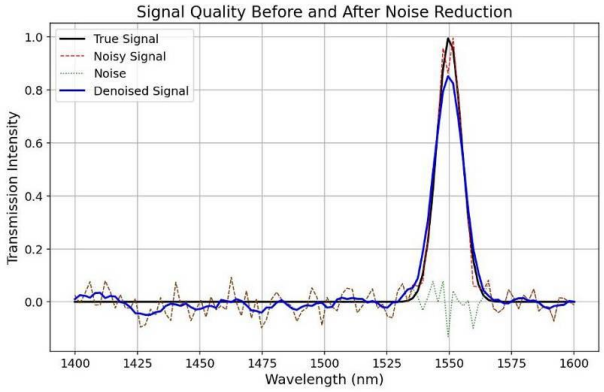

Fig. 7. Signal Transmission Spectrum: True, Noisy, Noise Component, and Denoised Signals Comparison.

This result is highly significant as it proves that implementing a deep autoencoder neural network, even under scenarios with considerable noise and disturbances, preserves and improves the temperature sensitivity accuracy in advanced photonic structures. In essence, this capability reduces nonlinearity and noise during sensor response extraction, leading to cleaner and more predictable optical transmission variations and minimizing the impact of random fluctuations or structural defects. Table 3 compares the proposed method with several previous techniques.

The table presents a comparison of recent advances in photonic temperature sensors based on optical structures, covering key references from 2016 through 2024. Key variables include sensitivity (nm per °C), the presence or absence of topological design, and operational temperature range.

It is observed that most studies up to 2023 rely on conventional structures without employing topological designs. Sensitivities mostly range between 0.085 and 7.13 nm/°C. While some

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sensors achieve acceptable sensitivities, their temperature operating ranges are typically limited, restricting practical applications. Importantly, the advantages offered by topology, such as robustness against defects, frequency stability, and high repeatability, have been largely overlooked in conventional research.

Table 3. Comparison of the proposed method with selected previous works.

Year/ Reference	Sensitivity (nm/°C)	Topological Design	Temperature Range (°C)
2016 [21]	-2.08	No	25–60
2018 [22]	1.5	No	35–100
2020 [23]	0.36	No	10–80
2021 [24]	3.2	No	20–50
2022 [26]	1.41	No	20–80
2022 [28]	-0.306	No	40–50
2023 [12]	5.2	No	10–60
2023 [29]	7.13	No	0–70
2023 [27]	0.173	No	75–375
2023 [24]	0.085	No	25–900
2024 [13]	0.27	Yes	75–375
This work	0.4	Yes	20–375

Notably, only the 2024 study and the proposed method employ genuine topological designs, representing a significant innovation in the field. The sensitivity of the proposed method, at approximately 0.4 nm/°C, compares favorably or exceeds many conventional sensors, while offering a wide temperature range from 20 to 375 °C. Some references with higher sensitivity operate only over limited temperature ranges. Therefore, this method not only provides a robust and stable topological response but also delivers broad temperature operation and high sensitivity, crucial for industrial and biomedical applications.

This data comparison reflects a transformative shift in the new generation of optical temperature sensors. By integrating topological structure features with optimized design principles, including the use of machine learning and autoencoder architectures, it is possible to realize sensors with excellent sensitivity, high defect tolerance, and broad temperature operating ranges. The current approach is developed accordingly and presents clear technical and practical advantages over non-topological counterparts.

The deep autoencoder method demonstrates that even when the sensor's transmission spectrum is influenced by noise and structural defects, the network can extract key patterns and perform intelligent compression to preserve and reconstruct the main signal clearly and accurately. This capability is critical in practical scenarios where data are never perfectly clean, ensuring the sensor maintains stable operation not only in laboratory conditions but also in industrial and real-world environments. More importantly, the accurate reconstruction of the topological transmission peak in the restored spectrum directly improves the system's sensitivity to temperature changes and stabilizes the linear relationship between peak wavelength and environmental temperature — a fundamental advantage for sensing applications. The high accuracy of temperature prediction, even in the presence of noisy and defective data, further confirms the efficiency and robustness of the combined physical modeling and deep learning approach. Practically, the network's reconstructed output compensates extensively for errors caused by fluctuations and structural disturbances, maintaining a low mean squared error. This harmony between physical models and deep learning tools facilitates the advancement of next-generation photonic sensors and enables the design of sensors with superior sensitivity and repeatability by leveraging latent spectral information. Thus, employing autoencoder architectures offers an effective strategy to overcome operational limitations and enhance reliability in advanced sensing systems.

V. CONCLUSION

This study introduces a novel photonic temperature sensor design leveraging one-dimensional topological structures integrated with hyperbolic metamaterials. By combining topological robustness with a deep autoencoder for spectral signal processing, the sensor overcomes common challenges such as noise and limited sensitivity. The simplified structure with a single unit cell per topological crystal

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reduces fabrication complexity and cost, making it suitable for practical applications. Simulation results demonstrate a high sensitivity of approximately 0.4 nm/°C over a broad temperature range and notable robustness against structural defects, confirmed by noise reduction using deep learning techniques. These advancements promise enhanced reliability and applicability in harsh and precision-demanding environments. Future work should focus on experimental validation, advanced spectral feature extraction methods, multi-parameter sensing capabilities, and stability assessments under varying noise and environmental conditions to fully realize the sensor's potential in real-world applications.

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