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Fiber Break Prevention Using Machine Learning Approaches

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Abstract - Modern fiber-optic communication systems are built around optical fiber, which allows data to be sent by emitting infrared light pulses. It is widely used by telecommunications firms and is essential to the smooth transmission of information in internet communication as well as the transmission of telephone signals. Nonetheless, optical fibers intrinsic fragility raises a problem, especially in areas where building projects are taking place. Especially nowadays construction-related impact and crushing pressures can cause physical damage that jeopardizes the fiber optic's integrity. Therefore, this research emphasizes the necessity of taking preventative and mitigating actions to reduce the possibilities of fiber optic breakages in response to these difficulties by using machine learning approaches. The data collected by an optical fiber sensor and a distributed acoustic sensing interrogator unit (DAS). Five tools are used to simulate fiber break threats on the road surface and the fiber optic signal is denoised by using the bandpass Butterworth filter. The filtered data is then transformed into spectrogram representation and trained by using the machine learning approaches. The results of the experiments in the research achieves the accuracy 99.78% which is a high accuracy which can be potentially applied in classifying the signals of the tools and preventing the breakage of the fiber optic cables.

Keywords— Fiber Optic Communications, Signal Processing, Machine Learning, Spectrogram, Road Surface Impact Classification

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1. INTRODUCTION

Optical fiber is a main component in fiber-optic communication which can transmit data between locations with the aid of optical fiber to emit infrared light pulses [1], [2], [3]. It is also widely used by the telecommunication companies to transmit the telephone signals and contribute to the internet communication. Telemetries through the local area or long-distance networks, voice and video can be transmitted well due to fiber has a high bandwidth and immunity to the electromagnetic inference. However, as optical fiber is fragile, it can break easily especially when there is construction project nearby. The impact and crushing which are from the construction area will cause the physical damages of the fiber optic. Besides this, the vibrations which are continuously from the machinery at the constructions will include a huge pressure on the fiber optic and hence the breakage of the fiber optic will occur. The consequences of fiber optic damages lead to the outage of the information when the transmission of the data is carried on. Furthermore, the repairs of the fiber optic are costly and time consuming.

Hence, precaution approaches are required to prevent and reduce the risk or possibilities of the breakage of the fiber optic. This study presents proactive measures to prevent fiber break occurrences from happening in the first place as proactive measures in detecting and responding to them promptly. A robust method to detect the signals of fiber break is developed using machine learning methods. In this research, the data is collected in a chosen open area of Multimedia University, Cyberjaya which is quiet and with less population. Five tools such as hammer, hoe, compactor, shovel and breaker are used to apply pressure on the road surface. With the aid of a sensing technology called Distributed Fiber Optic Sensing (DFOS), the environmental changes on the fiber optic cable such as vibrations are recorded as the input data. Bandpass Butterworth filter is utilized to remove the noise of the raw data by identifying the lower and upper cutoff frequency. The filtered signals in five categories are then transformed into spectrograms. Five machine learning classification approaches which are Support Vector Machine, Random Forest Classifier, KNN Classifier, Convolutional Neural Network and Artificial Neural Network are implemented to classify the spectrogram. A promising accuracy of 99.78% is reported in the experiments which demonstrates the effectiveness of the proposed method in detecting abnormal fiber optic signals.

2. LITERATURE REVIEW

2.1 Conventional Methods

During the earlier phase, conventional approaches like Support Vector Machine, Artificial Neural Network and others were applied widely by the researchers in the signal processing. Nitendra et al. (2017) proposed to use wavelet transform to classify the EEG signal by applying SVM and ANN [4]. STFT and WT were famous feature extraction techniques but difficulties arouse while applying STFT because it did not deliver multi-resolution information of the data where it constantly had fixed size. To overcome this problem, wavelet transform was introduced to signals which were not stationary. Discrete Wavelet Transform was selected as it was more efficient than Continuous Wavelet Transform when eliminating duplication and it could reduce the computational time. Based on results of experiment, the result of Support Vector Machine classification was 85.46% while Artificial Neural Network was 96%. Table 1 presents a comparison of the conventional methods.

Apart from that, Behnia et al. (2019) proposed to use kernel fuzzy c-means (KFCM) algorithm to detect cracking of reinforce concreate by integrating unsupervised learning algorithm into acoustic emission technique [5]. By establishing the memberships for a point of data throughout all the classes, FCM got over the probabilistic restriction. The manipulation generated formula for the updates of membership for an iterative algorithm. However, the primary drawback of FCM may be that, in the situation of data which was noisy, its data with uncommon features would result in incorrect data clustering.

Ahn et al. (2019) conducted a study on using acoustic emission to detect early leakage of pipeline for flow and temperature with the aid of machine learning [6]. A new signal processing approach was proposed to apply Intensified Enveloped Analysis (IEA) in signal preprocessing. IEA was a signal preprocessing technique which included envelope analysis and discrete wavelet transform. It was developed when the researchers found the disadvantages of envelope analysis. Finding the resonant modes by tests on rotating equipment was both expensive and impractical in practice as the modes might also vary depending on the operational circumstances. GA and PCA were applied to enable SVM to classify and estimate increase fault classification accuracy. These methods could transform the original features to a lower dimensional space. The authors found that the performance of IEA was better than raw signal with accuracies of 97.73% and 68.67%, respectively. The existence of noise in the AE signal affected the accuracy of the classification model.

Besides, Soltangharaei et al. (2021) proposed a new analysis approach to analyze the AE data to determine cracks by implementing an ANN model with clustering [7]. A new clustering method based on Euclidean distance and Ward's method which are agglomerative in nature was introduced by the authors. FFT was first applied to transfer the acoustic emission signal into frequency domain. PCA was applied after that to decrease the input matrix's dimension. Since the testing phase was characterized by dispersed crack formation and damage mechanisms occurring almost simultaneously throughout the specimen, experiments providing more control over the opening of the cracks were connected to the aircraft emissions. A backpropagation method known as Levenberg-Marquardt was to train the artificial neural network. The correlation between average FFTs of data for compression and bending test were between 0.9 to 1 and these outcomes showed that ANN performed well in categorizing a previously untested fresh dataset using the FPB test.

In 2022, Dai et al. (2022) proposed to use clustering approaches and supervised learning approaches such as SVM, ELM and RF to perform pattern recognition on the features of the AE waveform [8]. The signal pre-processing methods started with implementing FFT to carry out the transformation of the signal from time-domain into frequency-domain. Band-pass filter was applied to reduce the noise and feature selection is conducted. To confirm the efficacy of AE signal categorization, unlabeled acoustic emission signals were clustered using unsupervised technique. By referring to the developed acoustic emission labelled dataset, three supervised machine learning approaches were employed to categorize the unlabeled data to find crack patterns. During the clustering process, the authors integrated Simulated Annealing Algorithm into Fuzzy C Means algorithm. This approach enhanced the optimization of FCM to more swiftly and efficiently converge to the global ideal solution. SVM and RF obtained a better result than ELM model, with 97.05% for SVM and RF and 94.12% for ELM.

Table 1. A Comparison of Conventional Methods

Author	Method	Input for classification	Recognition Rate	Pros	Cons
Nitendra et al. (2017) [4]	Wavelet Transform based ANN and SVM	EEG signals from Kocaeli University Research Funding Center	96% (ANN)	Perform well in recognition of non-linear model (ANN)	High complexity (SVM)
Behnia et al. (2019) [5]	Kernel Fuzzy C-Means Clustering	Acoustic Emission signal from Steel Fiber Reinforce Concretes	SIb value between 0.92 – 1.06	Can automatically detect the boundaries between damage stages.	Sensitive to noise and other imaging artifacts
Ahn et al. (2019) [6]	IEA-DWT-GA SVM classification	Acoustic Emission signal from B&K pulse 3560	96.15%	Noise in high frequency can be eliminated easily, Adapt easily to the signal	Noise of the signal will affect the results of SVM classification easily.
Soltangharaei et al. (2021) [7]	Ward's Method and Levenberg-Marquardt Artificial Neural Network	Acoustic Emission signals from micro-30 sensor and B1025 sensors	99.14%	Perform well in classifying unseen data set	Increasing load near the end of the experiment
Dai et al. (2022) [8]	Supervised algorithms to classify Acoustic Emission signals	Signals from coal which are generated from MTS electro-hydraulic servo material testing machine	97.06% (RF)	Low running time and high stability if use RF as classification model	Long computational time if use SVM as classification model

2.2. Deep Learning Methods

Built from the simplicity of biological brain networks, deep learning employs models with several layers of information representation. Their foundation is ANNs arranged into levels with nodes defining them; each level is linked to the next through connections with weights indicating the relationship between two nodes. Throughout the training phase, the weights are maximized by backpropagation method which reduces network error by marginally changing the nodes' values.

In 2019, Ali et al. (2019) proposed a deep learning approach for heartbeat sound signal classification by applying RNN architecture which included Long Short-Term Memory, dropout, dense, softMax Layer and Input [9]. The layer of LSTM stored historical data in a memory cell and was utilized for time-series analysis. A few gates that could more accurately capture long-range information were utilized at each time step to handle the transfer of information along the sequence. LSTM layer stored historical data in a memory cell and was utilized for time-series analysis. A few gates that could more accurately capture long-range information were utilized at each time step to handle the transfer of information along the sequence. The Adam optimizer was employed in the RNN model. Because it arbitrarily removed part of the connection between the layers that aided in preventing over-fitting, the dropout layer was used to prevent overfitting. Furthermore, Decision Tree and Random Forest were also applied to perform classification. The experimental results showed the RNN model obtained the best accuracy when compared with other classification models.

In 2022, Pablo et al. (2022) proposed a deep learning approach for optical fiber distributed acoustic sensing to detect earthquake based on LeNet architecture [10]. The authors developed a CNN + LSTM deep learning model based on the CNN-RNN Earthquake Detector neural network architecture. The proposed CNN+LSTM model adjusted the convolutional kernel size into 1 times 3 to produce larger feature maps after each layer, offset by the one-dimensional DAS data representation's lower information compared to the original 3D seismograph data. In addition, in contrast to CRED, the suggested model consisted of a single neuron which resulted the probability that the whole input waveform was a seismic wave using a sigmoid activation function. During the trial phase, the CNN + LSTM model achieved 99.69% accuracy, while the CNN model yielded the highest accuracy of 99.82%.

Besides, Li et al. (2022) presented a deep learning approach to identify breakage of the wires in the bridge cables using LSTM [11]. The study proposed that the hidden layers of LSTM were not piled with numerous layer to prevent overfitting and maximizing the number of operations. The model composed of 22 dimensions that made up the input layer; 10 network module units made up the LSTM hidden layer; sigmoid and tanh functions were used as activation functions; two neurons were included in the fully connected layer for dimensional conversion; and two signal categories were connected to the output of the SoftMax classification layer.

In the same year, Tey et al. (2022) introduced a Convolutional Neural Network which applied improved Härmä syllable segmentation algorithm to recognize the species of the cicada based on the acoustic signals [12]. FFT was applied initially to visualize the audio signals in frequency domain and denoising was carried out to remove the noise of the background. When the signal pre-processing steps were performed, Härmä syllable segmentation algorithm was implemented. The syllables were segmented to remove unwanted noise. However, there were still signals which were not vital to the training process and were of low amplitude. Therefore, an improved Härmä syllable segmentation algorithm was proposed so that binary thresholding was not needed. The segmented signals were then converted into spectrogram for CNN classification. A benchmark result was also obtained by conducting a preliminary test. Butterworth filter was applied to denoise the signals and signals were represented by spectrograms. The Convolutional Neural Network trained model applied SGD, using 30 epochs and an 8-batch size. With this configuration, the best result was 77.78%. By referring to the CNN model using the full-length datasets, the accuracy of the CNN model which applied improved Härmä syllable segmentation algorithm was higher than the model which applies original Härmä syllable segmentation.

In addition, Guo et al. (2022) proposed to use Inception Time model to classify damages relied on the AE data [13]. Inception model was an ensemble that included five distinct Inception networks and each with a random initialization. Five distinct Inception networks, each with a random initialization, made up the Inception Time model. Six distinct inception modules were layered to form an inception network and three inception modules made up a single residual block. By enabling a direct gradient flow, the vanishing gradient issue was mitigated by transferring each remaining block's input via a shortcut linear connection and adding it to the input of the following block. The resultant multivariate time series were then averaged over the whole-time dimension using a GAP layer. Lastly, a last conventional fully connected SoftMax layer was employed, consisting of the same number of neurons as classes in the dataset. The Inception Time network reported an average test result of 99.8% and an average training or validation accuracy of 99.71%.

Lately, Li et al. (2024) proposed a semi-supervised model to improve event categorization of Φ-OTDR [14]. The proposed model was known as MT-ACNN-SA-BiLSTM. This model combined a dual attention mechanism with temporal and spatial bidirectional characteristics inside a Mean Teacher (MT) framework, SA mechanism and the new architectures such as Attention Convolutional Neural Network (ACNN) and Bidirectional LSTM. With just

1230 labelled examples, the model demonstrated considerable gains over conventional supervised learning models with a classification accuracy of 96.9%. A comparison of deep learning methods is presented in Table 2.

Table 2. A Comparison of Deep Learning Methods

Author	Method	Input for classification	Recognition Rate	Pros	Cons
Ali et al. (2019) [9]	LSTM based RNN	Dataset-B in study of classifying heart sounds PASCAL challenge competition	80.8%	LSTM helps in memorizing the previous information which connects to the present information, increasing dropout layer can increase accuracy.	When two or more neurons identify the same outcome, overfitting may occur.
Pablo et al. (2022) [10]	FC-ANN, LSTM based CNN and CNN classification	Stanford Earthquake Dataset	99.82% (CNN)	Large dataset is not necessary required, has good capability to adapt the waveforms	All DAS measurements are needed to be labelled.
Li et al. (2022) [11]	Classification using LSTM model, SVM, PSO-SVM, multilayer perceptron, KNN, decision tree and Naive Bayes	Acoustic emission signals from WG50, SR150M and SR40 sensors	100% (LSTM)	High accuracy will be obtained, the signals will be analyzed clearly during the training process.	Cross validation is not performed due to the limited numbers of data samples, model has not been applied to real field data, proposed approaches relies on professional expertise.
Tay et al. (2022) [12]	Improved Harma Syllable Segmentation based CNN	Cicada datasets from Freesound and online websites	100% (full-length dataset) 93.02% (cut dataset)	Overfitting has been reduced, Can show the important features of the signals	The size of the dataset is needed to be increased
Guo et al. (2022) [13]	CNN with Inception Time architecture	Acoustic emission signals from fiber bundle test, matrix tensile test and delamination experiment.	99.71%	The imbalance problems of the data can be solved, no overfitting occurs	Less accuracy when using frequency-domain sequence data.
Li et al. (2024) [14]	MT-ACNN-SA-BiLSTM	Signals which are collected from a Φ-OTDR	96.9%	Achieve high accuracy with limited labelled data, utilised unlabled data effectively, the robustness and adaptability are improved and the capabilities to process the long distance data effectively	The huge complexity of computational requires more processing time and power, highly depending on the parameters which is hyperparameter tuned, sensitive to the noisy data and limited application scope

3. RESEARCH METHODOLOGY

3.1 Dataset Collection and Preparation

Five tools are being used for data collection in this study, namely hammer, compactor, breaker, hoe and shovel. The vibrations generated while these tools are utilized are being recorded as the input by a technical team in Multimedia University, Cyberjaya. To ensure the consistency and precision of data collection, the serenity and a wide environment will be a first choice for conducting this experiment, for example the places which there are less students passing by or without other sound disturbances. DFOS is used to capture the environmental changes along the fiber optic cables such as vibrations when the tools are applied on the road surface. In this study, Distributed Acoustic Sensing (DAS) [15], [16] are utilized to detect and measure the vibrations or acoustic signals along the fiber optic cable. When the intrusion simulation action is performed by using the tools, the backscattered light is collected by the interrogator unit of DAS which contains information of the vibration generated by the tools. The vibration signals are then collected as the input data. Figure 1 depicts the locations the data are captured. The vibration pattern of using the different tools are also shown in Figure 2.

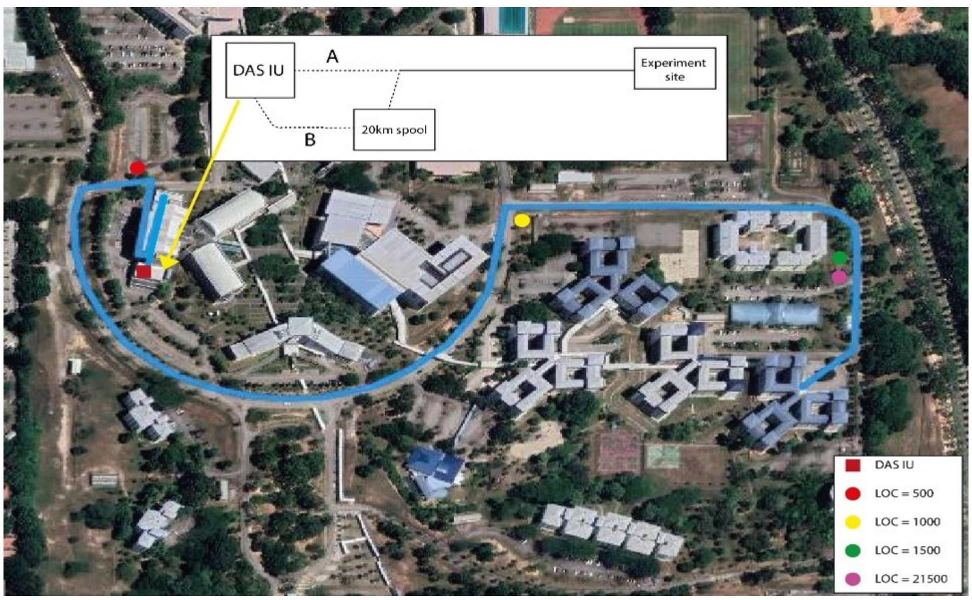

Figure 1. Location of Data Collection

3.2 Data Pre-processing

In this study, the IIR Butterworth filter [17], [18] is used to reduce the noise of the raw data. Butterworth filter is a filter which possess a passband frequency response. The passband can attenuate frequencies outside of a specific range while leaving the rest of signal mostly unaffected. In Butterworth bandpass filter, there are two cutoff frequencies which are lower cutoff frequency and upper cutoff frequency. These cutoff frequencies specify the passband and the flat response of frequency inside the passband is achieved by utilizing this filter. Hence, by combining the bandpass Butterworth filter transform function which are obtained by utilizing analogue filter design techniques, the transfer function of an nth-order Butterworth bandpass filter is generated.

(a) (b) (c) (d) (e)

Figure 2. Simulate Disturbances to The Fiber Optic Signal using (a) Compactor, (b) Breaker, (c) Hammer, (d) Shovel, and (e) Hoe.

The bilinear transform can be also implemented to convert continuous-time transfer functions into discrete-time domain function for digital implementation. To ensure the numerical stability and efficiency, the resultant digital filter transfer function is stated in terms of SOS. The equation of IIR Butterworth Bandpass filter is given by Equation (1).

$$H(s) = \frac{K}{\prod_{k=1}^{n}(s^2 + \alpha_k s + \omega_k^2)} \tag{1}$$

where $H(s)$ is the transfer function. K is a gain factor; s is the Laplace variable while α_k and ω_k are each pole's resonance frequency and damping coefficient. Lastly, n represent the order of the filter. Figure 3(a) illustrates the raw signal in 1-dimensional plot and the waterflow diagram that shows the filtered signal by using IIR Butterworth bandpass filter is shown in Figure 3(b). From Figure 3(a), we observe that before applying denoising filter, the signal is noisy and definitely this will affect the performance of the model. From Figure 3(b), the noise of the signal is greatly reduced after applying IIR Butterworth bandpass filter.

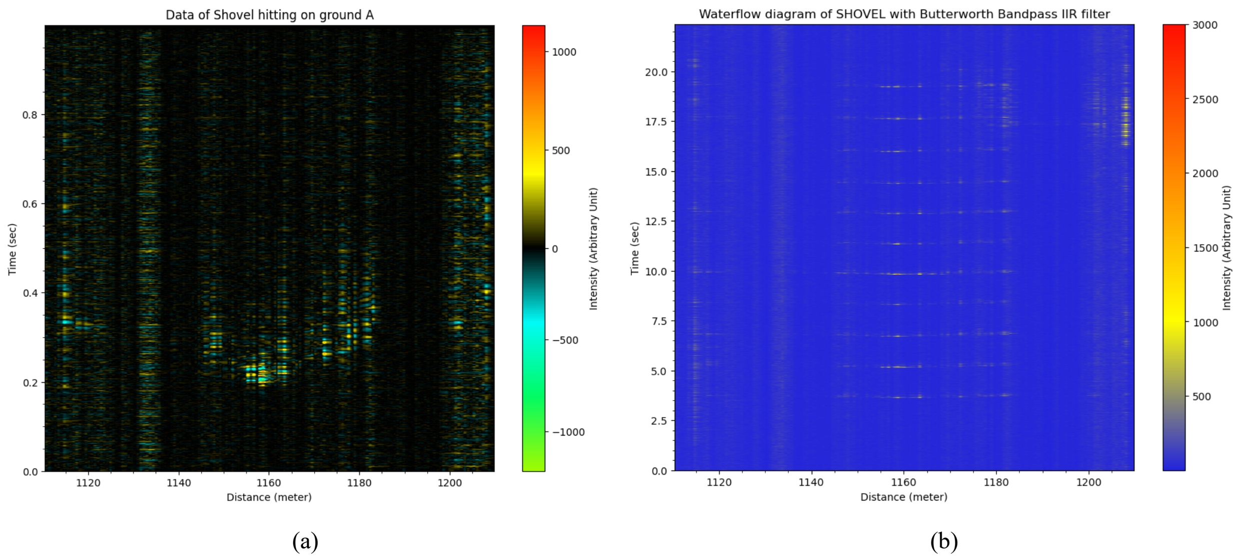

Figure 3. Waterfall Diagram of (a) Raw Shovel Signal, and (b) Signal After Applying IIR Butterworth Bandpass Filter

3.3 Data Transformation

After the raw data is being pre-processed, a set of filtered dataset is generated. As the filtered dataset are in non-image format (i.e. time series data), spectrogram is utilized as the input data in the classification model. It provides a detailed representation of how the frequency content of the signal evolves over time. The Short-Time Fourier Transform (STFT) [19], [20] is used to construct the spectrogram. It divides the signal into its frequency components during brief intervals. The STFT matrix is then converted to dB scale to improve dynamic range and perceived relevance. The equation of STFT is given by Equation (2),

$$X(m,k) = \sum_{n=u}^{N-1} x[n]\,.\,w[n-m]e^{-j\frac{2\pi kn}{N}} \tag{2}$$

where $x[n]$ is the input signal, $w[n]$ refers to the window function and m is the time index. k and N represent the index of frequency bin and the number of points of FFT respectively, while J is the unit of imaginary. The parameters used in this study are listed in Table 3.

Table 3. Parameters of Involves in Spectrogram Creation

Parameters	Values
Sampling rate	2000
Length of FFT window	266
Hop length	16
Duration	1

The spectrograms generated from the different classes are shown in Figures 4(a) to (e). We can observe that the differences between the spectrogram on their colours and patterns can be differentiated and classified clearly, especially there is a huge difference in breaker and compactor. There is only a small similarity on the pattern on hammer, shovel and hoe.

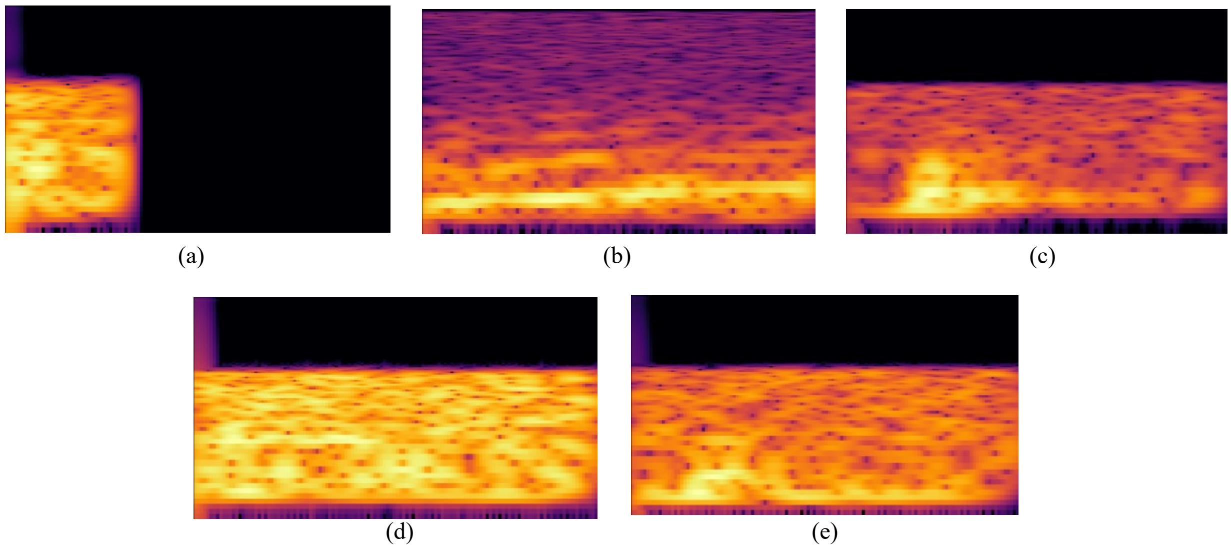

Figure 3. Spectrogram of (a) Breaker, (b) Compactor, (c) Hammer, (d) Shovel, and (e) Hoe

3.4 Feature Normalization

The data normalization technique which we choose to implement in our research is Standard Scalar. Standard Scalar can eliminate the mean and scaling to the unit variance for standardizing the data. By utilizing Standard Scalar, the mean of the data will become zero and the standard deviation will be one. In order to ensure that the features of the data are in the same scale, Standard Scalar will stop any feature from controlling the learning process because of its greater size. The mathematical equation of Standard Scalar is given as in Equation (30,

$$z = x - \mu/\sigma \tag{3}$$

where σ represents standard deviation; μ is the mean of the features and x is the initial value of the feature.

3.5 Dimension Reduction

Principal Component Analysis [21] is a popular method used to reduce the complexity of the huge dataset by retrieving the features which are vital and informative from the dataset and preserving the most pertinent information from the original dataset. Usually, issues like overfitting and multicollinearity can be prevented and reduced with PCA. By utilizing PCA, the huge dataset is condensed into smaller sets of uncorrelated variables. The linear combinations of the original variables that have the highest variance in relation to other linear combinations are known as principal components.

The first Principal Component shows the largest variance of the data and the form of the anticipated points are most accurately represented by this line. The amount of information maintained from the original dataset increases with the variability collected in the first component. The second Principal Component shows the second largest variance of the data. The next largest variance which was found by second Principal Component is required to be not correlated with first Principal Component which means the correlation between first Principal Component and second Principal Component is 0. We found the first two principal components play the most pivotal role in this study.

3.6 Classification Techniques

3.6.1 Support Vector Machines (SVM)

SVM is one of the machine learning algorithms which is utilized well in classification and regressions tasks [22]. SVM is particularly good at handling high-dimensional data and complex decision boundaries. This algorithm searches for an ideal hyperplane with the maximum possible margin of separation between data points from different classes.

The decision boundaries which areknown as hyperplanes help in data point classification. The data points that lie on each side of the hyperplane can be assigned to distinct classes. Furthermore, the hyperplane's size is influenced by the quantity of features. When input characteristics are limited to two, the hyperplane can be thought of as a line. If there are three input characteristics, the hyperplane transforms into a two-dimensional plane.

Data points that are close to the hyperplane and have an impact on its orientation and coordinates are called support vectors. By employing these support vectors, we raise the margin of the classifier. The removal of the support vectors will change the placement of the hyperplane. These are the concepts that support our SVM's development.

3.6.2 Random Forest Classifier

Random forest is an ensemble learning model which contains multiple numbers of random decision trees [22]. The decision trees will be combined by random forest to achieve a result. There are three hyperparameters which are size of nodes, number of trees and the number of features sampled. Each decision tree in the ensemble of decision trees used in the random forest technique is made up of a bootstrap sample, which is a sample of data taken from a training set with replacement. One-third of the training sample is designated as test data and this is referred to as the out-of-bag sample. Feature bagging is one of the parts of RF Classifier which assists increasing the variety of the dataset, randomizing the data and reducing the correlation of the decision tree. The decision of the prediction will manipulate based on the kind of difficulties. In a regression job, each decision tree will be averaged. The class which is predicted will be identified by either a majority vote or the most common categorical variable in the classification process.

3.6.3 K-Nearest Neighbours Classifier

In machine learning, KNN classifier is a straightforward yet effective technique that is used for both regression and classification problems [23]. As an instance-based learning technique, it maintains all instances that correspond to training data in n-dimensional space rather than attempting to build a generic internal model. Upon introducing a new data point, KNN determines which of the k training samples are closest to the new point in terms of distance. The Euclidean distance is the most often utilised distance metric, although alternative metrics, such as the Manhattan or Minkowski distances, may also be utilised based on the particulars of the situation.

To start the algorithm of KNN classifier, we must first determine the ideal value of k or the number of nearest neighbours to be selected when generating predictions. Following the selection of k, the target data point's distance from each data point in the training dataset is computed and the Euclidean distance metric is commonly used to quantify similarity. The closest neighbours are determined by calculating the distances between each of the k data points and the target location. When determining the projected class for a target data point in a classification issue, the nearest neighbours cast majority votes, and the class that appears the most frequently is selected as the prediction.

3.6.4 Artificial Neural Network (ANN)

ANN are computer models that are modelled after the functioning of organic neural networks in the human brain [23]. They are frequently employed in tasks like pattern recognition, classification, regression, and other forms of data processing. They are a subset of machine learning. Depending on how many complex neural networks are required to reveal the hidden patterns in the dataset, an ANN layer may include a few hundred or millions of units. Artificial neural networks typically consist of hidden layers, output layers, and input layers. The input layer which is the first layer of ANN is where the input data is sent into the neural network for analysis or education. Subsequently, the data passes through either one or more than one hidden layer that transform the input into information that is beneficial for the output layer. Lastly, the Artificial Neural Networks' reaction to the supplied input data is presented as an output by the output layer.

Weights are representations of connections between neurons. The signal that is passed between neurons is influenced by the weights of each connection which multiply the input. These weights are changed throughout training to maximize the network's efficiency. In ANN, every neuron has an activation function that, given its input, determines the neuron's output. Sigmoid, hyperbolic tangent (tanh) and rectified linear unit (ReLU) are examples of common activation functions. There are two main processes in ANN which are feedforward and backpropagation. Feedforward is the procedure by which input data is sent across a network to generate an output. Information moves from the input layer to the output layer via the hidden layers in a single path. For backpropagation, it is a training procedure that modifies the network's weights to reduce the discrepancy between the intended and expected output. To update the weights, it entails calculating the error and propagating it backward through the network. Backpropagation will continue until ANN model can perform the recognition well.

3.6.5 Convolution Neural Network (CNN)

CNN is a family of neural networks with a focus on processing input with a topology resembling a grid, such an image [24]. Convolutional neural networks perform classification well in image, voice, or audio signal inputs than other types of neural networks. In CNN, we can find that there are three layers inside which are convolutional layer, pooling layer and fully connected layer. The convolutional layer processes the input image to extract features, the pooling layer down samples the image to decrease computation, and the fully connected layer produces the final prediction. Gradient descent and backpropagation are used by the network to find the optimal filters.

The feature from input dataset is extracted in the convolutional layer. It applies a set of learnable filters, referred to as kernels, to the input images. The filters/kernels are typically matrices of size 2x2, 3x3, or 5x5. As it traverses the input image data, it calculates the dot product between the kernel weight and the corresponding input picture patch. If we apply 12 filters to this layer in total, the resulting volume will have 32 x 32 x 12 dimensions. These are the convolutional layers' learnable parameters. Filters are tiny matrices that are taught to recognize characteristics in pictures, such as edges, textures, or more intricate patterns.

The spatial dimensions of the feature maps generated by convolutional layers are down sampled by pooling layers. Common pooling processes include average pooling, which computes the average, and max pooling, which chooses the largest value from set of values. Pooling aids in controlling overfitting and lowering computing complexity. ReLU activation functions are commonly used by CNNs to add non-linearity to the model. ReLU enables the network to learn more intricate patterns by setting all negative values in the feature maps to zero. Feature maps are the result of several convolutional and pooling layers in the neural network which reflect the high-level reasoning. The process of turning these feature maps into a vector with one dimension is called flattening. Then, one or more completely linked layers are joined to the flattened vector. Based on the learnt characteristics, these layers conduct the final classification in a manner like that of classic neural network layers. The output layer of CNN performs classification and prediction at last

4. RESULTS AND DISCUSSIONS

4.1 Experimental Setup

This research is conducted by using a MacBook Pro and Visual Studio Codes IDE. The dataset contains 2,252 samples that are categorized into 5 categories, specifically hammer, hoe, compactor, shovel and breaker. The dataset is split into training and testing according to the 80%: 20% ratio. Table 4 presents the details of the data distribution used in the experiments.

Table 4. Details of Data Distribution

Classes	Number of samples	Training samples	Testing samples
Hammer	461	370	91
Hoe	482	385	97
Breaker	450	360	90
Shovel	392	314	78
Compactor	467	373	94

4.2 Experimental Results

4.2.1 Support Vector Machines

In this section, we assess the performance of SVM. The kernel used is the linear kernel and the value of C was set to 0.1. The classification reports of SVM with PCA and without PCA are presented in Table 5 and 6, respectively. We observe that while SVM with PCA achieves a slightly lower accuracy as compared to the SVM without PCA, the classification performance across different classes is still quite high with both approaches. The overall accuracy of the SVM without PCA is better than that of the SVM with PCA, indicating that PCA might introduce some loss of information affecting the model's classification performance. The SVM with PCA has a marginally lower testing time compared to the SVM without PCA. This suggests that while PCA can slightly speed up the classification process, it may come at the cost of reduced accuracy.

Table 5. Classification Report of SVM with PCA

Classes	Precision	Recall	F1-score	Support
Hammer	0.93	1.00	0.96	92
Compactor	1.00	1.00	1.00	94
Breaker	1.00	1.00	1.00	90
Hoe	1.00	1.00	1.00	97
Shovel	1.00	0.91	0.95	78
Average Accuracy	0.986			
Testing Time (second)	0.0306			

Table 6. Classification Report of SVM without PCA

Classes	Precision	Recall	F1-score	Support
Hammer	0.98	1.00	0.99	92
Compactor	1.00	1.00	1.00	94
Breaker	1.00	1.00	1.00	90
Hoe	1.00	1.00	1.00	97
Shovel	1.00	0.97	0.99	78
Average Accuracy	0.996			
Testing Time (second)	0.0313			

4.2.2 Random Forest

In this section, the performance of Random Forest is assessed. The parameters used in this experiment are set as follows where the *n* estimator is set to 30, criterion is set to 'entropy', random state is set to 0, max feature is set to 1 and the max depth is 7. The classification reports for with and without the use of PCA are presented in Tables 7 and 8, respectively. The compactor and breaker classes achieve perfect precision, recall, and F1-scores without PCA, compared to slightly lower scores with PCA. The precision, recall, and F1-scores are generally better without PCA for hammer and hoe. On the other hand, precision and recall are slightly worse without PCA for hoe. In general, we observe that the Random Forest classifier performs slightly better without PCA, with higher average accuracy and improved performance metrics (precision, recall, F1-score) for most classes.

Table 7. Classification Report of Random Forest with PCA

Classes	Precision	Recall	F1-score	Support
Hammer	0.86	0.98	0.91	92
Compactor	0.94	0.90	0.92	94
Breaker	0.99	0.83	0.90	90
Hoe	0.82	0.89	0.89	97
Shovel	0.94	0.78	0.85	78
Average Accuracy	0.91			
Testing Time (second)	0.0312			

Table 8. Classification Report of Random Forest without PCA

Classes	Precision	Recall	F1-score	Support
Hammer	0.92	0.87	0.89	92
Compactor	1.00	1.00	1.00	94
Breaker	1.00	1.00	1.00	90
Hoe	0.92	0.90	0.91	97
Shovel	0.80	0.87	0.83	78
Average Accuracy	0.92			
Testing Time (second)	0.0308			

4.2.3 K-Nearest Neighbours Classifier

The parameters of KNN used in this experiment are as follows. The value of the number of neighbours, n, is set to 11, the uniform weight is used and the manhattan metric is adopted. Tables 9 and 10 record the results of KNN with and without PCA. We find that PCA does not affect the classification accuracy or performance metrics of KNN in this specific case. Both models perform perfectly, achieving the same precision, recall, and F1-score across all classes. In terms of testing time, PCA helps reduce testing time for KNN. The model with PCA processes data faster than the one without PCA, likely due to fewer features being processed during distance calculations.

Table 9. Classification Report of KNN with PCA

Classes	Precision	Recall	F1-score	Support
Hammer	1.00	0.99	0.99	92
Compactor	1.00	1.00	1.00	94
Breaker	1.00	1.00	1.00	90
Hoe	1.00	0.99	0.99	97
Shovel	0.99	1.00	0.99	78
Average Accuracy	1.00			
Testing Time (second)	0.0251			

Table 10. Classification Report of KNN without PCA

Classes	Precision	Recall	F1-score	Support
Hammer	1.00	0.99	0.99	92
Compactor	1.00	1.00	1.00	94
Breaker	1.00	1.00	1.00	90
Hoe	1.00	0.99	0.99	97
Shovel	0.99	1.00	0.99	78
Average Accuracy	1.00			
Testing Time (second)	0.0302			

4.2.4 Artificial Neural Network

The architecture of ANN used in the experiment contains three layers which are input layers, hidden layers and output layers. In input layer, the spectrograms are flattened and transformed into 1D array from the original 100 x 100 x 3 spectrogram. While in the hidden layers, there are two dense layers which contains fine-tuned units. Lastly at the output layers, multi class classification is conducted with a fully connected layer containing 5 units with SoftMax activation function.

During hyperparameter tuning, the activation functions are set to ‘relu’ or ‘tanh’, and the values of integer are set between 1 and 1000 which is in the steps of 100 in unit first and second layer. Furthermore, the learning rate was set between ‘1e-2’ to ‘1e-4’. The best parameters identified after hyperparameter tuning are presented in Table 11.

Table 11. Best hyperparameters of ANN

Parameters	Values
Loss function	Sparse Categorical Crossentropy
Optimizer	Adam
Learning rate	0.001
Batch size	32
Epochs	50

Table 12 shows the classification report of ANN. It demonstrates excellent performance across all classes, with an average accuracy of 1.00. This suggests that the model has effectively learned to distinguish between different classes with minimal errors. The testing time is longer compared to some other classifiers, reflecting the increased computational complexity typically associated with neural networks. Despite the slightly higher testing time, the model's performance justifies its use, especially given its perfect accuracy on the test set.

Table 12. Classification Report of ANN

Classes	Precision	Recall	F1-score	Support
Hammer	0.99	0.99	0.99	92
Compactor	1.00	1.00	1.00	94
Breaker	1.00	1.00	1.00	90
Hoe	1.00	0.99	0.99	97
Shovel	0.99	0.99	0.99	78
Average Accuracy	1.00			
Testing Time (second)	0.0405			

4.2.5 Convolutional Neural Network

The architecture of the CNN model used in the experiment is provided in Table 13. Besides, the hyperparameters used are also listed in Table 14.

Table 13. Architecture of CNN

Parameters	Values
Input Layer	Convolutional layer which contains 64 filters with their 3x3 size. The input shape is set to (100,100,3) and the activation function is set as ‘relu’.
Layer 2	MaxPooling2D layer with pool size 2x2
Layer 3	Dropout Layer with its rate which is 0.2
Layer 4	Convolutional layer which contains 32 filters with their 3x3 size. The activation function is also set as ‘relu’.
Layer 5	MaxPooling2D layer with pool size 2x2
Layer 6	Dropout Layer with its rate which is 0.2
Layer 7	2D data is flattened and convert to 1D.
Layer 8	Dense layer which contains 64 units and its activation function is also ‘relu’.
Layer 9	Dropout Layer with its rate which is 0.2
Layer 10	Dense layer which contains 32 units and its activation function is also ‘relu’.
Layer 11	Dropout Layer with its rate which is 0.2
Output Layer	Dense layer which contains 5 units and its activation function is ‘SoftMax’ which is prepared for classification.

Table 14. Hyperparameters of CNN

Parameters	Values
Loss function	Sparse Categorical Crossentropy
Optimizer	Adam
Learning rate	0.001
Batch size	8
Epochs	40

The experimental results of CNN is shown in Table 15. Hammer shows slightly lower recall (0.97) compared to precision (1.00), leading to a slightly lower F1-score (0.98) compared to other classes. On the other hand, shovel shows a lower precision (0.95) but still has a high recall (0.99), which results in a high F1-score (0.97). This indicates good performance, though not as high as some other classes. Overall, we observe that CNN performs very well across most classes, with high precision and recall. The F1-scores are also high, indicating good performance in balancing precision and recall.

Table 15. Classification Report of CNN

Classes	Precision	Recall	F1-score	Support
Hammer	1.00	0.97	0.98	92
Compactor	1.00	1.00	1.00	94
Breaker	1.00	1.00	1.00	90
Hoe	1.00	0.99	0.99	97
Shovel	0.95	0.99	0.97	78
Average Accuracy	0.99			
Testing Time (second)	0.0526			

4.3 Overall Comparisons

The overall accuracies of all the models are presented in Figure 4. We find that both SVM and Random Forest show a decrease in performance with PCA, indicating that these models might be sensitive to the reduction in feature dimensionality. On the other hand, KNN shows an improvement with PCA, suggesting that KNN benefits from noise reduction and less redundant feature space. Therefore, PCA can sometimes lead to a loss of critical information, which affects models like SVM and Random Forest negatively.

4.4 Discussions

Following are some insights and interesting findings from the series of experiments:

- KNN and ANN perform exceptionally well with perfect accuracy in their respective cases, with KNN benefiting from PCA by reducing testing time.
- CNN achieves high performance but has the longest testing time, which is expected due to its complex computations.
- The experiments show that the effectiveness of PCA varies by model. While PCA improves testing time for KNN, it negatively impacts the performance of SVM and Random Forest.

- The results suggest that SVM and Random Forest might benefit from having access to the full feature set.
- The hoe and compactor classes have the highest accuracies. The reason might be because the number of samples for hoe and compactor is relatively high compared to other classes. A larger number of samples generally provides more information for training, leading to better model performance.

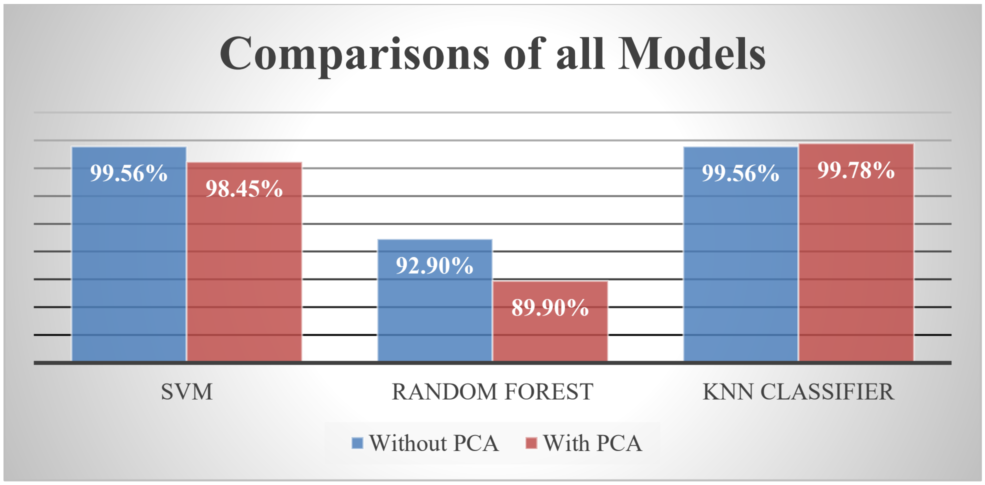

Figure 4. Comparisons of All Models

5. CONCLUSION

This study explores different machine learning approaches for classifying tools that generate pressure on the fiber optic wires. Based on the experimental results, the KNN Classifier with PCA emerge as the most effective model. This classifier demonstrates strong performance in accurately identifying and classifying tools, making it a valuable tool for authorities tasked with monitoring and preventing fiber optic damage.

The findings of this study highlight that different machine learning models perform differently depending on the datasets. Therefore one cannot assume that deep learning models are always superior to conventional models. The successful application of the KNN classifier to spectrograms derived from time series data suggests that it can be an effective alternative for certain classification tasks.

The experiment focused on five specific tools, but there are other tools and machinery commonly used at construction sites, such as drills and heavy vehicles, which were not included. Expanding the dataset to include these additional tools and increasing the number of classification categories will be the future work of this study. Besides, we will also investigate different feature extraction methods, such as using Mel-spectrograms, and experimenting with temporal deep learning models like LSTM and Inception Time Model CNN.

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CONFLICT OF INTERESTS

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