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ARAŞTIRMA MAKALESİ | RESEARCH ARTICLE

Deep Learning Based Threat Classification for Fiber Optic Distributed Acoustic Sensing Using SNR Dependent Data Generation

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SNR Bağımlı Veri Üretimi Kullanılarak Fiber Optik Dağıtılmış Akustik Algılama için Derin Öğrenmeye Dayalı Tehdit Sınıflandırması

***Abstract* -In this study, a novel method is proposed to generate SNR dependent database and classify threats for fiber optic distributed acoustic sensing (DAS) systems. Optical time-domain reflectometry (OTDR) is used to acquire DAS signals. Proposed data creation method generates signals with different SNR values which is based on real channel noise characteristics. By this way, from the limited dataset, huge dataset consists of three different man-made weak ground motion events such as hammer hit, digging with pickaxe and digging with shovel is generated. In the classification part, two different Deep Learning algorithm (Convolutional Neural Network and fully connected neural networks) are used to identify three different threats. Results show that remarkable identification accuracy for the three different SNR ranges is achieved.**

***Index Terms*: Deep learning classification, Distributed acoustic sensing, Optical time-domain reflectometry, Threat classification.**

Özet—*Bu çalışmada, SNR bağımlı veri tabanı oluşturmak ve fiber optik dağıtılmış akustik algılama (DAS) sistemler için tehdit sınıflandırmak yöntemi önerilmiştir. DAS sinyallerini almak için optik zaman alanı reflektometrisi (OTDR) kullanılmıştır. Önerilen veri oluşturma yöntemi, gerçek kanal gürültü özelliklerine dayanan farklı SNR değerlerine sahip sinyaller üretir. Bu şekilde, sınırlı veri kümesinden, çekiç vuruşu, kazma ile kazma ve kürekle kazma gibi üç farklı insan yapımı zayıf yer hareketi olaylarından oluşan büyük veri kümesi elde edilmiştir. Sınıflandırma bölümünde, üç farklı tehditi tanımlamak için iki farklı Derin Öğrenme algoritması (Evrişimsel Sinir Ağları ve tam bağlantılı sinir ağları) kullanılır. Sonuçlar, üç farklı SNR aralığı için dikkate değer tanımlama doğruluğunun elde edildiğini göstermektedir.*

Anahtar Kelimeler **—**Dağıtık akustik algılama, Derin öğrenme sınıflandırması, Optik zaman-alanı yansıtma ölçüsü, Tehdit sınıflandırması.

I. INTRODUCTION

MECHANICALvibrations around a fiber optic (FO) cable create micro mirrors along the FO cable. These micro mirrors reflect transmitted light back to the transmitter. This phenomenon is called as Rayleigh backscattering. By using this natural characteristic of fiber optic cable, Fiber Optic Distributed Acoustic Sensing (DAS) applications can be done [1]. In this method, light intensity of reflected light is used to locate the vibration source. With the development of phase sensitive optical time domain reflectometer (phi-OTDR) method, backscattered light intensity in the FO cable has been used for continuous pipeline monitoring [2] and perimeter monitoring for intruders [3]. From the recent works ([4], [5] and [6]) it can be seen that OTDR systems, supported by buried FO cables, locate and discriminate activities that creates vibration with the help of machine learning techniques so that pipeline or border security can be achieved.

The data acquisition system is one of the most important phases of OTDR vibration classification. In a typical OTDR system, optical pulse signals are transmitted into the FO cable which is usually buried underground. When the vibration signals hit to the cable, that creates Rayleigh backscattering. With the help of photo-detection systems, reflected signals can be collected. In literature, recent studies confirm that data acquisition can be done by using commercial devices or modular OTDR devices ([7], [8]). In addition to the signal acquisition system, signal to noise ratio (SNR) values of the collected signals should be taken into consideration. In this context, there are several studies in which the SNR values have been examined in the literature ([5] and [9]). However, the signals have either a high SNR value or have been increased to higher SNR levels by using various signal processing methods in these studies.

Feature extraction is another important part of the OTDR-based threat classification. As is known, in a typical classification problem, the features that are extracted from signals are critical to the classification performance. For this reason, in the ODTR vibration classification studies of various feature extraction methods such as energy of frequency bins [8], Speech Recognition features such as Tandem features [10], morphological feature extraction method [11] and Mel Frequency Cepstrum Coefficients (MFCC) features [12] have achieved significant performance.

As can be easily understood from the literature, machine learning methods offer solutions in different approaches for various problems. Therefore, the choice of method is relied on the problem and the extracted features to be used. In literature, there are some traditional machine learning methods exists such as Support Vector Machine (SVM) [13], k-Nearest Neighbor (k-NN) [14], Principal Component Analysis (PCA) and Artificial Neural Network (ANN) [15]. In addition, other machine learning methods includes Gaussian Mixture Model (GMM) [16] and Neural Network (NN) [17] methods come into prominence in ODTR classification studies. On the other hand, recently developed machine learning method Deep Learning (DL) [5] has also been used to achieve good performance in this context.

This paper organized as follows: In section 2, DAS signal acquisition system is presented. In section 3, threat detection method is given. SNR dependent data creation method is presented in section 4. Threat identification method is given in section 5. Lastly, discussion and conclusions are provided in section 6 and 7.

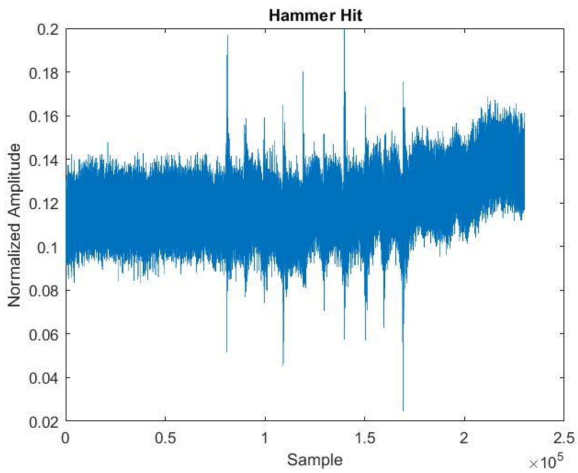
II. MEASUREMENT SYSTEM AND DATA ACQUISITION

Optical time domain reflectometry (ODTR) [18] system is used to obtain backscattered light caused by mechanical vibrations. In this system, coherent burst of pulses is transmitted with a constant pulse repetition frequency. ODTR system collects all optical reflections. The collected light signals between two consecutive pulses represents the location of backscattering [5]. These reflected light signals can be obtained after every pulse and can be mapped in a waterfall graph as given in Fig. 1.

X and Y axis of the waterfall graph, seen in Fig. 1, represents range bins and time bins, respectively. When this waterfall graph is analyzed, it can be seen that energy levels of range bins are different from others. These different energy levels lead to understand of possible vibration sources which can be caused by an event of interest or a stable vibration source such as building or road. When event of interest is extracted from the waterfall graph which means that one or more of the range bins, event of interest can be seen as Fig. 2.

In order to collect the ODTR data mentioned above, fiber optic cable was buried underground. One end of the cable is connected to the ODTR measurement system and the other end of the cable is connected to fiber optic cable terminator.

At specific locations, several mechanical vibration activities such as hammer hit, digging with shovel, digging with pickaxe and walking were processed one by one. Backscattered light intensity were recorded with respect to time and range bins as mentioned above [19].



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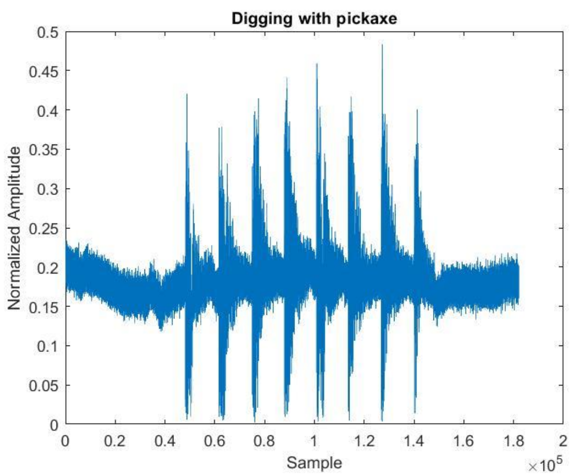

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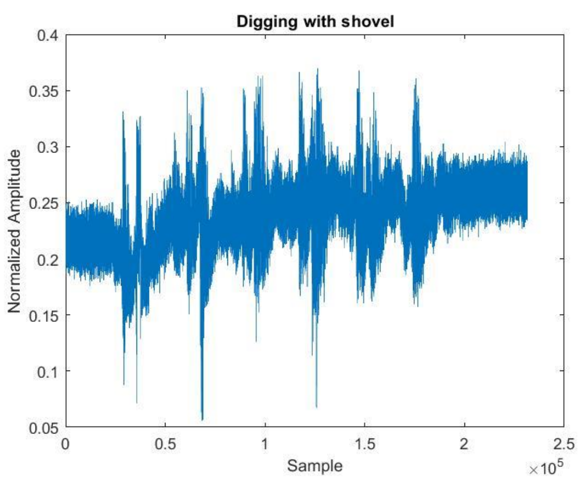


(c)

Fig. 2. Typical sample of event of interest where a) Hammer Hit, b) digging with pickaxe and c) digging with shovel.

Various man-made weak ground motion activities were recorded with several sampling rates which can be described with PRF(Pulse Repetition Frequency) of light pulses. Parameters of the collected database are given as Table I.

TABLE I
DATABASE SPECIFICATIONS

Event Type	Sample Rate	Event Number	Event Bins
Hammer hit	10 kHz	10	119-124
Hammer hit	10 kHz	11	144-148
Hammer hit	10 kHz	11	144-152
Hammer hit	10 kHz	10	140-144
Hammer hit	1 kHz	10	140-148
Hammer hit	10 kHz	10	118-126
Digging with pickaxe	20 kHz	5	144-151
Digging with pickaxe	10 kHz	5	144-150
Digging with pickaxe	10 kHz	7	144-151
Digging with pickaxe	25 kHz	5	144-151
Digging with pickaxe	25 kHz	5	144-151
Digging with pickaxe	25 kHz	2	142-144
Digging with shovel	10 kHz	6	144-148
Digging with shovel	10 kHz	10	145-149
Digging with shovel	25 kHz	5	144-148
Digging with shovel	10 kHz	9	145-149
Walking	10 kHz	45 seconds	890-896
Walking	1 kHz	45 seconds	144-148
Walking	2.5 kHz	45 seconds	890-896
Walking	2.5 kHz	45 seconds	890-896
Walking	20 kHz	45 seconds	144-148

III. EVENT DETECTION

It is known that received signals have two components. One of them is backscattered signal due to man-made weak ground motion events near the FO cable. The other one is considered as background noise due to thermal noise and geographical channel noise. In the literature, there are various methods which extract backscattered signal from noise. Wavelet denoising [20] is known as best fit for this kind of problem. In order to eliminate unwanted signal characteristics, Wavelet

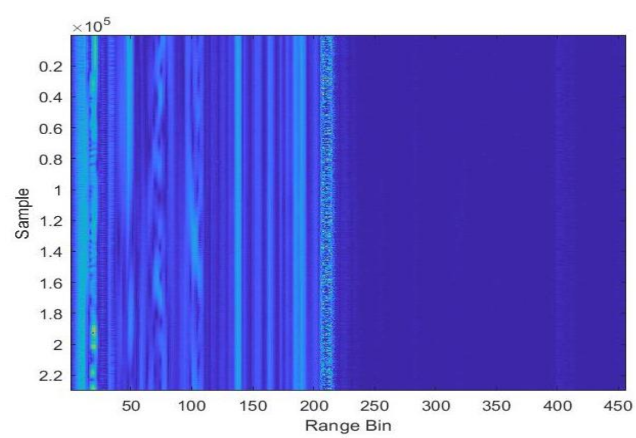


Fig. 1. Waterfall representation of reflected light intensity

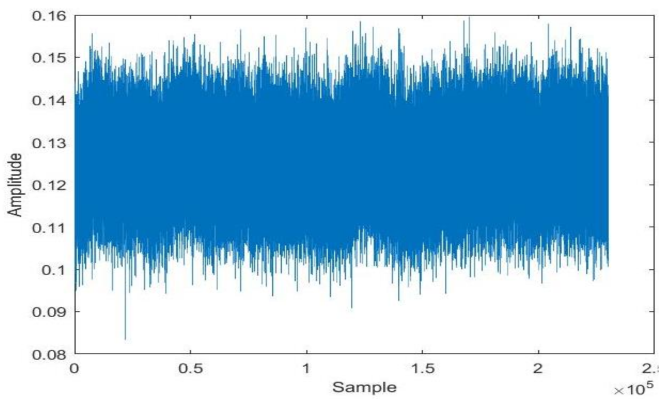


Fig. 3. Typical sample of channel noise

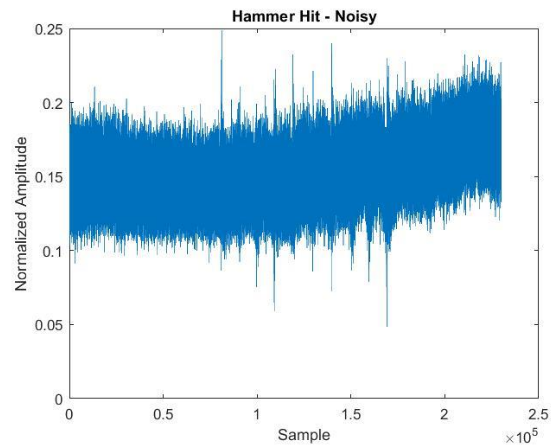
denoising method at level 5 with sym 5 symlet wavelets have been used in this work. It is known that external disturbance on FO cable does not change in short time. In this context, after using Wavelet method, a high pass filter is employed to extract abrupt changes in the signal.

Time delayed signal of each range bin has used for autocorrelation to reveal threat located at range bins. However, this process reveals some of the unwanted range bins and desired range bins. To separate these, power of the correlated signals at each range bin has calculated. By sorting them from maximum to minimum, the range bin which consists threat can be extracted.

IV. SNR DEPENDENT DATA CREATION

First of all, to create a new data, the bins which includes threats are extracted. The remaining noisy channels were analyzed. In this analyze, noise characteristics of channels were observed. It was experienced that some of the channels have unstable noise characteristics due to the location of fiber optic cables. The channels with steady noise characteristics which can be seen in Fig. 3, were extracted.

SNR value of bins which have threats were calculated by dividing event power to noise power. The SNR value of threats in the range bins were compared with noise power of channels with steady noise. In order to keep SNR value between -5dB and 10 dB, noise channels were selected by comparing their power levels. The selected noise channels were added to all bins of the data. A sample of generated data and noise added to a collected threat can be seen in Fig. 4 and Fig. 5, respectively.



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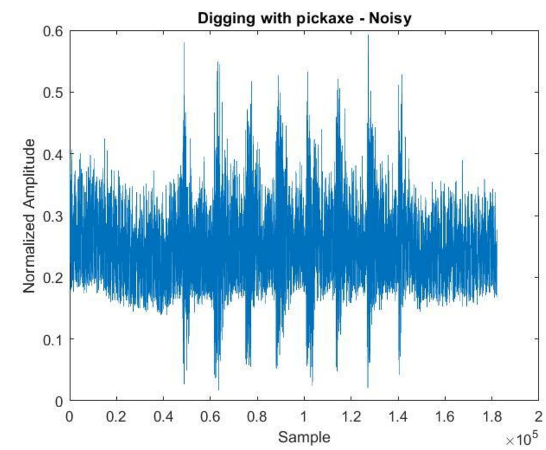

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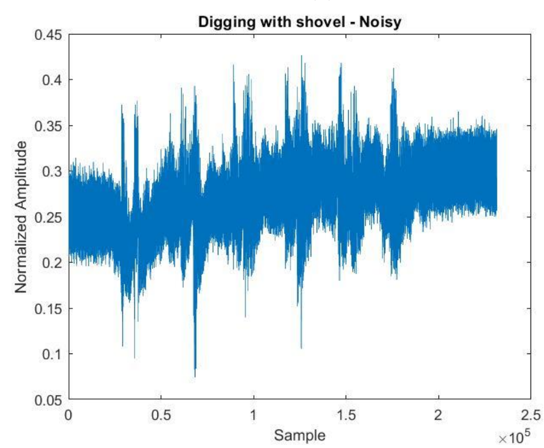

(c)

Fig. 5. Noise added sample event where a) Hammer Hit, b) digging with pickaxe and c) digging with shovel.

TABLE II
GENERATED DATABASE

Event Type	Low SNR Samples (-7 dB to 3 dB)	Medium SNR Samples (2 dB to 7 dB)	High SNR Samples (10 dB to 20 dB)
Hammer	5077	10214	4532
Pickaxe	1492	4596	5465
Shovel	996	4318	1860

By this study, new data which has different channel noise characteristics were achieved. The events were extracted from the new data by using its original position of events.

Due to its continuous characteristics, “walking” (which can be easily classified by using event duration parameter) data was eliminated from the database. Only “hammer”, “pickaxe” and “shovel” data is used. By this way, all event characteristics are close to each other. So that, difficulty of classification problem can be slightly increased. By using above data creation method, a new database is formed. In this database, every new signal is generated by using each event in a single bin from original database. Generated signals are divided into three groups according to their SNR level. So that, effect of different SNR levels on threat classification can be analyzed. Generated database specifications are given in Table II.

V. SIGNAL PROCESSING

A. PRE-PROCESSING

In order to prepare database for machine learning phase, several pre-processing operations were done. First of all, FFT (Fast Fourier Transform) of every generated data is calculated with 1 Hz resolution sensitivity. Sampling rate of signals are from 1 kHz to 25 kHz. This means that FFT spectrum can be generated 500 Hz to 12.5 kHz. In order to equalize length of each signal, FFT data is limited up to 500 Hz. By this way, every FFT vector has length of 500 points. Next step is to generate RGB image from FFT data. To do this, absolute logarithmic value of magnitude of FFT, imaginary part of FFT and real part of FFT are used as a layer of RGB data. These three vectors are reshaped in to 20x25 matrix form. By this way RGB images are formed as rectangular as in Fig. 6.

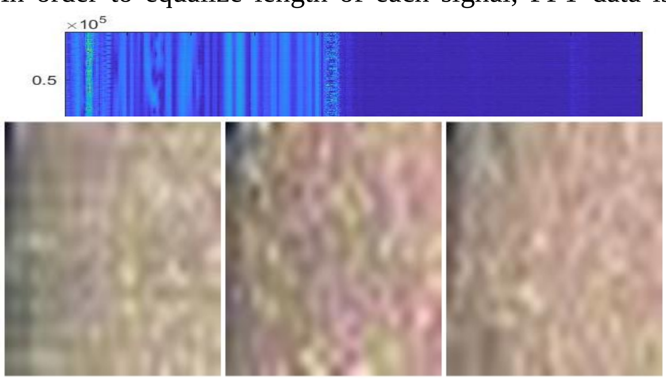

Fig. 6. Hammer, Pickaxe and Shovel images

TABLE III
DATA DIVISION FOR MACHINE LEARNING

Type of Data	Percentage
Training	70 %
Validation	15 %
Testing	15 %

From Table II, it can be seen that data numbers of events in each SNR group are not same. By using unequal size of training data in a machine learning algorithm causes poor classification performance. In order to eliminate this problem, data size is equalized by using lowest number of data in each SNR group which are 996, 4318 and 1860. From each class, this lowest number of data is taken and divided into three parts which are used for

TABLE IV.
CNN BASED DL STRUCTURE

Layer Name	Parameters	Description
Input	20x25x3	Takes FFT images
Convolutional 2D	20 Filters 7x7	Convolutional Filtering
ReLU	-	Activation Function
Convolutional 2D	50 Filters 5x5	Convolutional Filtering
ReLU	-	Activation Function
Convolutional 2D	100Filters 3x3	Convolutional Filtering
ReLU	-	Activation Function
Fully Connected Layer	200 Neurons	Neural Network
ReLU	-	Activation Function
Fully Connected Layer	500 Neurons	Neural Network
ReLU	-	Activation Function
Fully Connected Layer	3 Neurons	Neural Network
Softmax	-	Activation Function
Output Layer	-	Gives Output

TABLE V.
CNN BASED DL CLASSIFICATION PERFORMANCE

Accuracy Type	Low SNR	Medium SNR	High SNR
Hammer	60.9 %	58.2 %	67.7 %
Pickaxe	66.7 %	56.1 %	85.7 %
Shovel	77.9 %	56.1 %	84.3 %
Validation	84 %	64 %	88 %
Test	68 %	57 %	77 %

training, validation and testing phase of machine learning. Division ratio can be seen in Table

B. CNN BASED DL CLASSIFICATION

After the completion of preprocessing, database is moved to machine learning phase. In this context, performance criteria of DL (deep learning) structures come into prominence in success. Therefore, first of all database was used to train CNN (Convolutional Neural Network) based DL. This structure (described in [5]) has 14 layers and described in Table IV.

Machine learning structure that is given in Table IV, was trained with three SNR based datasets. Training accuracy, validation performance and loss graphs for all three databases are presented in Fig. 7.Performance analysis of the trained networks and their classification accuracies of events with respect to SNR levels are given in Table V.

C. NN BASED DL CLASSIFICATION

It was observed that CNN based DL performance was lower than expected. Input images are too small (500 pixels) to convolutional filtering method. When 2D Convolutional filters are applied to the input image, the pixels which have event data are overlapping. This confuses the leaning algorithm and reduces the performance of the system. Therefore, NN (Neural Network) based DL structure was decided to apply. In this context, a DL structure was developed. The structure of the deep network and its parameters can be seen in Table VI. Training accuracy, validation performance and loss graphs for all three databases are presented in Fig. 8. Performance analysis of the trained networks and their classification accuracies of events with respect to SNR levels are given in Table VII.

VI. DISCUSSION

By using small database, a bigger database can be generated. However, with this data generation method, classification problem is getting harder. Because, data generation method adds almost same noise characteristics to each signals while reducing SNR level which is also counted as performance reduction factor.

TABLE VI
NN BASED DL STRUCTURE

Layer Name	Parameters	Description
Input	20x25x3	Takes FFT images
Fully Connected Layer	1500 Neurons	Neural Network
ReLU	-	Activation Function
Fully Connected Layer	750 Neurons	Neural Network
ReLU	-	Activation Function
Fully Connected Layer	250 Neurons	Neural Network
ReLU	-	Activation Function
Fully Connected Layer	125 Neurons	Neural Network
ReLU	-	Activation Function
Fully Connected Layer	3 Neurons	Neural Network
Softmax	-	Activation Function
Output Layer	-	Classification Output

TABLE VII
NN BASED DL CLASSIFICATION PERFORMANCE

Accuracy Type	Low SNR	Medium SNR	High SNR
Hammer	94.3 %	89 %	100 %
Pickaxe	46.9 %	51.4 %	81.8 %
Shovel	52.9 %	89.5 %	94.2 %
Validation	70 %	76 %	96 %
Test	63 %	68 %	91 %

By this way, machine learning algorithm tries to classify both noise and event signals. Because of this, classification becomes problematic and classification performance is achieved less than expected level. In this work, three different SNR levels that is [-7 dB to 3 dB], [2 dB to 12 dB] and [10 dB to 20 dB] were used to train three classifier. Also, it is assumed that 10 dB to 20 dB

SNR range is high level and classifier was trained without using any noise reduction methods. However, in the literature, it can be seen that more than 50 dB SNR [5] ratio has achieved by using Wavelet based denoising method. By using 50 dB SNR ratio, very high classification accuracy has been achieved. Moreover, in another threat classification work [21], it can be seen that [0 dB to 10 dB] SNR range is used to train classifier with comprehensive feature extraction. By this way, highly accurate classification accuracy has been achieved. In addition, it can also be seen that for threat classification by using Wavelet based features gives high classification accuracy [22]. Proposed method offers acceptable accuracy without using preprocessing to increase signal SNR.

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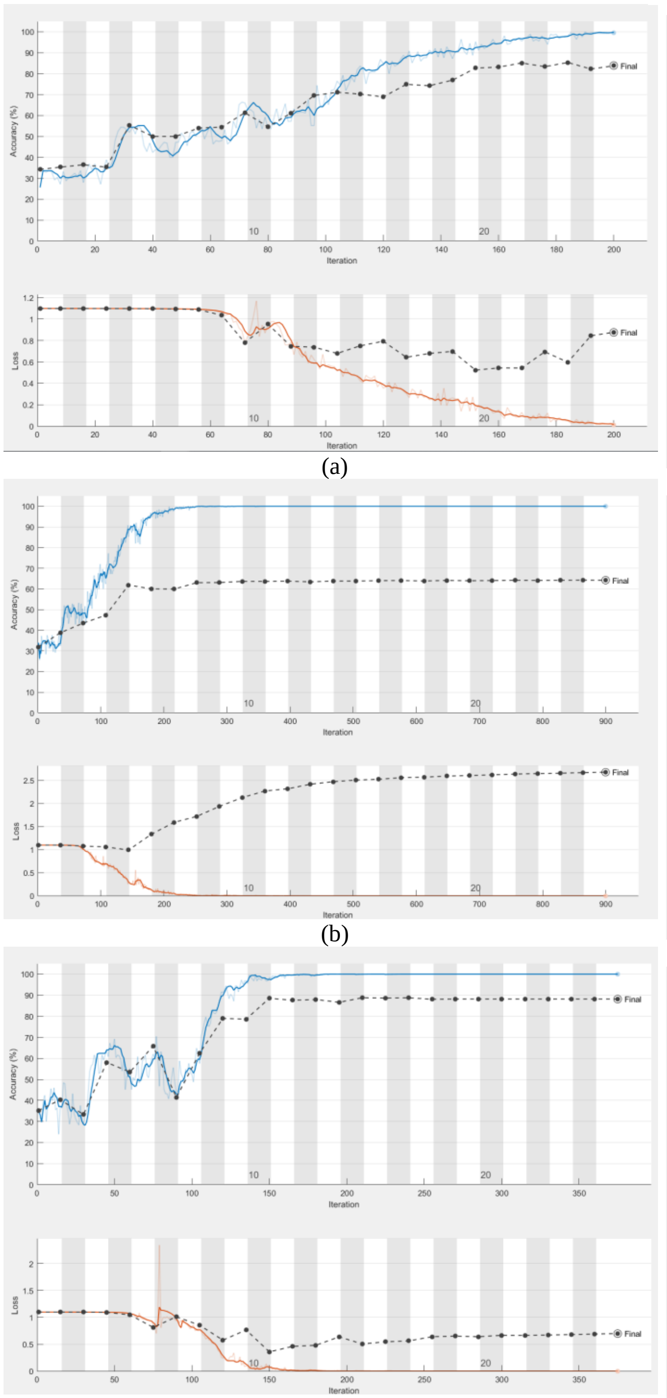

(a) (b) (c)

Fig. 8. NN based DL training where a) Low SNR training, b) Medium SNR training and c) High SNR training

By using small database, a bigger database can be generated. However, with this data generation method, classification problem is getting harder. Because, data generation method adds almost same noise characteristics to each signals while reducing SNR level which is also counted as performance reduction factor.

From the classification performances of proposed two different machine learning methods, it can be seen that number of pixels in an image is an important parameter for CNN algorithm. 3x3 CNN filter takes at least 9 pixels' data to generate a filtered image. Proposed images have 500 pixel (20x25) and filtering concentrates big portion of the image for classification. Because of that limitation, NN based DL algorithm gives better results. Instead of concentrating image to a compressed one, NN based algorithm used weights for each pixel. It is known that frequency spectrum of an event has approximately 50 Hz frequency length which means that 50 pixels in proposed image. So that, every image has approximately 10 % of useful information and 90 % noise characteristics. Extracting this 10 % and classification of three close event characteristics that is pickaxe, hammer and shovel, can be accepted as challenging scenario.

However, NN based algorithm has achieved that scenario and gave acceptable results. Instead of concentrating pixels, this algorithm gives weights for each pixel. By this way, high level of classification is achieved.

In order to increase CNN based DL algorithm performance, resolution of FFT (fast Fourier transform) algorithm can be improved. Proposed method has 1 Hz frequency bin resolution. By using resolution improvement, frequency bin resolution can be reduced to less than 0.1 Hz and number of pixel in an image can be increased more than 5000 pixels or more. So that, CNN filters extract more information from an image which is generated using proposed method. This will lead classification performance improvement.

VII. CONCLUSION

In this work, a fiber optic distribution acoustic sensing system for threat classification is presented with its signal collection, processing and classification parts. Basically, OTDR system is used to capture backscattered light signals. These signals were used to generate new data that has three different SNR ranges. After that, FFT algorithm was employed and spectrum information of the signals were used to generate RGB images. Generated images were used to train and test two different DL structures. The results show that even a small signal can be classified successfully by NN based DL structures rather than CNN based DL structures.

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