An AI-Driven Methodology for Classifying Transient Signals in the Evaluation of Optical Fiber Amplifiers

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***Abstract*—Transient testing of the Erbium-Doped Fiber Amplifier (EDFA) is crucial for assessing the transient response to abrupt channel add/drop occurrences in Dense Wavelength Division Multiplexing (DWDM) systems. Nevertheless, anomalous transient signals, frequently resulting from inadequacies in the testing apparatus or photodetector saturation, may result in erroneous computations of critical parameters, including overshoot, undershoot, gain offset, and settling time. This study presents an artificial intelligence-driven method for the automatic classification of normal and pathological transient signals in EDFA testing. The methodology entails preprocessing transient signals via uniform downsampling, implementing feature extraction techniques such as Classical Principal Component Analysis (PCA), Linear Discriminant Analysis (LDA), and Partial Least Squares–Discriminant Analysis (PLS-DA), and subsequently training and assessing five machine learning models (Naïve Bayes, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression, and Multi-Layer Perceptron (MLP)) for performance evaluation. Experimental findings demonstrate that the number of features and the extraction techniques substantially affect classification accuracy, Area Under the Curve (AUC), precision, recall, F1-score, and processing duration. The optimal performance was attained using 1000 features produced through uniform downsampling, integrated with PLS-DA and categorized using SVM, resulting in an AUC of 0.9977. The findings illustrate a dependable and effective AI-driven method for automated classification of transient signals, augmenting the validation of EDFA transient testing and potentially enhancing signal data analysis in the assessment of optical fiber communication systems.**

***Keywords*—artificial intelligence, Erbium-Doped Fiber Amplifier (EDFA), feature extraction, machine learning, transient signal, uniform downsampling**

I. Introduction

In contemporary times, optical fiber communication has emerged as a fundamental technology that underpins the ever-growing demand for data transfer. High-speed network systems specifically depend on Dense Wavelength Division Multiplexing (DWDM) systems, which provide the concurrent transmission of many optical channels. Optical networks extensively utilize the Erbium-Doped Fiber Amplifier (EDFA) as a crucial element to efficiently amplify these multi-channel wavelengths. The utilization of the EDFA is essential for enabling long-distance, high-speed data transmission and offering adaptability in network reconfiguration.

However, a significant concern related to the EDFA is the emergence of transients, which generally occur during the installation or removal of channels in the DWDM system. The resultant variations in optical power can induce overshoot and undershoot events, which directly impact signal quality by elevating the Bit Error Rate (BER) and diminishing overall system performance [1]. Furthermore, if the EDFA fails to manage these abrupt fluctuations adequately in output optical power, it may result in system instability, particularly in network architectures where numerous EDFAs are interconnected [2].

In the EDFA manufacturing sector, product development initiatives have concentrated on reducing transient effects, supported by specialized testing tools to assess the transient properties of the EDFA. A study presented an automated testing system created in Python to simultaneously manage many measuring devices and document real-time test findings, thereby minimizing human errors and enhancing the precision of transient characterization in the EDFA [1]. Simultaneously, an alternative method has combined Automatic Gain Control (AGC) approaches with artificial intelligence and neural networks to alleviate transient intensity and reduce system recovery time [2].

The transient test of an EDFA is performed to assess its reaction to abrupt variations in several input optical channels while preserving a consistent output gain for the surviving channel. The transient testing procedure often entails capturing and documenting the waveform with an oscilloscope. The collected data are subsequently analyzed by testing software to calculate several transient parameters, including overshoot, undershoot, gain offset, and settling time. Consequently, acquiring precise transient parameters necessitates the utilization of reliable transient signals during calculations. Should we obtain an anomalous transient signal, the computed parameters might not accurately represent the true transient characteristics of the EDFA. Abnormal transient signals may originate from various factors, including inadequacies in the testing apparatus or high optical power that saturates the photodetector in the optical receiver, leading to distorted transient waveforms on the oscilloscope.

This project seeks to create an artificial intelligence-based system that can classify normal and abnormal transient signals in EDFA testing prior to accurately calculating transient parameters for legitimate signals. The methodology utilizes machine learning algorithms alongside data reduction and feature extraction approaches to categorize transient waveforms obtained from the oscilloscope. This approach facilitates the automatic identification of anomalous signals that may otherwise result in erroneous parameter estimates; hence, it enhances the reliability and automation of EDFA transient characterization.

The researcher aims to improve the precision and dependability of the EDFA testing procedure through this study. The system is designed to autonomously identify and categorize anomalous transient signals before calculating essential transient characteristics, including overshoot, undershoot, gain offset, and settling time. This minimizes transitory measurement discrepancies and decreases the manual effort needed by engineers to examine signal waveforms. Moreover, the suggested methodology can be expanded to create automated systems for inspecting signal quality in additional optical fiber-based devices in production lines. This improvement enhances quality control efficiency, decreases testing duration and expenses, and facilitates the creation of more robust and standardized optical communication technologies.

II. Literature Review

A. Transient Signal

Fig. 1 illustrates a transient waveform together with its corresponding properties, such as overshoot, undershoot, settling time, and gain offset.

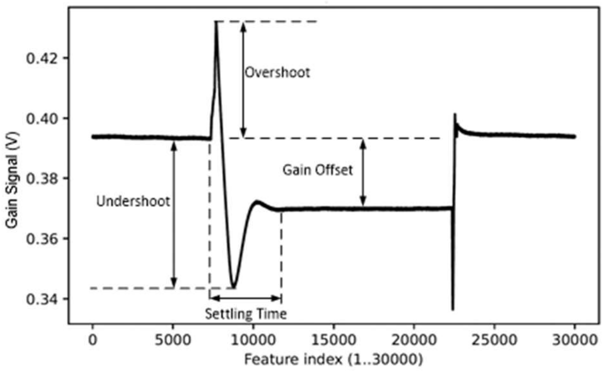

Fig. 1. Transient waveform of the EDFA.

As illustrated in Fig. 1, the overshoot and undershoot denote the maximum upward and downward deviations, respectively, of the surviving-channel gain in relation to the desired steady-state gain during transient conditions [1]. The settling time refers to the period necessary for the surviving-channel gain to undergo a sudden change and thereafter revert to a stable condition following the addition or removal of channels. The gain offset shows the difference in the steady-state gain of the surviving channel before and after the add or drop events.

B. Signal Pre-Processing

The input data comprises transient signal waveforms acquired via an oscilloscope, reflecting time-domain voltage measurements. The signals are archived as data files and thereafter aggregated and structured into a transient signal dataset containing 500 entries in total. The dataset comprises 70% normal transient signals and 30% aberrant transient signals.

The uniform downsampling methodology is a way of systematically lowering the number of data points rather than selecting them randomly or according to specific signal attributes. For instance, if an oscilloscope signal has 30,000 data points and the objective is to condense it to 1000, only one point of every 30 is preserved. The corresponding equation delineates the original signal as Eq. (1):

$$x[n], n = 0, 1, 2, \ldots, N-1 \tag{1}$$

where N denotes the total number of data points.

If the signal is to be downsampled by a factor of M (for example, $M = 30$), the downsampled signal can be expressed as Eq. (2).

$$y[m] = x[mM], m = 0,1,2, \ldots, \left[\frac{N}{M}\right] - 1 \tag{2}$$

where,

$x[n]$—Original signal data.

$y[m]$—Data after Uniform Downsampling.

M—Downsampling ratio.

$x[mM]$—Data sample of the original signal at index mM, where the index is formed by multiplying the downsampled index m by the downsampling ratio M.

The uniform downsampling approach is utilized to diminish the quantity of data points in the transient signal while completely maintaining the overall waveform features. This procedure reduces computational complexity and aids later phases of feature extraction and signal categorization. The technique samples data points at uniform intervals along the time axis, ensuring that the downsampled signal accurately preserves the shape and fundamental dynamics of the original waveform.

To prevent issues arising from an inadequate resampling rate beneath the necessary threshold, this method employs the principle of "retaining only every M-th sample" while discarding the remainder. For instance, sampling a signal at 40 kHz and subsequently downsampling by a factor of 2 will lower the sampling rate to 20 kHz, hence directly diminishing the sampling frequency [3].

The Nyquist–Shannon sampling theorem stipulates that to accurately sample a signal with a maximum frequency of f_{max}, the sampling rate must be no less than $2f_{\max}$ to prevent aliasing. In real applications, sampling at merely twice the maximum frequency frequently fails to maintain the integrity of waveform features. To ensure accurate digital representation and maintain signal fidelity [4], a higher sampling rate, typically 4 to 10 times the maximum frequency, is often employed.

This study comprises transitory signals, each consisting of 30,000 data points, with each point representing a time interval of $\frac{1}{3}$ microsecond. Thus, the overall signal duration is 10 milliseconds. The square pulse signal produced by the electronic function generator driving the device exhibits a rising and falling transition of approximately 300 points, corresponding to 100 microseconds (10 kHz). Consequently, to guarantee that the sampling process encompasses this frequency range, a sample rate of no less than 40 kHz to 100 kHz is necessary. This rate yields between 200 and 1000 data points per downsampled segment, effectively maintaining transient characteristics while optimizing computational efficiency.

Pan *et al.* [5] introduced various downsampling techniques for Electroencephalogram (EEG) signals, such as direct, average, and maximum decimation, to diminish the computing complexity of a deep learning-based epilepsy detection system. While their research concentrated on EEG data, the core principle of uniform temporal sampling reduction aligns with the uniform downsampling method utilized in this study.

C. Feature Extraction Method

Following the signal pre-processing phase, feature extraction is a vital step that allows the classifier to group datasets into distinct classes based on the values of pertinent features obtained from the signals [6]. This study utilizes 3 feature extraction techniques.

1) Principal Component Analysis (PCA)

The PCA technique is employed for the reduction of data dimensionality while maintaining maximal data variability. It converts the original variables into a new collection of uncorrelated principal components, arranged in descending order of their variances. The components are derived using eigenvalue-eigenvector decomposition or Singular Value Decomposition (SVD), of the mean-centered data matrix. When variables exhibit disparate scales, normalization is advisable, and the correlation-matrix PCA approach should be utilized to achieve more accurate findings. The quantity of principal components is generally determined by the ratio of explained variance. PCA functions primarily as an exploratory and descriptive instrument, necessitating no assumptions on data distribution in this setting [7]. The computation of the covariance matrix and the extraction of eigenvectors in PCA commences with the calculation of the mean of all data samples, represented as Eq. (3).

$$\bar{x} = \frac{1}{M}\sum_{i=1}^{M} x_i \tag{3}$$

where, $\bar{x}$ denotes the mean vector computed over all data samples, M denotes the number of observations, and x_i represents the i^{th} data vector. Each data vector is then mean-centered by subtracting the mean vector $\bar{x}$ from each observation to obtain the mean-centered sample a_i as Eq. (4).

$$a_i = x_i - \bar{x} \tag{4}$$

This step ensures that the dataset has zero mean across all dimensions. The covariance matrix C, which characterizes the degree of correlation among different variables, is computed as Eq. (5).

$$C = \frac{1}{M-1}AA^T = \frac{1}{M-1}\sum_{n=1}^{M} a_n\, a_n^T \tag{5}$$

where A is the matrix of centered data vectors. The superscript T denotes the transpose of the corresponding matrix. To identify the principal directions of maximum variance, the eigenvalue problem is solved as Eq. (6).

$$Cy_j = \lambda_j y_j \tag{6}$$

where y_j and λ_j denote eigenvectors and their corresponding variance contributions. The number of retained components is selected based on cumulative explained variance, ensuring compact representation while discarding redundant information.

2) Linear Discriminant Analysis (LDA)

LDA, which stands for linear discriminant analysis, is a supervised learning methodology that divides the input space into several decision regions, delineated by decision boundaries. The purpose is to categorize data samples into separate classes using linear decision functions [8]. Belhumeur *et al.* [9] state that Fisher's Linear Discriminant (FLD) seeks to identify an ideal linear projection matrix W_{opt} that maximizes the ratio of between-class scatter to within-class scatter. This optimization problem is characterized as Eq. (7).

$$W_{opt} = \arg\max_{W} \frac{|W^T S_B W|}{|W^T S_W W|} = [w_1\, w_2\, \dots w_m] \tag{7}$$

where, W denotes the linear projection matrix composed of the discriminant vectors w_i. S_B is the between-class scatter matrix and S_w is the within-class scatter matrix, expressed respectively as Eq. (8) and Eq. (9).

$$S_B = \sum_{i=1}^{c} N_i\, (\mu_i - \mu)(\mu_i - \mu)^T \tag{8}$$

$$S_W = \sum_{i=1}^{c} \sum_{x_k \in X_i} (x_k - \mu_i)(x_k - \mu_i)^T \tag{9}$$

where c denotes the number of classes, N_i the number of samples in class i, μ_i the mean vector of class X_i, μ the global mean vector across all classes, and x_k represents the k^{th} data vector belonging to X_i. The eigenvectors w_i are obtained by solving the generalized eigenvalue problem as Eq. (10).

$$S_B w_i = \lambda_i S_W w_i \tag{10}$$

The corresponding eigenvalues λ_i represent the discriminative strength of each projection direction. The dimensionality of the discriminant subspace is limited to $c-1$, so $W_{opt} = [w_1\, w_2\, \dots w_m]$ with $m \le c - 1$

3) Partial Least Squares-Discriminant Analysis (PLS-DA)

The PLS-DA technique has been extensively utilized as both a feature selection method and a classifier for high-dimensional data. Ruiz-Perez *et al.* [10] indicated that PLS-DA showed exceptional efficacy when the class structure displays clustered distributions inside a signal-bearing subspace, even in the presence of several extraneous factors obscuring the pertinent characteristics. This strategy remains effective when the classes are arranged as N-orthotopes. In instances when class separation relies predominantly on general linear or nonlinear correlations, PLS-DA may offer restricted insights compared to alternative methods like PCA. Rosipal *et al.* [11] proposed PLS-DA is a supervised dimensionality reduction method based on Partial Least Squares (PLS) regression, intended to model the association between the predictor matrix $X \in R^{nxN}$ and the class membership matrix $Y \in R^{n \times M}$. Both matrices are decomposed as Eq. (11) and Eq. (12).

$$X = TP^T + E \tag{11}$$

$$Y = UQ^T + F \tag{12}$$

where T and U are matrices of latent score vectors, P and Q are loading matrices, and E and F are residuals. The superscript T denotes the transpose of the corresponding matrix. By aligning the extracted components with class-relevant variation, PLS-DA provides improved separability between normal and abnormal waveforms, particularly in scenarios where the discriminative structure resides in correlated multidimensional subspaces. In this work, PLS-DA demonstrated strong effectiveness in extracting discriminative features for abnormal-signal detection.

D. Classifiers

This research utilizes 5 machine learning models: Naïve Bayes (NB), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Logistic Regression (LR), and Multi-Layer Perceptron (MLP), a type of artificial neural network.

The Naïve Bayes method is a probabilistic machine learning technique based on Bayes' theorem that is widely used for classification tasks. This algorithm functions under the assumption of feature independence, indicating that each characteristic is regarded as independent of the others, conditional on the class label [12]. Stanescu *et al.* [13] utilized the Naive Bayes classifier as one of three classifiers, alongside Support Vector Machine and K-Nearest Neighbors, after extracting phase-diagram characteristics from power-grid transient signals. The NB model was then employed to identify 3 categories of transitory phenomena:

- high-amplitude, long-duration events.
- periodic pulse trains.
- partial discharges.

The Support Vector Machine is a traditional classification technique aimed at identifying a hyperplane in a multi-dimensional space that optimally divides data into various groups [14]. Stanescu *et al.* [13] employed SVM as a multiclass classifier by partitioning the problem into several binary one-to-one subproblems, determining the best separation hyperplane for each class pair. The classification delineation is contingent upon the kernel type utilized; in their research, a second-order polynomial kernel was employed. The SVM model was trained utilizing phase-diagram features, such as Phase-Diagram Entropy (PDEn), Angular Mean (AM), Length of the First Gap (LFG), and Spatial Entropy (SE), to categorize 3 types of transient occurrences seen in an actual 3-phase power system:

- strong/long bursts from external loads.
- periodic pulses.
- cable partial discharges.

The K-Nearest Neighbors algorithm is a straightforward instance-based classifier that designates a class to a new sample according to the predominant class among its nearest neighbors in the feature space. Averyanov *et al.* [15] conducted a study on transient signal classification using the KNN model, analyzing characteristics derived from current and voltage waveforms. The experimental findings demonstrated an accuracy of 0.78 and a precision of 0.794, which were roughly 7–8% inferior to those achieved with a decision-tree baseline model, albeit with reduced processing time. Furthermore, the authors indicated that KNN is susceptible to outliers frequently present at the onset of the transitory process.

Logistic Regression is a linear probabilistic classifier that determines class membership probability by utilizing the logistic function on a linear amalgamation of input features. Despite being fundamentally a binary classifier, logistic regression can be adapted for multiclass situations using the one-vs-rest strategy, wherein an individual logistic regression model is developed for each class against all remaining classes, and the ultimate prediction is established by evaluating the resulting decision boundaries. Averyanov *et al.* [15] identified the features with the greatest connection to the target variable prior to training a multiclass logistic regression model in their work on transient signal categorization. Despite the class structure demonstrating partial linearity owing to the inclusion of the binary variable Short-Circuit Transient (SCT), the logistic regression model attained an accuracy of 0.57 and a precision of 0.57, both inferior to those reached by the decision-tree and KNN models.

Artificial Neural Networks (ANN) are utilized as data-driven classifiers for Transient Stability Assessment (TSA). The subsequent applications have been documented.

1) Multilayer feedforward networks for online TSA assessment.
2) Classifiers for fault-induced transients, including the differentiation between stable and loss-of-excitation circumstances, as well as for encoding and estimating the Critical Clearing Time (CCT).
3) Deep models employing Phasor Measurement Unit (PMU) data, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, have been utilized to categorize brief post-disturbance intervals into stable, aperiodic-unstable, or oscillatory-unstable classification.

In addition, the survey also mentioned ANN architectures capable of directly estimating the Critical Clearing Time (CCT) for short-circuit or line-outage scenarios [16].

III. Methodology

To improve the efficacy of distinguishing normal and abnormal transient signals through machine learning models, the methodology and procedural framework of this study are illustrated in Fig. 2, which seeks to establish a suitable solution for consistent downsampling and feature extraction of transient signal datasets acquired from an oscilloscope during the EDFA testing. The transient signal dataset was first processed using uniform downsampling to reduce the original 30,000 samples into compact feature sets of 10,000, 1000, and 100 features, preserving waveform characteristics while decreasing computational complexity. 3 feature extraction techniques PCA, PLS-DA, and LDA were then applied to improve separation between normal and abnormal waveforms, and the resulting features were used for model training.

The dataset was divided into 70% training and 30% testing, using stratified sampling to maintain class proportions This ensured that the class distributions were preserved throughout the data partitions and prevented sampling bias. For Naïve Bayes, SVM, KNN, and Logistic Regression, hyperparameter optimization and performance assessment were conducted via 5-fold stratified cross-validation within the training subset, enabling performance to be reported as mean ± standard deviation across folds.

The MLP model employed a validation split from the training subset and incorporated early stopping and regularization to reduce overfitting. The close agreement between training and validation metrics indicated stable model behavior and generalization.

All models were finally evaluated using the unseen 30% test set, with performance measured using AUC, precision, recall, accuracy, and F1-score. Confusion matrices were also generated to visualize prediction distributions and support reliability assessment of the classification results.

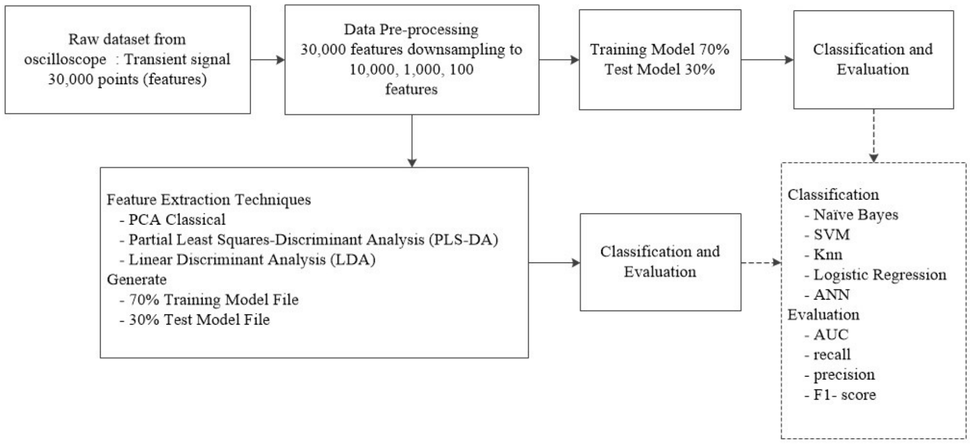

Fig. 2. The framework of methodology.

The transient signal dataset was obtained from the oscilloscope in the transient testing system, as shown in Fig. 3. The system comprises a full-comb optical source that produces multiple wavelength channels, which are then injected into an Acousto-Optic Modulator (AOM) to emulate the addition or removal of channels in a DWDM system. An electronic function generator controls the AOM. It switches between ON and OFF states at set time intervals to create transients in the system.

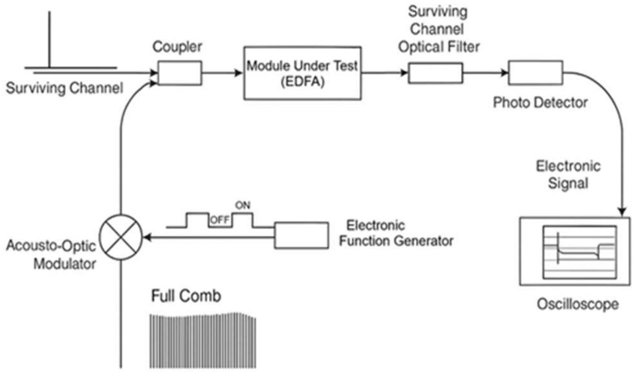

Fig. 3. EDFA transient test diagram.

Simultaneously, one channel in the system is identified as the primary channel, which remains perpetually active. This channel is connected to the signals from the AOM through a coupler and thereafter directed into the module under examination (EDFA), which functions as the optical amplifier being assessed.

Following amplification, the output signal from the EDFA is subjected to filtration via a surviving-channel optical filter to isolate the desired wavelength. The filtered signal is subsequently transmitted to a photodetector, which transforms the optical signal into an electrical signal. The electrical waveform is ultimately transmitted to an oscilloscope to document the time-domain transient reaction. The ephemeral data obtained from the oscilloscope is subsequently utilized for processing and analysis through machine learning algorithms. The experimental protocol of this study has 3 primary phases, detailed as follows.

A. Data Acquisition and Preprocessing

The transient waveforms acquired from the oscilloscope were saved as time-series data files, each including 30,000 data points. This investigation collected 500 transient signal samples. The dataset was divided into 2 categories: normal transient signals, comprising 70% of the total samples, and abnormal transient signals, including the remaining 30%. To ensure the reliability of the dataset and the accuracy of model training, a structured labeling and preprocessing procedure was implemented as described below.

1) Normal and abnormal transient waveform criteria

A waveform was classified as normal if it exhibited physically consistent transient behavior, including the presence of measurable overshoot and undershoot responses followed by stabilization at steady-state gain levels, as illustrated in Fig. 4 that depicts instances of normal transient waveforms demonstrating characteristic responses, including fast overshoot and undershoot, which thereafter stabilize at steady-state levels.

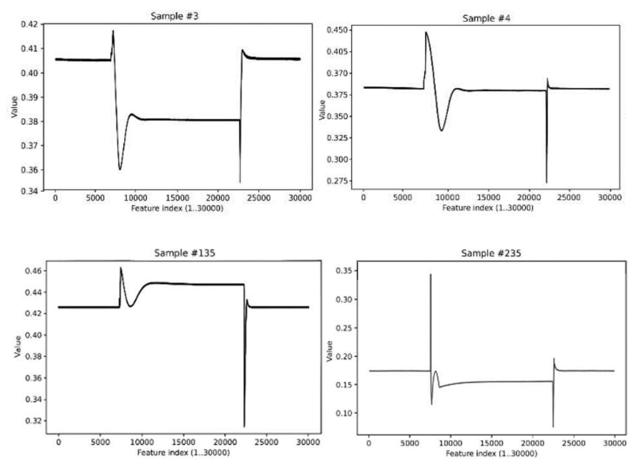

Fig. 4. Normal transient waveform.

In contrast, a waveform was classified as abnormal if it displayed non-physical or corrupted characteristics, such as excessive noise, clipped transitions, flat-line behavior, or distorted response dynamics beyond expected EDFA operational limits, as illustrated in Fig. 5.

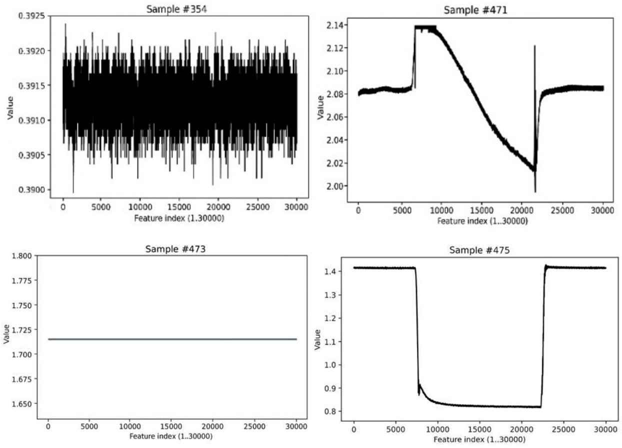

Fig. 5. Abnormal transient waveform.

2) Labeling procedure and annotation

The labeling process was conducted manually by a group of optical test engineers familiar with EDFA transient characterization. Normal waveforms were assigned label 1 (Negative) and abnormal waveforms were assigned label 0 (Positive).

To ensure labelling reliability, cross-checking among multiple annotators was performed and quality control was maintained by re-checking randomly selected sample to ensure label consistency and adherence to the classification criteria.

3) Uniform downsampling

To establish a suitable methodology for data preparation and enhance the efficiency of transient signal classification in terms of performance and processing time, the uniform downsampling technique was utilized to systematically decrease the data points from 30,000 to 10,000, 1000, and 100 points per transient signal, while maintaining the fundamental waveform characteristics. This procedure was employed to assess categorization accuracy and processing duration. Uniform downsampling significantly decreases computing burden and processing duration. The dataset including 1000 data points was subsequently chosen and underwent feature extraction.

B. Feature Extraction

Following the consistent reduction of the transient signal data to 1000 points, feature extraction techniques were employed to convert the dataset into a format conducive to assessing the efficacy of machine learning models. The methods utilized comprise PCA, LDA, and PLS-DA. The aim of these feature extraction procedures is to minimize data redundancy and improve the capacity to differentiate between normal and aberrant transient signals.

C. Classification and Evaluation

The present research assessed the efficacy of the proposed data preparation methods, namely uniform downsampling and Feature Extraction, by utilizing five classification techniques: NB, SVM, KNN, LR, and MLP. Each classifier was trained with its default parameter settings to maintain a consistent foundation for comparing results across various models.

The classifiers' performance was assessed using the Area Under the Curve (AUC) metric, which illustrates the correlation between the True Positive Rate (TPR) and the False Positive Rate (FPR). The AUC value spans from 0 to 1, with a value approaching 1 signifying superior classification performance of the model [17]. Furthermore, other evaluation measures like Recall, Precision, and F1-score were utilized to further evaluate the model's correctness and its proficiency in accurately identifying samples inside each class. The processing duration was assessed to gauge the computational efficiency and feasibility of model implementation within the testing system.

This research technique includes the complete process of transient signal data preparation, uniform downsampling, feature extraction, machine learning model training, and performance evaluation utilizing standard metrics. The aim is to formulate a proficient method for diminishing and extracting features from transient data acquired during EDFA testing, thus optimizing the classification efficacy of transient signals.

D. Implementation Details

This subsection provides the key implementation details required for reproducibility, including the software environment, model settings, dimensionality reduction parameters, and hardware platform.

1) Programming language and main libraries

Python 3.13.5 with Spyder 6.07, using NumPy, Pandas, Scikit-Learn, Matplotlib, and TensorFlow/Kears.

2) Model hyperparameters

The Naïve Bayes classifier was implemented using GaussianNB() with default smoothing parameters. The SVM model employed an RBF kernel for nonlinear separation in the transformed feature space. The KNN classifier used K = 5 neighbors for distance-based classification. Logistic Regression was trained using the liblinear solver with a maximum of 2000 iterations for convergence. Finally, the MLP neural network consisted of 2 fully connected hidden layers with 128 and 64 neurons, respectively, using ReLU activation functions.

3) Retained components in PCA/LDA/PLS-DA

PCA retained components covering 95% variance, LDA yielded one discriminant component for the binary classification, and PLS-DA retained 10 latent components.

4) Hardware environment

All experiments were executed on a Lenovo ThinkPad T480 with an Intel Core i5-8350U CPU (4 cores, 8 threads, 1.70 GHz) and 32 GB RAM, without GPU acceleration.

IV. Result and Discussion

This section elucidates and analyzes the experimental outcomes derived by assessing diverse machine learning models alongside data reduction and feature extraction methodologies. The aim of the investigation is to examine the influence of uniform downsampling and feature extraction algorithms on the classification efficacy of transient signal datasets obtained from EDFA testing.

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A. Performance Overview

Each model was evaluated with conventional performance indicators as outlined below.

The NB model achieved optimal performance with the uniform downsampling method and PLS-DA feature extraction, as detailed in Table 1. The model produced exceptional values for all performance parameters, with AUC = 0.9913, F1-score = 0.8217, Recall = 0.8400, and Precision = 0.8602.

Table 1. Results for Naïve Bayes on test set

Model	Technique	AUC	F1-score	Recall	Precision	Training Time	Testing Time
Naïve Bayes	Original dataset (30,000 features)	0.6571	0.7510	0.7867	0.8068	6.689	0.109
	Downsampling (10,000 features)	0.6571	0.7510	0.7867	0.8068	2.019	0.003
	Downsampling (1000 features)	0.6571	0.7510	0.7867	0.8068	0.245	0.004
	Downsampling (100 features)	0.6587	0.7510	0.7867	0.8068	0.092	0.001
	Downsampling (1000 features) + PCA	0.8315	0.7510	0.7867	0.8068	0.149	0.002
	Downsampling (1000 features) + LDA	**0.9913**	**0.8217**	**0.8400**	**0.8602**	0.116	0.001
	Downsampling (1000 features) + PLS-DA	0.8491	0.7567	0.7867	0.8068	0.130	0.001

Table 2. Results for SVM on test set

Model	Technique	AUC	F1-score	Recall	Precision	Training Time	Testing Time
SVM	Original dataset (30,000 features)	0.9748	0.7510	0.7867	0.8068	1006.700	0.676
	Downsampling (10,000 features)	0.9956	0.9525	0.9533	0.9543	302.280	0.134
	Downsampling (1000 features)	0.9853	0.9525	0.9533	0.9543	22.390	0.028
	Downsampling (100 features)	0.9858	0.9569	0.9600	0.9622	6.494	0.005
	Downsampling (1000 features) + PCA	0.3962	0.7625	0.8000	0.8444	6.455	0.012
	Downsampling (1000 features) + LDA	0.9833	0.9540	0.9533	0.9570	5.910	0.002
	Downsampling (1000 features) + PLS-DA	**0.9977**	**0.9668**	**0.9667**	**0.9670**	6.133	0.003

The SVM model, in conjunction with the uniform downsampling method and PLS-DA feature extraction, got the highest AUC value of 0.9977 among all machine learning models. It yielded the highest results for the F1-score, Recall, and Precision, with values of 0.9668, 0.9667, and 0.9670, respectively, as shown in Table 2.

The KNN model, in conjunction with the uniform downsampling approach and LDA, attained the highest AUC performance. The integration of uniform downsampling and PLS-DA produced the greatest metrics across all machine learning models for the F1-score, Recall, and Precision, with values of 0.9933, 0.9933, and 0.9934, respectively, as presented in Table 3.

Table 3. Results for KNN on test set

Model	Technique	AUC	F1-score	Recall	Precision	Training Time	Testing Time
KNN	Original dataset (30,000 features)	0.9746	0.9668	0.9667	0.9670	44.256	0.138
	Downsampling (10,000 features)	0.9746	0.9668	0.9667	0.9670	14.632	0.124
	Downsampling (1000 features)	0.9746	0.9668	0.9667	0.9670	2.083	1.535
	Downsampling (100 features)	0.9666	0.9668	0.9667	0.9670	0.493	0.010
	Downsampling (1000 features) + PCA	0.9917	0.9535	0.9533	0.9537	0.638	0.004
	Downsampling (1000 features) + LDA	**0.9941**	0.9735	0.9733	0.9741	0.680	0.014
	Downsampling (1000 features) + PLS-DA	0.9889	**0.9933**	**0.9933**	**0.9934**	0.845	0.013

The LR model, in conjunction with the uniform downsampling method and LDA feature extraction, attained the optimal overall performance. The evaluation results, presented in Table 4, provide superior values for all important performance metrics: AUC, F1-score, Recall, and Precision, with respective values of 0.9913, 0.9688, 0.9667, and 0.9670.

The MLP model, in conjunction with the uniform downsampling approach and LDA feature extraction, attained the maximum performance regarding AUC. The integration of uniform downsampling and PLS-DA feature extraction produced the most favorable outcomes. The evaluation results, presented in Table 5, indicate enhanced values for the F1-score, Recall, and Precision, with respective values of 0.9801, 0.9800, and 0.9802.

Table 4. Results for logistic regression on test set

Model	Technique	AUC	F1-score	Recall	Precision	Training Time	Testing Time
Logistic Regression	Original dataset (30,000 features)	0.9826	0.9542	0.9533	0.9596	160.330	0.036
	Downsampling (10,000 features)	0.9545	0.8967	0.8933	0.9160	37.357	0.011
	Downsampling (1000 features)	0.9331	0.8464	0.8400	0.8886	4.402	0.005
	Downsampling (100 features)	0.3970	0.7625	0.8000	0.8444	1.081	0.004
	Downsampling (1000 features) + PCA	0.3962	0.7625	0.8000	0.8444	0.297	0.002
	Downsampling (1000 features) + LDA	**0.9913**	**0.9688**	**0.9667**	**0.9670**	5.544	0.002
	Downsampling (1000 features) + PLS-DA	0.9663	0.9607	0.9600	0.9647	5.155	0.004

Table 5. Results for MLP on test set

Model	Technique	AUC	F1-score	Recall	Precision	Training Time	Testing Time
MLP	Original dataset (30,000 features)	0.9344	0.9030	0.9067	0.9098	20.520	0.166
	Downsampling (10,000 features)	0.9113	0.8248	0.8200	0.8363	20.470	0.135
	Downsampling (1000 features)	0.9234	0.8901	0.8933	0.8932	10.490	0.127
	Downsampling (100 features)	0.9323	0.9038	0.9067	0.9075	7.370	0.097
	Downsampling (1000 features) + PCA	0.9211	0.8901	0.8933	0.8932	14.440	0.110
	Downsampling (1000 features) + LDA	**0.9913**	0.9735	0.9733	0.9741	9.990	0.124
	Downsampling (1000 features) + PLS-DA	0.9812	**0.9801**	**0.9800**	**0.9802**	21.230	0.130

The experimental findings illustrate the performance variations among the machine learning models under various uniform downsampling and feature extraction configurations. The principal conclusions are encapsulated as follows.

The LDA and PLS-DA approaches significantly enhanced both classification performance (F1-score) and discriminative capability (AUC) in all models, especially in SVM, KNN, and MLP. This discovery demonstrates that linear feature extraction techniques prioritizing inter-class separability significantly diminish redundancy and improve classifier decision bounds. PCA, however, often diminished the efficacy of specific models, like SVM and LR, as it prioritizes the reduction of data dimensionality by preserving only the axes of largest variance, which may not correspond with the axes that optimally differentiate the classes.

The experimental findings indicated that KNN and MLP attained the highest overall performance, with AUC values surpassing 0.99 and F1-scores over 0.98. These results demonstrate the robust ability of both models to proficiently manage data characterized by non-linear decision limits. Despite being fundamentally a linear model, LR yielded results comparable to SVM when integrated with the LDA approach, which improves linear separability among classes. Simultaneously, SVM attained an exceptional F1-score and Recall, especially with PLS-DA features, illustrating its capacity to classify signals with accuracy and consistency while maintaining a favorable Precision–Recall balance.

The experimental findings showed that uniformly reducing the dataset to 1000 data points efficiently preserved a high degree of model performance while substantially saving training time compared to the complete 30,000-point dataset. This discovery aligns with the notion of dimensionality reduction, which reduces computing load and data redundancy while maintaining classification efficacy. Nevertheless, when the data points were further diminished to 100, a decrease in accuracy was noted in certain models, such as Naive Bayes and Logistic Regression, suggesting that extreme data reduction may result in the loss of critical transient signal attributes.

The temporal study indicated that the integration of uniform downsampling and feature extraction methodologies substantially decreased the model training duration. The training duration of the SVM model significantly reduced from 1006 s (about 17 min) to merely 6 s while employing PLS-DA. Despite the MLP necessitating a rather extended training duration as a deep learning model, it remained feasible for real-world implementation in automated testing systems, achieving an average processing time per signal of under 0.15 s.

B. Per-Class Metrics

Although all 5 classification models (NB, LR, SVM, KNN, and MLP) were initially evaluated, per-class analysis in this section focuses specifically on SVM, KNN, and MLP because these models demonstrated the highest overall classification performance and achieved ROC-AUC values exceeding 0.99. Additionally, these 3 models offer complementary behavior: SVM provides maximum class separability, KNN exhibits aggressive fault detection with high abnormal sensitivity, and MLP delivers balanced learning capability via nonlinear representation. Therefore, they represent the most relevant candidates for deeper per-class evaluation and discussion.

To further examine model behavior for each class (normal vs. abnormal), per-class precision, recall, and F1-score were computed for SVM, KNN, and MLP using PLS-DA with 1000 features. As summarized in Table 6, all 3 models deliver high discriminative capability; however, the difference between performance on abnormal (class 0) and normal (class 1) reveals important insights regarding model sensitivity to fault detection.

For the abnormal class (class 0), KNN achieved the strongest overall performance with a precision of 1.0000 and recall of 0.9778, resulting in an F1-score of 0.9888. This indicates that KNN produced zero false positives for classifying abnormal signals and missed only one actual abnormal sample (out of 45), demonstrating highly conservative detection behavior.

Table 6. Per-class metrics for SVM, KNN, and MLP

Model	Technique	Class	Precision	Recall	F1-score	Support
SVM	Downsampling (1000 features) + PLS-DA	0 (abnormal)	0.9348	0.9556	0.9451	45
		1 (normal)	0.9808	0.9714	0.9761	105
KNN	Downsampling (1000 features) + PLS-DA	0 (abnormal)	1.0000	0.9778	0.9888	45
		1 (normal)	0.9906	1.0000	0.9953	105
MLP	Downsampling (1000 features) + PLS-DA	0 (abnormal)	0.9565	0.9778	0.9670	45
		1 (normal)	0.9904	0.9810	0.9856	105

In contrast, SVM yielded a precision of 0.9348 and recall of 0.9556 (F1-score = 0.9451) for the abnormal class, showing that although its class-separation capability is high, it produced more false positives and false negatives than

KNN. Meanwhile, MLP achieved precision of 0.9565 and recall of 0.9778 (F1-score = 0.9670), outperforming SVM but slightly falling behind KNN in false-negative suppression.

For the normal class (class 1), all models achieve recall and precision greater than 0.97, confirming that normal test waveforms are consistently recognized by all classifiers. This indicates that the main performance differentiation lies in abnormal detection, which is the more safety-critical classification objective in real-world testing environments.

These results demonstrate that KNN offers the best reliability for abnormal detection by virtually eliminating false positives, while MLP provides balanced performance between recall and precision. SVM, although yielding the highest ROC-AUC, presents more uncertainty in abnormal classification and therefore may be best suited when overall boundary separation is prioritized rather than fault-risk avoidance.

C. Confusion Matrix

To illustrate the classification behavior of the most safety-critical model, the confusion matrix for KNN using PLS-DA features is shown in Fig. 6. The KNN classifier correctly detected 44 out of 45 abnormal waveforms (class 0), resulting in a single false negative (FN = 1), where one abnormal signal was misclassified as normal. Although such misclassification represents a potentially critical oversight in safety-sensitive environments, the overall detection rate for abnormal signals remains high (recall = 0.9778). Importantly, the classifier produced no false positives (FP = 0), avoiding unnecessary false alarms for normal signals.

This performance reflects a relatively balanced diagnostic behavior, with strong capability for detecting transient faults, although not fully eliminating the risk of missed abnormal events. In environments such as EDFA transient testing, this highlights the trade-off between sensitivity and reliability, emphasizing the importance of continued improvement toward minimizing false negatives.

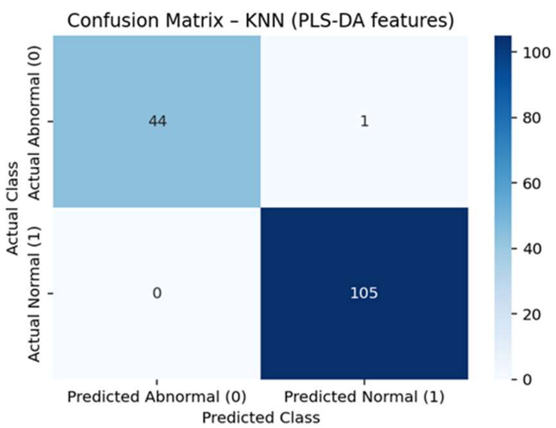

Fig. 6. Confusion matrix of KNN using PLS-DA features.

D. Analysis of Precision-Recall Trade-offs

From Table 6 and Fig. 6, a clear pattern emerges with respect to the balance between precision and recall for abnormal signal detection. The KNN model achieved precision = 1.0000 and recall = 0.9778 for class 0 (abnormal), demonstrating total elimination of false positives and nearly total elimination of false negatives. The perfect precision indicates that every predicted abnormal case was truly abnormal, while the high recall confirms that the majority of abnormal signals were successfully detected, with only a single missed case.

In contrast, SVM and MLP introduce a small number of false negatives, reflecting a slightly more conservative preference toward minimizing false alarms at the cost of occasionally missing abnormal signals. From a risk-management standpoint, this reflects a trade-off between specificity-driven classification (SVM, MLP) and sensitivity-driven classification (KNN). Given the testing context, where undetected abnormal events may propagate uncertainty or operational risk, the high-recall profile of KNN provides a more reliable detection strategy in production-oriented EDFA transient analysis.

E. ROC and PR Curves

To further assess the capability of KNN in distinguishing abnormal and normal signal patterns, the ROC and PR curves were evaluated as shown in Fig. 7 and Fig. 8. The ROC curve achieved an AUC of 0.9889, indicating excellent separability between class 0 (abnormal) and class 1 (normal). The curve rises sharply toward the top-left corner with a minimal false-positive rate, highlighting efficient discrimination even under slight threshold adjustments.

The PR curve demonstrated an average precision of 0.9906, with precision maintained near 1.0 across almost the entire range of recall. This behavior confirms that the KNN classifier can sustain high precision even as recall increases, ensuring reliable abnormal-signal detection in imbalanced scenarios where abnormal cases are less frequent.

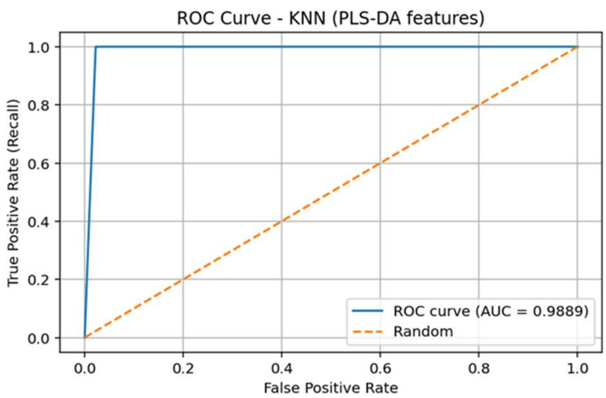

Fig. 7. ROC curve of KNN using PLS-DA features.

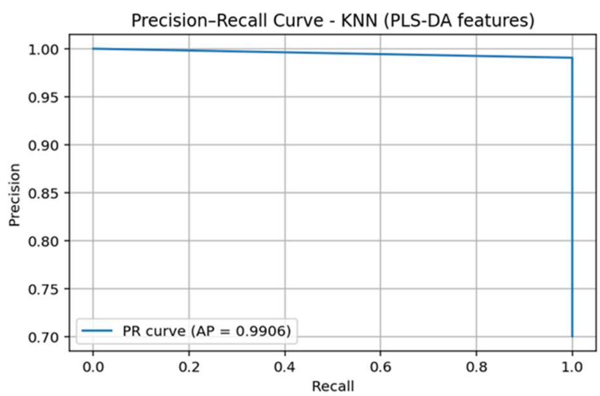

Fig. 8. Precision-recall curve of KNN using PLS-DA features.

F. Threshold Selection

To investigate the adaptability of KNN for real-world operation, the effect of decision-threshold variation was examined. Reducing the threshold below the standard value of 0.5 increases recall, thereby reducing false negatives and preventing abnormal signals from being misclassified as normal. This comes with the potential trade-off of introducing occasional false positives.

In the context of EDFA transient analysis, the operational impact of false negatives is significantly more critical than that of false positives. Accordingly, a lowered threshold setting is preferable when the primary objective is to avoid missing abnormal waveforms. This highlights the practical necessity of threshold tuning based on application-specific risk tolerance and operational safety requirements.

V. Conclusion

In the evaluation of the EDFA, the transient waveforms recorded by the oscilloscope are automatically analyzed to extract key transient parameters. However, irregular transient signals such as containing noise or waveform distortion, can produce inaccurate transient parameter results, requiring manual review by the optical test engineer. This paper presents an AI-based methodology for automatic transient classification, enabling early detection of abnormal transient signals and significantly improving test reliability while reducing the need for manual transient waveform inspection.

The experimental findings indicated that the integration of the uniform downsampling technique with LDA and PLS-DA markedly improved the overall efficacy of the machine learning models. The KNN and MLP models attained AUC values above 0.99 and F1-scores over 0.98, demonstrating their exceptional proficiency in reliably classifying transitory signals. Moreover, uniformly lowering the dataset to 1000 points significantly diminished both training and testing durations without sacrificing accuracy, offering a pragmatic benefit for real-world implementation in automated testing systems that necessitate rapidity and precision.

The suggested method allows the EDFA testing system to autonomously and swiftly identify abnormal transient signals, thus minimizing engineers' manual analysis time and enhancing the dependability of test outcomes.

Although the current results were obtained under a stable and consistent laboratory measurement environment, industrial deployment may introduce variations such as test equipment recalibration, Unit Under Test (UUT) manufacturing variance, temperature fluctuations, or aging-induced optical changes. To ensure long-term reliability of the classifier, future work should evaluate robustness under such distribution shifts and explore retraining or domain adaptation strategies, including incremental learning or periodic re-estimation of the feature transformation model, to maintain classification integrity when the test setup changes.

Future research could expand to encompass a broader spectrum of EDFA operating conditions and investigate the application of sophisticated deep learning models, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), to further improve performance and facilitate the advancement of intelligent testing systems.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Peerasut Anmahapong conceptualized the research problem, performed data collection, verified the analytical results, and contributed to writing the final manuscript. Nuntawut Kaoungku and Parin Sornlertlamvanich supervised the research, provided guidance on data interpretation, and contributed to the final manuscript. All authors reviewed and approved the final version of the manuscript.

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