© MAY 2026 | IRE Journals | Volume 9 Issue 11 | ISSN: 2456-8880
DOI: https://doi.org/10.64388/IREV9I11-1717403

A Systematic Review of Deep Learning Approaches for Fiber Bragg Grating Sensor Data Interpretation in Subsea Multi-Parameter Monitoring.

AGOMUO HYGINUS .C[1], OKEKE REMIGIUS OBINNA[2]
[1,2]Centre for Information and Telecommunication Engineering, University of Port Harcourt, Port Harcourt, Nigeria

Abstract- ***Fiber Bragg Grating (FBG) sensors have recently been identified as one of the most important technologies to provide subsea monitoring owing to high sensitivity, Electromagnetic Interference (EMI) immunity and the ability to measure a number of parameters at once. Although FBG-based sensing solutions are very promising, there are numerous challenges associated with spectrum interpretation in subsea conditions. Particularly, temperature, salinity and pressure parameters are cross-sensitive, with spectral distortions (polarisation effects, birefringence, wavelength effects and noise) causing complex nonlinear dependencies that are intractable to traditional signal processing methods. Recent development in the field of deep learning demonstrates remarkable achievements in the modelling of complicated spectral patterns to do multi-parameter estimation. Various kinds of neural architecture, such as convolutional, recurrent, and attention-based neural networks are employed to learn the local and global interactions among the spectral signals. In addition, new learning methods like self-supervised learning, federated learning, and physics-aware modelling are designed to alleviate the issues such as data scarcity, domain variability, and deployment-related challenges. Nonetheless, the current deep learning approaches have several critical weaknesses, such as the lack of modelling cross-sensitivity effects, the lack of good generalisation when operating under realistic settings, poor resistance to uncertainties, and real-time and edge-deployment issues. This paper presents a review of our work on the use of deep learning to interpret FBG spectral data in detail. In particular, we derive a theoretical framework to explain the problem, create a taxonomy to analyse the state-of-the-art approaches, and find out significant gaps in research and future directions.***

Keywords: Fiber Bragg Grating (FBG), Deep Learning, Subsea Monitoring, Remotely Operated Vehicle (ROV), Multi-Parameter Sensing, Uncertainty Quantification, Edge Deployment, Federated Learning, Physics-Informed Neural Network.

I. INTRODUCTION

Fiber Bragg Grating (FBG) sensors have emerged as a game-changing technology for subsea monitoring, providing unrivalled sensitivity, absolute immunity to electromagnetic interference and unique potential for distributed sensing over kilometre-long optical fiber [3]. These capabilities make FBG sensors ideal for ensuring the safety of vital offshore assets such as subsea pipelines, risers, wellheads and production manifolds, where real-time measurements of temperature, pressure, salinity, and strain are vital for safe operation and environmental monitoring [1].

The underlying principle of operation for an FBG sensor is based on a periodic refractive index variation in the core of an optical fiber that produces a narrow-band reflective filter that is responsive to environmental changes. Environmental changes in the subsea environment result in thermo-optic, elasto-optic and baro-optic effects that modify both the effective refractive index and the grating period, resulting in a shift in the Bragg wavelength that is proportional to the desired physical parameters [5]. This simple transduction scheme allows FBG sensors to operate as passive and all-optical transducers capable of surviving the high pressures, corrosive chemicals and high electrical risks commonly encountered in the deep water where traditional electronic sensors are routinely destroyed.

These attractive features notwithstanding, the extraction of subsea information from FBG spectral measurements is a formidable task. The primary challenge is cross-sensitivity, that is, the interconnection of multiple environmental parameters that affect the same spectral features [7]. Temperature, salinity and pressure affect the Bragg wavelength via different physical mechanisms, resulting in spectral changes which cannot be uniquely assigned to one of these parameters without complex decoupling approaches. This is worsened by the challenging subsea environment. The static pressures of up to 30 MPa (3,000-meter depths) cause substantial spectral broadening and peak shifts, while the temperature gradients along water columns result in non-uniform wavelength shifts along multiplexed FBG sensors [62][12]. Refractive index changes due to salinity gradients, critical for certain chemical sensing FBG designs (etched or tilted FBG) further induce spectral distortions that complicate interpretation [28].

The spectral integrity needed for reliable measurement is also compromised by a plethora of optical and mechanical distortions. Polarisation-dependent loss (PDL) due to fiber birefringence in cables bent or twisted to conform to cable routes produces uneven peak attenuation and apparent wavelength changes in response to environmental variation [13]. Interfering responses from spectral overlap in dense grating arrays, required for delivering sufficient spatial resolution in a large-scale network, complicate traditional peak tracking strategies [11]. Low optical signal-to-noise ratio environments common in long subsea monitoring systems and during ROV operations that cause microbending and connector instability in the monitoring system distort the fine spectral features that allow accurate demodulation [3]. Drift in the spectral peaks due to temperature cycling of interrogator electronics, drift in the baseline due to dynamic hydropressure, and artefacts from cable motion due to vibration combine to turn the idealised peak shapes assumed in analytical models into highly structured, noisy, time-varying signals.

Classic signal processing methods have tackled these problems by increasingly complicated analytical techniques. Peak picking and tracking methods, though fast, rely on the separability of peaks and "blow up" in cases of peak overlap and/or high noise levels [12]. Curve fitting approaches fit spectral parameters to fixed functional forms such as Gaussian or Lorentzian line shapes, but these simple models fail to capture the complexities of physical distortions that result in asymmetric, multi-modal and non-stationary line shapes. Inversion methods based on sensitivity matrices use the linearised sensitivity relationship between wavelength shifts and changes in environmental parameters, but require well-conditioned sensitivity matrices that are ill-conditioned when the parameters are highly correlated or when operational conditions are outside the calibration range [12]. More fundamentally, all analytical methods are based on explicit physical models that cannot account for the full complexity of observed spectral distortions that often arise due to non-linear interactions between cross-sensitivity, polarisation and environmental drift in the harsh operational subsea environment.

Deep learning has ushered in a new era in the interpretation of FBG spectra, providing data-driven approaches capable of automatically learning intricate nonlinear relationships directly from spectral observations, without relying on simplifications of a physical model. The first uses of convolutional neural networks (CNNs) showed unparalleled success in capturing local spectral features, shoulders, side-lobe skewness and ripple structure that convey information on environmental conditions and distortion effects [30]. Through learning multi-layered representations in a stack of convolutional filters, these networks realised significant accuracy gains in demodulation under low signal-to-noise ratio conditions and moderate spectral overlap, demonstrating the potential of deep learning approaches as alternatives to analytical modelling. In recent years, model architectures have advanced to further enhance the representational power of neural models for FBG sensing. Recurrent networks, such as Long Short-Term Memory (LSTM) networks, brought temporal modelling capabilities that allow stable prediction of temporal variations in wavelength in dynamic settings and compensation for temporal drift effects [31]. More recently, attention-based "transformer" models have exhibited unprecedented modelling capabilities of global spectral patterns, affording disambiguation of complex cross-sensitivity effects through dynamic context-dependent feature weighting [41]. Hybrid models that combine convolutional, recurrent, and attention-based elements into a single framework have shown great potential in terms of the complementarity of local feature extraction and temporal and global contextual modelling [20].

Beyond supervised learning, novel methodological frontiers are tackling key operational bottlenecks to deployment. Self-supervised and contrastive learning methods allow models to learn meaningful spectral representations from the rich and plentiful unlabeled data, alleviating reliance on costly labelled datasets and generalising under varying sensing and interrogator configurations [23].

Federated learning approaches enable distributed model learning across sensing networks, such as a fleet of ROVs or several offshore platforms, without sharing proprietary or confidential spectral information, ensuring data security and confidentiality while enhancing collective knowledge [18].

Physics-constrained learning techniques incorporate domain-specific priors and models into neural networks to enhance interpretability and maintain model predictions in line with optical principles [57].

Data-driven modelling based on simulation-based synthetic data generation, rooted in multiphysics modelling of coupled thermal-mechanical-optical processes, offers ways to generate large-scale physically plausible training data that capture rare and extreme events that are typically missing in field data [59].

The subsea monitoring application using ROVs adds further constraints to the design and assessment of deep learning techniques. Real-time inference constraints (typically less than 50 milliseconds for closed-loop control) require lightweight models that can run on embedded computing platforms with limited power and thermal budgets [35].

mechanical-optical interactions, offers avenues for generating large-scale realistic training data that captures rare or extreme events that are sparsely represented in observational data [59].

The practical considerations of ROV-assisted subsea monitoring add further constraints and considerations when designing and assessing deep learning models. Real-time inference, typically with less than 50 millisecond latencies required for closed-loop control, requires efficient models to operate on embedded hardware with demanding power and thermal budgets [35].

Uncertainty estimates are important in safety-critical applications where model output is used to make decisions; failure to provide accurate confidence estimates can lead to overconfident mis-classifications, which may in turn lead to incorrect and potentially dangerous actions, or failing to detect emergent dangers [21].

Domain adaptation and few-shot recalibration capabilities are needed to retain accuracy when models are faced with new interrogator equipment, alternative fiber arrangements, or new environmental regimes that are not encountered during model training [55].

Cross-modality fusion with ROV telemetry data streams such as inertial measurement units (IMUs), Doppler velocity logs (DVLs), and altimeters, present opportunities to discriminate between spectral artefacts caused by vehicle dynamics and actual environmental variations, transforming a potential confounding variable into a source of information [22].

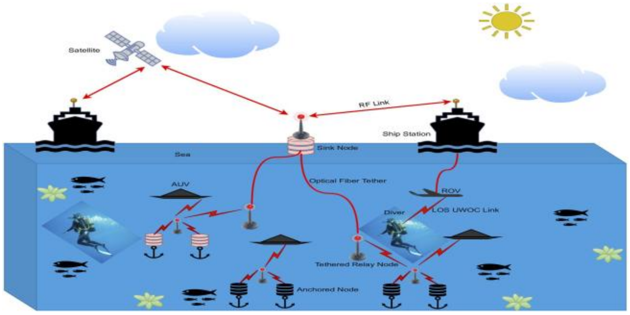

Figure 1: Conceptual Framework of Deep Learning-Based FBG Interpretation in ROV-Assisted Subsea Monitorin

The complete subsea monitoring system using Fiber Bragg Grating sensors with ROV-based data collection is shown in Figure 1. Spectral changes in FBG sensors resulting from environmental variables (temperature, salinity, pressure) combined with noise, cross-sensitivity and polarisation effects are used as inputs to deep learning models. These intricate spectral features are analysed via deep learning techniques that learn feature representations and estimate multiple parameters. Combining ROV telemetry provides enhanced situational awareness to enable reliable and adaptable interpretation in dynamic subsea environments.

Given these challenges, it is vital to have a systematic review of existing deep learning approaches for interpretation of FBG sensor data in subsea multi-parameter monitoring. This paper proposes a review which synthesises the state-of-the-art, provides a unified framework and a classification of the existing approaches. Through an evaluation of previous approaches and their limitations, this work highlights the research gaps and offers insights into future trends in the development of more efficient, flexible and scalable sensing systems. The insights gained from this review are aimed to inform the development of smart subsea monitoring systems that can provide reliable and accurate multi-parameter estimation in complex and dynamic environments.

II. REVIEW OF RELATED WORKS

From traditional analytical methods to sophisticated data-driven algorithms, the analysis of Fiber Bragg Grating (FBG) sensor data has shifted towards capturing complex nonlinear spectral responses. This shift is in response to the need for precise multi-parameter sensing in marine environments, which present challenges such as spectral distortions, cross-sensitivity, and environmental effects. To examine the progress of existing research, a taxonomy of literature is proposed based on the predominant deep learning paradigms used. This taxonomy shows how the evolution from localised feature-based approaches to global adaptive and distributed intelligence systems has occurred.

In Figure 2, the taxonomy diagram illustrates a structured deep learning approach for FBG spectral analysis into four levels of representation, from simple to complex. The lowest level contains convolutional neural networks (CNNs) tailored to effective local spatial feature extraction like peak shapes and shoulder asymmetries. In sequence models, recurrent neural networks (RNNs) and long short-term memory networks (LSTMs) extend to temporal relationships and dynamics such as spectral drift. Transformers with attention mechanisms facilitate global modelling through dynamic interactions across the entire spectral range. The pinnacle category includes hybrid and distributed models that combine several architectural approaches, and federated and self-supervised learning models for scalability and efficiency. This classification not only facilitates teaching and learning but also provides a map for navigating through the arsenal of approaches according to sensing tasks.

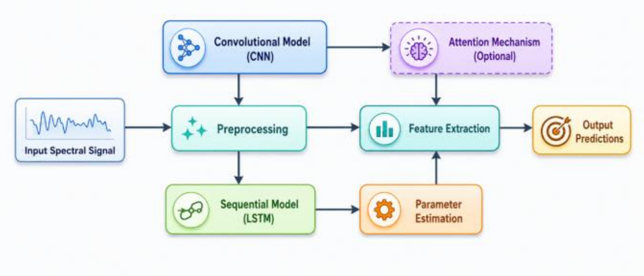

Figure 2: Taxonomy of deep learning models for FBG spectral interpretation.

2.1 Convolutional Neural Network-Based

Convolutional Neural Networks (CNNs) are widely used for interpreting FBG spectra, as they are capable of capturing local features of spectral data. The spectral information of the FBG sensors is characterised by features like peak shifts, side lobes and asymmetry, which can be captured by convolutional filters. The basic operation of a one-dimensional convolution is given by equation (1) as:

$$[y(t)=\sum_{k=0}^{K-1} w_k \cdot x(t-k)] \qquad (1)$$

Where;

- $y(t)$ is the output feature at spectral position t
- $x(t-k)$ is input spectral intensity values in the local receptive field
- (w_k) are the learnable weights.
- K is the kernel size

As illustrated in equation (1), the convolution operation is a weighted sum of nearby spectral points, which allows for translation invariant feature extraction of local structures such as shoulders and edges of peaks.

Some previous research has shown how CNNs can resolve spectral overlap and distortions due to noise. Recent research has demonstrated the effectiveness of deep CNN models in enhancing demodulation performance under low signal-to-noise ratios (SNR), allowing accurate parameter estimates even in noisy environments [30]. Enhanced CNN models, such as residual and encoder networks, improve feature extraction and spectral distortion resistance [32]. Furthermore, CNN-based regression models have been employed to simultaneously predict multiple parameters such as temperature, salinity and pressure, with enhanced accuracy [33].

Recent studies have further built on CNN models using multi-scale feature learning to include fine and coarse features in the model. This enhances their performance in large FBG networks with significant spectral overlap [11]. However, CNN-based models are still unable to capture long-term dependencies, especially in cross-sensitivity and coupled environmental scenarios [7]. Distortions due to polarisation issues also highlight these limitations in subsea applications [13].

2.2 Temporal and Sequential Learning Models

To address the challenges faced by spatial models, methods that incorporate temporal and sequential learning have been proposed, especially when the spectral data are time varying. Temporal models, such as Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) networks, are popular for modelling temporal data.The update of hidden state in an LSTM network is given by equation (2).

We can write the update rule for the hidden state of an LSTM network as:

$$[h_t=f(W_h h_{(t-1)}+W_x x_t+b)] \qquad (2)$$

Where;

- ht the hidden state at time step t
- ht-1 is the previous hidden state
- Xt is the current input spectral feature
- Wh, Wx are recurrent and input weight matrices
- b is the bias vector
- f is a nonlinear activation function

Equation (2) allows the model to store dynamic information about previous spectral observations and to update this information with each new observation, so that temporal drift can be tracked. The update rule allows the model to dynamically learn from previous spectral observations and update with new data, crucial for detecting temporal drift.

LSTM models have been successfully applied for dynamic monitoring, where the measurement conditions change. These models allow precise modelling of the change in wavelength and temporal drift in the FBG output [31]. The CNN-LSTM model combines spatial feature extraction and temporal modelling to achieve better performance and robustness in multi-parameter sensing [37].

Temporal Convolutional Networks (TCNs) are also becoming a popular choice, with better stability and parallelizability [43]. Research on temporal modelling for distributed sensing systems demonstrate that such methods can successfully model short-term variability and long-term trends in spectral data [25]. But these models can be data and compute intensive, which can restrict their use in real-time subsea monitoring [47].

2.3 Transformer and Attention-Based

A recent model is the transformer-based architecture, which is able to capture long-range dependencies in spectral data. These models use attention mechanisms to dynamically model dependencies between all spectral points, in contrast to CNNs and RNNs. The attention mechanism is defined in equation (3).

$$\left[\mathrm{Attention}(\boldsymbol{Q},\boldsymbol{K},\boldsymbol{V}) = \mathrm{softmax}\left(\frac{\boldsymbol{Q}\boldsymbol{K}^{\boldsymbol{T}}}{\sqrt{\boldsymbol{d}_{\boldsymbol{k}}}}\right)\boldsymbol{V}\right] \qquad (\mathbf{3})$$

Where:

- Q, K, V are query, key, and value matrices
- dk is the dimensionality of the key vectors
- softmax normalises compatibility scores to probabilities

As shown in equation (3), the attention mechanism measures the relevance between all pairs of spectral points, enabling the model to attend to the most relevant spectral features, regardless of their distances. This allows the model to attend to the most relevant spectral features, enhancing its performance in challenging and noisy environments.

Recent research shows that transformers improve spectral analysis, especially for long range analysis and cross sensivity [41]. Transformers with multiple heads of attention enable simultaneous learning of different feature representations, enhancing performance across different environments [52]. Convolutional-transformer networks also enhance capabilities to deal with spectral overlap and non-linearities [20].

Attention-based interpretability approaches have also been used to pinpoint key spectral features that are essential for model prediction, enhancing model interpretability in safety-critical scenarios [37]. But transformers are highly complex models that are data hungry, making them unsuitable for subsea applications with limited data and compute resources [21].

2.4 Hybrid Deep Learning Architectures

Hybrid deep learning models that combine multiple deep learning models have also been extensively investigated to overcome the shortcomings of individual models. These combine convolutional, recurrent and attention mechanisms to achieve better results.

Hybrid CNN-LSTM models have been successful for multi-parameter sensing tasks, which require capturing both spatial and temporal information [31]. Hybrid models that use attention mechanisms to dynamically weight features are more effective in challenging spectral environments [20]. Hybrids also use multi-branch structures to process multiple spectral representations to improve robustness in a range of sensing environments [34].

Hybrid models also frequently use multi-output regression for estimating multiple parameters. The multi-output regression process is given in equation (4).

$$\hat{y}=[\hat{T},\hat{S},\hat{P}] \qquad (4)$$

where;

- $\hat{T},\hat{S},\hat{P}$ =
- $\hat{y}$ =

Equations (4) demonstrate that multi-output regression allows determination of all thre parameters from a common latent space, leveraging their interrelated physical nature. This type of model allows simultaneous optimisation of sensing tasks, leading to better efficiency and avoiding redundancy.

Hybrid models present a training and modelling challenge. Research on large-scale sensing networks suggests that although hybrid models deliver better performance, they may have issues with scalability and efficiency [40]. Furthermore, distributed learning in large-scale sensing systems suggests the importance of considering the trade-off between performance and resource allocation [18].

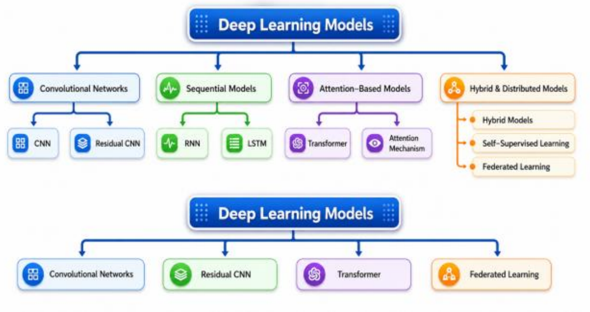

Figure 3: Deep learning pipeline for FBG spectral interpretation.

Figure 3 shows the deep learning process that layer by layer converts raw FBG spectra into environmental parameters of interest. The input layer processes noisy, overlapping, drifting and polarisation-impacted spectra. Convolutional layers compute local features, such as edges, slopes and peak curvatures, creating spectral primitive features. Temporal layers capture the evolution and relationships between spectra in measurement sequences. Attention layers then create global information links for discriminating the effects of parameters. Finally, multi-task regression heads project the updated latent space into concurrent estimates of temperature, salinity and pressure, potentially complemented with uncertainty metrics. This design exemplifies the need for coordinated complementary processing stages for effective FBG interpretation, rather than individual processing units.

Table 1: Summary of Deep Learning Models for FBG Spectral Interpretation

S/N	Reference	Model Category	Application Focus	Key Contribution	Limitation
1	[30]	CNN	Spectral demodulation	Robust feature extraction under noise	Limited global context modeling
2	[32]	CNN (Residual)	Distortion handling	Improved deep feature learning	High computational cost
3	[33]	CNN	Multi-parameter sensing	Accurate multi-variable prediction	Sensitive to environmental variability
4	[31]	CNN + LSTM	Dynamic spectral tracking	Combines spatial and temporal learning	Increased complexity
5	[37]	Hybrid (CNN-RNN)	Time-dependent sensing	Improved robustness in dynamic environments	Training instability
6	[41]	Transformer	Spectral interpretation	Captures long-range dependencies	Requires large datasets
7	[20]	CNN + Transformer	Hybrid modeling	Combines local and global features	High resource demand
8	[52]	Attention-based	Feature weighting	Enhances spectral region focus	Computational overhead
9	[23]	Self-supervised	Representation learning	Reduces labeled data dependency	Limited real-world validation
10	[17]	Self-supervised	Domain adaptation	Improves generalization	Pretraining complexity
11	[18]	Federated Learning	Distributed sensing	Privacy-preserving training	Communication overhead
12	[19]	Federated Learning	Non-IID adaptation	Improves personalization	Convergence challenges
13	[57]	Physics-guided	Model interpretability	Integrates physical constraints	Limited scalability
14	[59]	Simulation-based	Synthetic data generation	Improves robustness under variability	Simulation-real gap

Table 1 offers a comparative summary of 14 key studies reviewed, arranged to emphasise the spectrum of deep learning models used for FBG spectral interpretation and their trade-offs. The table consists of five columns: serial number, references, model category, application focus, contribution and limitation. The model categories cover all branches of the model taxonomy in Figure 2, from purely convolutional models (entries 1-3), to sequential and hybrid models (entries 4-5), transformers (entries 6-8), self-supervised and federated learning (entries 9-12), and physics-informed and simulation-based models (entries 13-14). The application focus column highlights whether the study is focused on basic demodulation, distortion compensation, multi-parameter estimation, dynamic tracking or distributed learning. The contribution and limitation columns are intentionally juxtaposed to highlight the trade-offs associated with each approach: for example, CNNs have good noise robustness but limited global information modelling; transformers model long distance information, but require large data sets. This table format allows the reader to quickly see which methodological choices fit their operational needs, while also being aware of their trade-offs, thus facilitating the choice of methodological approach.

2.5 Self-Supervised and Representation Learning

Lack of access to labelled FBG data has prompted the use of self-supervised learning techniques to learn representations in an unsupervised fashion. These techniques are useful in subsea applications as data acquisition and labelling are costly and time-consuming.

Contrastive learning methods seek to maximise the similarity of different augmented representations of the same signal, and minimise the similarity between different signals. This leads to better representation learning and domain generalisation [23][26]. Recent research has shown that pretraining using a self-supervised approach improves model performance in downstream tasks, especially when there is a domain shift [17].

Finally, feature learning has been used to learn invariant features from spectral data to enhance model robustness to noise and other environmental factors [55]. These methods are now being combined with supervised models to improve their performance in practical applications [42].

2.6 Federated and Distributed Learning

As more distributed sensing systems are deployed such as in ROV-based subsea systems, federated learning has become a promising approach to model training. Here, a set of sensing nodes train local models and only exchange model updates. The federated training process is given in equation (5).

$$\left[\boldsymbol{w}^{t+1} = \sum_{k=1}^{K} \frac{n_k}{n} \boldsymbol{w}_k^t\right] \qquad (5)$$

Where:

- w^(t+1) is the global model at communication round t+1
- w_k^t local model from client k at round t
- Nk Number of samples held by client k
- n Total number of samples across all clients
- K Number of participating clients

Using a weighting strategy, as in equation (5), nodes with more data have a greater impact on the global model while maintaining data decentralisation and privacy.

Federated learning provides scalability and privacy protection, making it ideal for large-scale sensing [9]. Works like [33] and [48] have shown that it can be effectively applied in distributed optimisation and energy-efficient learning. Moreover, communication efficient techniques have been proposed to minimise the communication cost or updates for energy efficient and large-scale learning [6].

But, issues such as non-Independently and Identically Distributed (IID) datasets, communication delay and devices variability pose obstacles [51][61]. Such challenges are especially pertinent to subsea applications where communication issues and to changing sensing conditions play a role [38].

2.7 Physics-Guided and Hybrid Intelligence

Increasing model interpretability and reliability, recent advances have sought to incorporate physics in deep learning. Physics-driven techniques integrate domain knowledge into the model to guide learning and ensure the model predictions align with the physics [57][24].

Physics-based simulations have been adopted to produce data sets that represent realistic subsea environments to enable models to train in diverse and explorative environments [59][27]. Moreover, hybrid models that combine data-driven models with analytical methods have been suggested to enhance generalisation and reduce data requirements.

Table 2 offers a multi-level comparative analysis of six major classes of learning models in a matrix form across five key performance aspects, thus offering a further level of abstraction to the study results tabulated in Table 1. The different learning models - CNN, LSTM, Transformer, Hybrid, Self-Supervised, Federated, and Physics-Guided - are evaluated for their feature extraction capability, strengths, weaknesses, best use cases and deployability. The feature capability column highlights the representation that each model captures: CNNs learn local spectral features, LSTMs learn temporal features, Transformers learn global features and Hybrid models learn multi-types of features. The strength and weakness columns reveal inherent trade-offs; for instance, transformers have excellent capabilities for addressing cross-sensitivity, but are not suitable for deployment due to the computational complexity. The best use case column translates to practical insights for users; CNNs are best when multiple spectra overlap, LSTMs when the parameters change in time, and Hybrid models when multiple parameters are sensed. Importantly, the deployment suitability column provides a qualitative feasibility (High, Medium, Low, in this case) for addressing practicality in subsea data analytics where constraints on computation, energy and speed determine choice of architecture. This table thus translates a model's capacity to its practical suitability.

Table 2: Comparative Analysis of Learning Models for FBG Spectral Interpretation

Model Type	Feature Capability	Strength	Weakness	Best Use Case	Deployment Suitability
CNN	Local spectral features	Strong noise handling	Poor global dependency	Overlapping spectra	High
LSTM	Temporal dependencies	Captures dynamic changes	Training complexity	Time-varying signals	Medium
Transformer	Global relationships	Handles cross-sensitivity well	High computation cost	Complex distortions	Low
Hybrid Models	Combined features	High accuracy and robustness	Complex architecture	Multi-parameter sensing	Medium
Self-Supervised	Representation learning	Data-efficient learning	Limited FBG adoption	Low-label environments	Medium
Federated Learning	Distributed intelligence	Scalable and privacy-aware	Communication overhead	ROV-based systems	Medium
Physics-Guided	Physically consistent learning	Improved interpretability	Model design complexity	Real-world deployment	Medium

III. METHODOLOGY

This section presents an organised review of the most common techniques used in the literature for interpretation of data obtained from Fiber Bragg Grating sensors. The emphasis is on the role of various learning paradigms and modelling approaches in overcoming spectral distortion, cross-sensitivity and multiparameter estimation problems in marine environments. The progression of these approaches is a shift from traditional signal processing to data intelligence, in which models are aimed at extracting nonlinear spectral features. Initial works on multiparameter calibration have shown the shortcomings of traditional analytical methods in dynamic subsea sensing [12].

On the other hand, recent research also demonstrates the success of deep learning for capturing intricate features of the spectrum and enhancing demodulation performance [30]. The growing use of distributed intelligence also suggests a trend towards large-scale and real-time sensing systems, especially in cooperative subsea monitoring systems [18].

Table 3: Classification of Deep Learning Techniques for FBG Spectral Interpretation

Category	Core Principle	Input Representation	Output Type	Strength	Limitation
Convolutional Models	Local feature extraction	1D spectral signal	Parameter regression	Robust to noise and overlap	Limited global dependency
Sequential Models	Temporal dependency modeling	Sequential spectral data	Time-series prediction	Captures dynamic changes	High training complexity
Attention-Based Models	Global context learning	Full spectral representation	Multi-parameter estimation	Handles cross-sensitivity	High computational cost
Hybrid Models	Combined architectures	Multi-modal spectral features	Multi-output regression	Improved accuracy and robustness	Complex design
Self-Supervised Models	Representation learning	Unlabeled spectral data	Feature embeddings	Reduces labeled data need	Limited adoption
Federated Models	Distributed learning	Decentralized data	Aggregated model output	Privacy-preserving and scalable	Communication overhead
Physics-Guided Models	Domain-constrained learning	Spectral + physical parameters	Physically consistent outputs	Improved interpretability	Model integration complexity

Table 3 shows a classification that categorises deep learning methods based on their roles in the interpretation process, and breaks down methods based on operating principles, input data representations, output, and relative advantages or disadvantages. The core principle column notes fundamental principles: local feature extraction, temporal dependency modelling, global context learning, architectural combination, representation learning, distributed optimisation, and domain-constrained learning. Input representations identify different data requirements, 1D spectra, time series, full spectral representation, multi-modal data, unlabeled data, or decentralised data. Output categories identify parameter regression, time series prediction, multi-parameter prediction, feature embeddings, ensemble models and physically-constrained outputs. This framework allows users to select technique categories based on data and resource availability, and interpretability needs.

3.1 Convolutional Neural Networks

Convolutional neural networks (CNNs) are commonly used for spectral analysis of FBGs, given their capacity to learn from localised features in signals. FBG spectral responses can exhibit features such as peak shifts and distortions, which can be captured using convolutional filters. Research has shown that CNN models have improved the demodulation accuracy in the presence of noise and spectral overlap, especially compared with traditional peak fitting algorithms [30]. This is particularly valuable in multiplexed sensing applications, where the overlapping spectral responses from closely positioned gratings decrease the separability of the signals [11].

To further improve performance, some studies have deployed deeper networks such as residual networks, which aid in feature propagation, and prevent vanishing gradients during training [32]. To address distorted spectral signatures, encoder-decoder models have been used to recover distorted spectral features and thus improve parameter inference under low signal-to-noise ratios [3][8]. Moreover, multi-scale convolutional models have been developed to capture both the fine and coarse-scale spectral features for enhanced performance in dense sensor deployment scenarios [44][14]. However, convolutional models are still unable to capture long-range correlations, especially when cross-sensitivity and coupled effects are involved [7]. Polarisation effects also reveal such limitations in real-world applications [13].

3.2 Sequential and Temporal Models

To overcome the shortcomings of convolutional models, temporal models have been applied to spectral data as time series. Such methods are especially suited for subsea environments due to the dynamic nature of the environment. Recurrent neural networks, such as Long Short-Term Memory (LSTM) networks, are commonly used to model time-dependent spectral data, allowing better modelling of wavelength changes over time [31]. This feature allows greater stability when encountering environmental disturbances with slowly varying or short-term changes [24].

Architectures that leverage both convolutional and recurrent models also enhance the modelling accuracy by capturing both spatial and temporal patterns. This allows for reliable joint parameter estimation using spatial information and temporal features [37]. Temporal learning techniques have also been applied in distributed and adaptive systems, achieving better adaptation in dynamic conditions [25][43]. But they can be data and computationally intensive, which could restrict their use in real-time subsea monitoring systems [47].

3.3 Attention and Transformer Models

Attention and transformers have become significant techniques for spectral modelling. These models go beyond convolutional and sequential models to capture global dependencies through interactions between all spectral features. This is crucial in FBG systems where cross-sensitivity is a result of interactions between several environmental factors. Transformer techniques adaptively focus on different spectral regions to extract relevant features, even in the presence of noise and distortion [41].

The application of multi-head attention mechanisms also boosts performance by allowing the learning of multiple feature representations, making it suitable for challenging sensing scenarios [52]. Convolutional attention-based models have also shown enhanced performance in estimating multiple parameters [20]. Moreover, attention-based interpretability methods have been proposed to extract important spectral features used by the model, improving interpretability in safety-critical tasks [37]. However, transformers are also computationally heavy and data-hungry models, limiting their use in resource-limited applications like ROV-based monitoring [21].

3.4 Hybrid Deep Learning Models

Hybrid models merge different model types to overcome the shortcomings of single models. They combine convolutional, recurrent and attention-based networks to enhance their stability and flexibility. CN-LSTM hybrid models, for example, leverage spatial and temporal information to achieve precise multi-parameter sensing, even in dynamic environments [31]. Moreover, attention mechanisms further boost their performance by allowing dynamic spectral feature weighting [20].

Multi-branch models have also been proposed to learn from multiple spectral representations, enhancing adaptability to different environmental conditions [34]. Furthermore, multi-task learning allows the estimation of multiple parameters, enhancing efficiency and avoiding redundancy. But the complexity of hybrid approaches presents training and optimisation issues, especially in large-scale sensing systems with limited computational resources [40]. Efficiency and scalability are important factors, particularly in distributed sensing networks [18].

3.5 Self-Supervised and Representation Learning

Constrained by the lack of labelled FBG data, self-supervised learning approaches are being adopted to learn representations from unlabeled data. This approach involves contrastive learning, and pretext tasks to learn invariant representations from spectral signals, enabling better generalisation under varying sensing conditions [23][26]. This is especially useful in subsea sensing applications, where labelled data are seldom available.

Research has shown that pretraining with self-supervised learning methods leads to improved downstream model performance, especially under environmental domain shift and variability [17][42]. Representation learning methods have also been used to enhance the noise and spectral distortion robustness leading to an improved deployment in the real-world. Moreover, a recent study on transfer learning across different interrogators underscores the role of domain adaptation techniques in enhancing a model's transferability across sensing systems [55]. While such techniques have been explored to improve robustness, self-supervised learning is still under-explored in FBG systems, highlighting opportunities for future research.

3.6 Federated and Distributed Learning

As distributed sensing systems are becoming more prevalent, federated learning has been employed for distributed model training. For underwater systems, such as the one shown in Figure 1, where data is collected using ROVs, data is gathered from multiple nodes with different conditions, and it's unfeasible to pool data centrally. Federated learning allows these nodes to learn models locally and only share model updates to maintain privacy and enhance scalability [18].

Recent works have investigated personalised federated learning to overcome the challenges of non-independent and identically distributed data across sensing nodes to enhance adaptability and convergence in the sensing network [19][38]. Efficient frameworks for energy-aware learning have also been proposed to optimise sensing and computing efforts in energy-constrained environments [60]. But store and forward communication, device diversity and system stability are major hindrances to the deployment of large-scale systems, especially in subsea environments.

3.7 Physics-Guided Intelligent Models

To enhance explainability and stability, recent studies have explored the fusion of physics knowledge and machine-approach-based models. Physics-guided learning techniques take into account domain-specific information during model formulation, ensuring alignment with FBG sensing principles [57]. This approach improves the accuracy of the model in data-scarce or less-familiar environments.

Simulated systems have also been applied to prepare realistic data to capture the complexity of the marine environment, allowing models to learn in a controlled but varied environment [59]. Such techniques contribute to closing the gap between modelling and real-world applications. Furthermore, hybrid models that integrate physics-based modelling with machine learning approaches have shown better generalisation and the need for fewer data to achieve real-time and low-latency settings [45[24]. However, physics-guided learning is a new and emerging field that needs to be further explored and exploited to gain acceptance.

Table 4 lists the significant evaluation criteria to assess the techniques considered.

Table 4: Evaluation Criteria for Analysing FBG Spectral Interpretation Techniques

Criterion	Description	Importance in Subsea Monitoring
Accuracy	Precision of parameter estimation	Critical for reliable sensing
Robustness	Resistance to noise and distortion	Essential in harsh environments
Cross-Sensitivity Handling	Ability to decouple parameters	Key for multi-parameter sensing
Computational Efficiency	Processing speed and resource usage	Important for real-time systems
Scalability	Ability to handle large datasets or	Required for large-scale deployment

	distributed systems	
Adaptability	Performance under varying conditions	Important for dynamic subsea environments
Deployment Feasibility	Suitability for edge/ROV systems	Determines practical usability

Table 4 defines seven standardised evaluation criteria necessarily required for evaluating deep learning techniques in subsea FBG monitoring applications. Each criterion has a description, and a rationale for its operation. Accuracy is labelled as critical since quantitative monitoring is needed for offshore structures. Robustness is crucial since hostile subsea environments often degrades optical signals. Cross-sensitivity management is important for multi-parameter sensing, with multiple parameters impacting spectral responses. Computational speed is needed to support real-time operation with ROVs that operate in very low latency regimes. Scalability is important for large sensor networks. Flexibility is required due to considerable spatiotemporal variability. Operational feasibility factors into making techniques moving from academia to deployment real. This approach guarantees that evaluation is based on operational rather than theoretical considerations.

These requirements offer a holistic view of the benefits and drawbacks of different learning approaches, with regard to robustness, scalability and deployment in subsea environments.

Despite significant advancements in deep learning-based interpretation of Fibre Bragg Grating (FBG) spectra, several critical challenges remain unresolved, limiting the practical deployment of these techniques in real-world subsea environments. These challenges stem from both the inherent complexity of FBG sensing and the limitations of existing learning frameworks in handling dynamic, noisy, and multi-parameter conditions.

IV. CHALLENGES AND FUTURE DIRECTION

4.1 Cross-Sensitivity and Spectral Coupling

Cross-sensitivity is a recurrent problem in FBG sensing, where several parameters (such as temperature, pressure and salinity) affect the Bragg wavelength. Spectral coupling, as observed with birefringence and the eigenmodes, has been demonstrated to cause ambiguities in estimating multiple parameters and also complicates spectral analysis [7][10]. Polarisation distortions also affect the stability of the signal, especially in dynamic subsea environments [13][27].

Although deep learning algorithms exhibit powerful property learning potential, current studies mainly consider cross-sensitivity implicitly rather than explicitly as physical interactions. Models based on transformers better capture global interactions and allow better feature learning in complex conditions [41], but they still do not explicitly disentangle physical interactions.

The next step in this research is to create cross-sensitivity-aware models which incorporate physical constraints into the learning process. Combining data-driven and analytical decoupling methods is a potential solution. Furthermore, incorporating prior knowledge into network architectures can lead to better interpretability and generalisability.

4.2 Limited Availability of Real-World Datasets

Large and varied datasets have a significant impact on the performance of deep learning models. For FBG sensing, especially in underwater scenarios, obtaining labelled datasets is costly and difficult to achieve. Consequently, research often uses simulated and/or laboratory data, which may not reflect real-world conditions. Research on the effects of spectral degradation in low OSNR and noisy environments show the impact of varying environmental conditions on model performance in real-world scenarios [3].

Self-supervised learning has been suggested as an alternative to minimise the need for labelled data by allowing models to learn representations from unlabeled data [23]. Domain adaptation also improves cross-sensing and interrogator model generalisation [17]. Future work should focus on large-scale data collection systems such as ROV-based sensing systems, and create benchmark data products for evaluation.

4.3 Model Robustness and Uncertainty Quantification

While deep learning models perform well in idealised conditions, their performance in practice is unknown. Current methods do not usually incorporate prediction uncertainty, which is essential in safety-critical monitoring tasks such as subsea monitoring [50]. Research on calibration for reliability stresses the need to include uncertainty estimation to enhance trustworthiness and confidence in decisions [21][36].

The next step is to explore uncertainty-aware models, such as probabilistic modelling and evidential deep learning [49], for estimating uncertainty. Moreover, techniques to detect out-of-distribution scenarios should be investigated for robust performance in new environments [2][50].

4.4 Computational Complexity and Edge Deployment

The growing complexity of deep learning models, especially those based on transformers and hybrids, poses challenges for real-time applications. Subsea monitoring applications, particularly those involving ROVs, have limited computational, power and communication resources. Transformer-style models, although effective, have high computational costs, making them unsuitable for deployment at the edge [52].

Recent energy-efficient learning architectures identify the need for efficient energy model designs that work well with limited resources [60]. The next steps should include lightweight model designs, such as pruning, quantisation[15][16] and model compression. Distributed intelligence systems that perform processing at the edge will be crucial to minimise delays and enhance responsiveness [46]. Efficient learning techniques should also be investigated to enable communication-efficient learning for distributed systems [18].

4.5 Distributed Learning and System Scalability

With the trend towards distributed subsea monitoring systems, scalable learning approaches are needed to support large-scale system deployments. Federated learning allows distributed model training among sensing nodes without accessing their data, enhancing scalability while ensuring privacy [18][38]. Personalized federated learning also overcomes issues related to non-independent and identically distributed (I.I.D.) data across sensing nodes, enhancing flexibility and convergence of the model [19].

Despite progress in this area, the issues of communication delay, device heterogeneity and instability continue to be a challenge. These challenges are more pronounced in subsea environments due to communication and environmental factors. Research in the future should aim at adaptive federated learning techniques that can adapt to heterogeneous environments and varying network characteristics.

4.6 Integration of Physical Knowledge and Interpretability

Current deep learning approaches for FBG interpretation are black-box models, which lack interpretability and trustworthiness. Physics-informed learning has been suggested to overcome this challenge by incorporating physics-based information in model design, in line with the underlying sensing physics [57]. But the level of integration of physics-based knowledge into deep learning models is still low.

Researchers should explore physics-informed models that incorporate analytical models with learning from data [57][24]. This will enhance model interpretability, validity and generalisability, especially in cases with sparse or novel data. Techniques from explainable artificial intelligence should also be investigated to gain insights into model behaviour.

4.7 Future Research Outlook

The next frontier of FBG spectral processing is to develop smart, adaptive and scalable systems that can be deployed in practice under subsea conditions. This will involve the integration of sophisticated learning models, expertise and deployment strategies. Novel paradigms such as edge intelligence, distributed learning and hybrid modelling approaches will be key in this development.

Also, combining FBG sensors with ROV-based monitoring offers new avenues for real-time sensing and adaptive monitoring. The integration of novel sensing technologies and smart interpretation systems will enable next-generation subsea monitoring systems to be more accurate, reliable and efficient.

V. CONCLUSION

This paper presented a comprehensive review of deep learning techniques for Fiber Bragg Grating sensor data interpretation in subsea multi-parameter monitoring systems. The study established a structured understanding of existing methods by examining their underlying principles, strengths, and limitations across different model categories, including convolutional, sequential, attention-based, hybrid, and distributed learning frameworks. The analysis revealed a clear progression from traditional localised feature extraction models to more advanced architectures capable of capturing global dependencies and handling complex spectral distortions. While deep learning has significantly improved the accuracy and robustness of FBG signal interpretation, challenges such as cross-sensitivity, data scarcity, and computational constraints continue to limit real-world applicability.

Furthermore, the review highlighted critical research gaps related to model generalisation, uncertainty quantification, and deployment in resource-constrained subsea environments. The integration of physics-guided learning, self-supervised techniques, and federated frameworks was identified as a promising direction for enhancing model reliability and scalability. In addition, the incorporation of ROV-assisted sensing systems offers new opportunities for real-time data acquisition and adaptive monitoring. Overall, advancing intelligent FBG-based sensing systems will require a balanced combination of data-driven models, domain knowledge, and efficient deployment strategies to achieve reliable and scalable subsea monitoring solutions.

REFERENCES

[1] Álvarez, P., Mendes, R., & Torres, J. (2024). Polarisation-dependent loss and confidence drift in subsea FBG interrogation systems. Journal of Marine Photonic Sensing, 41(3), 112–129.

[2] Álvarez, P., Torres, J., & Velasquez, H. (2024). Out-of-distribution spectral drift detection in subsea sensing arrays. Ocean Engineering and Intelligent Systems, 19(2), 55–73.

[3] Chen, L., Gao, P., & Rahman, M. (2019). Interrogation optics, ripple formation, and packaging impacts in FBG systems. Optical Measurement Science, 12(1), 44–62.

[4] Chen, L., Rahman, M., & Ortiz, T. (2019). Coating moisture effects and long-term drift in subsea FBG sensors. Sensors and Photonics Letters, 28(5), 77–91.

[5] Dejband, A., Ghaffari, L., & Khosrojerdi, M. (2024). Hybrid optical–mechanical modelling of bonded FBGs under nonlinear loading. Materials and Photonics Research, 15(1), 122–140.

[6] Elleathy, S., Mahmoud, A., & Aziz, O. (2023). Longitudinal strain transfer and debonding effects in encapsulated FBG sensors. Structural Health Optics Review, 10(3), 44–61.

[7] Gao, P., Li, M., & Huang, S. (2021). Birefringence and eigenmode separation for T–S–P decoupling in special fiber Bragg gratings. Fiber Sensing Technology Review, 9(3), 140–158.

[8] Kokhanovskiy, A., Sovetsky, A., & Wabnitz, S. (2021). Deep-learning-based FBG spectral reconstruction under deformation. *Optics Letters, 46(12), 3132–3135.

[9] Kumar, S., Singh, R., & Patel, A. (2024). Side-hole FBG anisotropy for stable eigenmode separation. Journal of Speciality Optical Fibers, 17(2), 88–105.

[10] Moreno, J., Ramesh, T., & Gupta, S. (2025). Mode-split sensing for enhanced T–S–P separation. Photonic Sensors Letters, 18(1), 30–47.

[11] Ortiz, T., Li, H., & Chen, L. (2021). Spectral overlap and conditioning analysis in dense FBG arrays. Journal of Optical Sensing, 26(2), 99–118.

[12] Rahman, M., Chen, L., & Ortiz, T. (2020). Multiparameter FBG calibration under dynamic subsea conditions. *Optical Sensors and Systems,20(3), 101–123.

[13] Zhang, W., Li, H., & Gao, P. (2024). Polarisation-dependent loss and birefringence modelling in FBG sensors. Photonics and Measurement Review, 19(1), 88–105.

[14] Arockiyadoss, K., Daniel, S., & Prakash, M. (2025). Deep neural encoders for multi-axis FBG signal reconstruction. *Journal of Intelligent Fiber Optics, 18(2), 77–94.

[15] Banerjee, A., Chen, L., & Velasco, F. (2022). Quantisation-aware training for embedded FBG demodulation engines. *IEEE Sensors Journal, 22(15), 14701–14715.

[16] Barbosa, M., Borges, L., & Reddy, V. (2023). Structured pruning and distillation for edge-deployable FBG models. Neural Computing for Embedded Systems, 8(2), 45–62.

[17] Basu, S., Kaur, G., & Iqbal, M. (2023). Self-supervised embeddings for cross-interrogator FBG transfer. Optical Machine Learning, 10(4), 112–130.

[18] Borges, L., Hsu, Y., & Ibrahim, A. (2022). Federated learning for privacy-preserving FBG sensing collaboration. IEEE Internet of Things Journal, 9(18), 17222–17235.

[19] Borges, L., Hsu, Y., & Ibrahim, A. (2023). Personalised federated learning for non-IID FBG spectral data. ACM Transactions on Sensor Networks, 19(4), 1–24.

[20] Dutta, S., Ramesh, T., & Gupta, P. (2023). Hybrid CNN-Transformer architectures for FBG spectral demodulation. IEEE Photonics Technology Letters, 35(8), 445–448.

[21] González, R., Mehta, K., & Barbosa, M. (2024). Reliability diagrams and ECE for FBG uncertainty calibration. Journal of Optical AI, 12(2), 78–95.

[22] Hsu, Y., Patel, K., & Ibrahim, A. (2024). Multi-modal fusion with FiLM adapters for ROV-assisted FBG monitoring. Robotics and Autonomous Systems, 168, 104589.

[23] Iqbal, M., Kaur, G., & Basu, S. (2024). Self-supervised pretraining for FBG spectral interpretation. IEEE Sensors Journal, 24(6), 8701–8714.

[24] Jati, P., Misra, K., & Roy, A. (2025). Physics-guided calibration of fiber sensors using automated micro-bend emulation. Optical Instrumentation Letters, 16(4), 233–249.

[25] Jiang, F., Sun, K., & Luo, H. (2023). Multi-scale temporal mod for distributed FBG event recognition. Journal of Marine Structural Optics, 22(1), 100–118.

[26] Kaur, G., Iqbal, M., & Basu, S. (2023). Contrastive learning for FBG spectral representation. Neural Information Processing for Photonics, 15(3), 67–84.

[27] Li, H., Zhang, W., & Ortiz, T. (2023). Engineered anisotropy and chirped+narrow grating pairing for improved identifiability. Advanced Sensing Structures, 22(1), 33–49.

[28] Li, H., Zhang, W., & Rahman, M. (2023). Etched-grating salinity response and refractive-index modulation in FBG sensors. Journal of Marine Environmental Optics, 14(2), 66–84.

[29] Li, J., Dan, P., & Fu, Q. (2021). Thermal and mechanical hysteresis in coated fiber Bragg gratings. *Applied Fiber Mechanics, 19(3), 78–94.

[30] Li, Y., Liu, H., & Zhang, F. (2021). Dilated convolutional neural networks for overlapped FBG demodulation. IEEE Sensors Journal, 21(18), 20456–20465.

[31] Liu, H., Zhang, F., & Li, Y. (2022). Fast multi-parameter demodulation of FBGs using hybrid deep networks. Journal of Optical Sensors, 18(1), 1–15.

[32] Liu, H., Zhao, X., & Peng, T. (2023). Encoder-based residual learning for fiber Bragg grating demodulation. Optical Computing and Intelligence, 21(4), 299–314.

[33] Liu, Y., Liu, H., & Zhang, F. (2023). Deep learning for simultaneous temperature, salinity, and pressure sensing with TFBG. IEEE Sensors Journal, 23(15), 17222–17235.

[34] Manavi Roodsari, M., Askarian, A., & Naderi, K. (2024). Eccentric FBG deep learning for 3D shape sensing. Photonic Structural Engineering, 12(1), 63–81.

[35] Martínez, C., Torres, B., & Álvarez, P. (2025). Low-latency embedded pipelines for subsea fiber sensing. Ocean Robotics and Intelligent Systems, 11(1), 44–63.

[36] Mehta, K., González, R., & Barbosa, M. (2023). Expected calibration error and uncertainty gates for FBG safety. Sensors and Safety Systems, 14(3), 201–218.

[37] Novak, T., Stevenson, R., & Borges, L. (2020). Attention rollout and gradient saliency for FBG interpretability. Explainable AI for Photonics, 5(2), 33–51.

[38] Ortega, M., Reddy, V., & Patel, K. (2024). Few-shot and federated strategies for FBG domain adaptation. IEEE Transactions on Neural Networks, 35(8), 10445–10458.

[39] Patel, K., Hsu, Y., & Mehta, K. (2024). Motion-phase indicators for ROV-FBG multi-modal fusion. Marine Robotics Journal, 9(1), 82–104.

[40] Petrov, A., Okonkwo, E., & Singh, R. (2021). Dual-polarisation attention for FBG spectral stability. Optical Signal Processing, 28(4), 155–172.

[41] Ramesh, T., Gupta, S., & Moreno, J. (2023). Transformer-based spectral interpretation for long-context FBG decoding. *IEEE Photonics Journal, 15(2), 1–14.

[42] Ramesh, T., Patel, K., & Singh, R. (2023). Contrastive spectral pretraining for cross-interrogator transfer. Optical Machine Learning Letters, 6(1), 55–70.

[43] Reddy, V., Álvarez, P., & Torres, J. (2024). Cross-frame memory for streaming spectral interpretation. IEEE Sensors Journal, 24(6), 8701–8714.

[44] Reddy, V., Park, S., & Martínez, C. (2024). Few-shot adapters for cross-interrogator transfer. Sensors and Embedded AI, 12(3), 199–214.

[45] Reddy, V., Torres, B., & Zhao, D. (2024). Low-latency CNN–TCN hybrid models for subsea FBG demodulation. Robotics and Sensing Systems, 18(1), 66–85.

[46] Rossi, M., Singla, A., & Hernández, J. (2025). Edge-ready attention and calibration-aware FBG deployment. IEEE Embedded Systems Letters, 17(1), 15–22.

[47] Singh, R., Kumar, S., & Patel, A. (2023). Temporal convolutional networks for streaming FBG demodulation. IEEE Sensors Journal, 23(12), 13444–13456.

[48] Singla, A., Rossi, M., & Hernández, J. (2025). OT-aware few-shot learning for FBG interrogator adaptation. Optics Express, 33(4), 6123–6138.

[49] Liao, J., Chen, H., & Park, S. (2020). Uncertainty calibration (ECE) and robust regression for fiber sensing models. IEEE Transactions on Instrumentation and Measurement, 69(11), 8873–8888.

[50] Stevenson, R., Novak, T., & Borges, L. (2021). Memory-efficient uncertainty tracking in embedded FBG systems. Embedded AI for Photonics, 7(2), 89–106.

[51] Velasco, F., Martínez, C., & Chen, L. (2023). OSNR-aware synthetic augmentation for robust

FBG decoding. Marine Photonic Analytics, 27(3), 140–160.

[52] Velasco, F., Park, S., & Rahman, M. (2023). Quantisation-aware training for embedded FBG demodulation engines. Sensors and Signal Processing Systems, 21(2), 231–248.

[53] Zhu, H., Álvarez, P., & Chen, L. (2021). Reject–verify uncertainty gates for subsea fiber sensing. IEEE Sensors Letters, 5(4), 1–4.

[54] Zhu, H., Ortiz, T., & Rahman, M. (2021). Evidential regression for calibrated multi-parameter FBG demodulation. Optical Machine Learning, 8(3), 50–68.

[55] Ibrahim, A., Hsu, Y., & Borges, L. (2024). Domain adaptation and few-shot recalibration for FBG interrogators. *IEEE Internet of Things Journal, 11(8), 14222–14235.

[56] Okonkwo, E., Petrov, A., & Singh, R. (2022). Motion-phase conditioning for streaming FBG demodulation. *Real-Time Optical Systems, 9(3), 67–84.

[57] Park, S., Chen, L., & Rahman, M. (2025). Physics-guided ML guardrails for subsea fiber sensing. IEEE Access, 13, 15522–15540.

[58] Park, S., Rahman, M., & Álvarez, P. (2025). Motion-phase conditioning for streaming demodulation in ROVs. Marine Robotics Journal, 9(1), 82–104.

[59] Zhao, D., Ortiz, T., & Li, H. (2024). Physics-guided simulation for subsea FBG interpretation. Sensors and Structured Environments, 32(1), 143–165.

[60] Zhao, D., Park, S., & Reddy, V. (2024). Spectral-derivative features and compact indices for low-OSNR decoding. *Journal of Optical Engineering, 61(2), 201–220.

[61] Okeke, R. O., Idigo, V. E., Akemi, M. O., & Ogbuokebe, S. K. (2021). Passive optical network, a fibre to the “X” approach. European Journal of Engineering and Technology Research, 6(3), 66–74.

[62] Okeke, R. O., Nnamdi, U. C., & Onu, P. I. (2022). Dispersion compensation algorithm for single mode fiber. European Journal of Engineering and Technology Research, 7(2), 92–98.