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Comparative DNN Model Analysis for Detection of Various types of Optical Noise

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Abstract—Throughout the next millennium, there will be an ongoing demand for more network capacity. The massively increasing number of users, as well as the duration of each user, and therefore the bandwidth, is a crucial factor. For many years, Internet traffic has grown rapidly. These characteristics have led to the development and, surprisingly, quick adoption of high-capacity optical grid systems on commercial sites. In this paper, we will examine the noises that arise in optical fiber communication. Because of the impact of noise and distortion, linear fiber-optic connections must ensure compliance with physics principles, design standards, and recognized engineering practice. The following forms of noise problems are commonly encountered in optical signal propagation: phase noise, ASE noise, and dispersion. In this case, all three forms of noise are recovered from the optical signal by utilizing variational mode decomposition (VMD) and the Wavelet Transform (WT). In this paper, we compare various deep neural models used to identify optical noise. We also displayed the performance analysis of each model as well as the execution time. The suggested technique outperforms the competition and has the potential to be a contender for automatic noise detection in a fiber communication link.

Index Terms—Optical Fiber Communication, Variational mode decomposition (VMD), Wavelet Transform, Deep Neural Network, Optical noise, Automated noise detection (AMD).

I. INTRODUCTION

WHILE the modern era begins, the telecommunications industry is undergoing massive development with far-reaching implications. There are several elements that contribute to these shifts. First and foremost, there is an ongoing and unabated need for additional network capacity in the context of Communication Engineering (CE). This urge is sparked by a variety of factors. For many years, Internet traffic has been steadily increasing. There have been substantial variances in growth expectations over the years, with rapid growth predictions tripling in four to six months. Despite the fluctuations, these growth projections are typically considerable, with more recent forecasts of over 50% per year. Meanwhile, large-scale access technologies such as DSL or cable modems that provide a user with 1 Mb/s of bandwidth have been widely deployed. In the United States, for example, approximately 55% of people had broadband connections in their homes in 2008, while only 10% had access via 28–56 Kb/s dial-up [1].

In contrast to traditional speaking traffic, data traffic dominates network traffic. Previously, the reverse was true, and as a result, legacy networks were designed to serve voice

more successfully than information. In today's world, data transmission services are widely available and can provide high-quality service for sensitive and demanding applications such as audio and video. These factors have resulted in the development and, unexpectedly, rapid commercialization of high-capacity optical grids from research centers.

Machine learning, on the other hand, is a rising technology that benefits all sorts of businesses in all industries. There are no restrictions on the applications. Machine learning can help many different sorts of enterprises, from medical to investment banking, aviation to information technology, and advertising to administration, adapt and advance in a more agile manner. We may be capable of screening a hugely structured table and detecting patterns, but computers can screen far larger data sets and discover patterns faster than any person or human-generated table function thanks to AI and Machine Learning. ML helps any system to gather insights quickly and efficiently, reducing analytical time. As a result, machine learning plays a critical role in organizing and analyzing massive amounts of data.

In this study, we will look into sounds that occur in optical fiber transmission. Due to the effects of noise and distortion, linear fiber-optic connections are responsible for guaranteeing conformity with principles of physics, design standards, and established engineering practice. Here we compare different DNN models performance and accuracy in detecting optical noises.

II. METHODOLOGY

A fiber-optic link consists of transmitters, fiber cable, and receivers. With the incoming radio frequency signal, the transmitter adjusts the optical laser output. This modular optical signal is converted to the original signal through a fiber-optic link to the receiver. In OFC, there are several sorts of noises arise. In our research, we considered amplified spontaneous emission noise, phase noise, and dispersion. We compute the VMD for each form of noise to recover the noise signal since fiber noise occurs over a large frequency range. After noise separation, the wavelet transform will be used to understand the basic concepts of the noise signal as well as the power associated with it and save this noise output as scalogram images as shown in figure:1. Now this data can be used to train and test the network.

VMD

The empirical mode decomposition approach allows any difficult data set to be broken down into a finite and frequently small number of intrinsic mode functions, which

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Fig. 1. Wavelet transform of noise signals

allows Hilbert to convert well-conformed. This method of breakdown is adaptive and hence very efficient. Since the breakdown is dependent on the local management of data, it applies to nonlinear and non-stationary operations [2].

In 2014, Dragomiretskiy introduced Variational Mode Decomposition as a novel conscience signal decomposition approach inspired by Huang and Gills [3]. The VMD implies that the signal is the compact support of the Fourier spectrum, like other EMD-like techniques. Based on this assumption, a variable set of Wiener filters is built, which extracts all modes concurrently [4]. The VMD thus works well to resolve closely related modes and reduce the aliasing mode [5]. A clear need for VMD mentioned in Ref. [3] by Dragomiretskiy is that it is necessary to identify the number of modes before VMD is applied. Although it is possible to intentionally detect the number of modes in the frequency domain or after the VMD processing is adapted, Wang in Ref. [6] recently analyzed the filter-bank feature of VMD and various research has been done to improve the VMD adaptability. Most of these improvements are needed to first process the VMD and then optimize variables or integrate the IMFs iteratively [7] [8] [9].

An EMD's undeniable mode is as a signal with a maximum number of local extremes and null crossings. In following research, the concept of modulation criterion was modified somewhat into so-called intrinsic mode functions [2]. The decomposition variable mode (DVM) is an adaptive and almost orthogonal method of decomposition of signals [3]. The method of VMD decomposes the $x(t)$ signal into a finite number of intrinsic band-limited functions $x_k(t)$. VMD incorporates Wiener filtering, Hilbert transformation and analysis, and frequency change through harmonic mixing and the alternating multiplier direction method (ADMM) [3]. This technique provides good precision and reliability for low-frequency spectrum extraction features. It is extensively used in different domains, such as biomedical picture de-noise [10], bearing error detection [11] [12] and pressure fluctuation signal analysis [13]. VMD is a new approach that can degrade a whole signal to a number K of modes u_k out around the central frequency ω_k in such a variable step signal decomposition. VMD is a new approach that can degrade a whole signal to a number K of modes u_k around the central frequency in such a variable step signal decomposition. A limited variational challenge

that is defined as follows should be resolved using VMD [14]:

$$\min_{\{u_k, \omega_k\}} \left\{ \sum_k \left\| \left(\delta(t) + \frac{j}{\pi t} \right) * u_k(t) \right\| e^{(-j\omega_k t)} \right\|_2^2 \right\} \quad (1)$$

where f is really the primary decomposable signal; $u_k : (u_1, u_2, u_k)$ $\omega_k : (\omega_1, \omega_2, \omega_k)$ are abbreviation notes used to indicate the set among all modes and associated center frequencies.

In addressing the restrictions, the penalty term and the Lagrangian multipliers are represented by $\lambda(t)$. These two terms are combined in line with the good convergence characteristics of the finite weight quadratic penalty and the tight implementation by the Lagrangian multiplier of the constraint.

Wavelet Transform

Wavelet transformations are mathematical techniques that may be used to analyse data with characteristics that change across scales. Frequencies that change over time, transients, and slowly shifting trends are all examples of signal characteristics. Edges and textures are examples of characteristics in pictures. Wavelet transformations were developed to overcome the shortcomings of the Fourier transform. Wavelet analysis is based on decomposing signals into shifted and scaled copies of a wavelet, whereas Fourier analysis is based on decomposing signals into sine waves of specified frequencies. In contrast to a sine wave, a wavelet is a fast-fading, wave-like oscillation. This allows wavelets to represent data at different sizes.

DNN

Deep learning refers to a type of machine learning techniques that employ many layers to extract higher-level characteristics from raw data [15]. Lower layers in image processing can detect edges, whereas higher layers can identify human-relevant concepts like numerals, characters, and faces. Artificial neural networks, especially convolution neural networks (CNN), are used in the majority of contemporary deep learning models [16]. Unsupervised learning problems can benefit from deep learning algorithms [17]. This is a significant advantage since unlabeled data is more plentiful than labelled data [18]. Deep learning techniques for supervised learning remove feature engineering by converting data into compact intermediate representations similar to main components. A greedy layer-by-layer technique can be used to build deep learning architectures. The objective is to deconstruct these abstractions and determine which characteristics boost performance.

Keras DNN Models

Keras is a Python interface for ANNs that is available as open-source software. It is a front-end for Tensor-Flow and supports a variety of back ends, such as Microsoft Cognitive Toolkit and others. It is easy to use and extendable, with the objective of facilitating quick DNN research. We are using here all the keras application models to compare the each model's accuracy on the optical data.

All models used for comparison are listed below:

- 1) Xception
- 2) VGG16
- 3) VGG19
- 4) ResNet50
- 5) ResNet101
- 6) ResNet152
- 7) ResNet50V2
- 8) ResNet101V2
- 9) ResNet152V2
- 10) InceptionV3
- 11) InceptionResNetV2
- 12) MobileNet
- 13) MobileNetV2
- 14) DenseNet121
- 15) DenseNet169
- 16) DenseNet201
- 17) NASNetMobile
- 18) NASNetLarge
- 19) EfficientNetB0
- 20) EfficientNetB1
- 21) EfficientNetB2
- 22) EfficientNetB3
- 23) EfficientNetB4
- 24) EfficientNetB5
- 25) EfficientNetB6
- 26) EfficientNetB7

Transfer-Learning

Transfer-learning (TfL) is basically some the CNN that are designed which is actually giving state of art algorithm to classify different images. It is best first to know about image-net. Every year a competition is held where in every year people come up with new type of CNN to classify thousand of different types of images and whichever have the highest accuracy get the prize money. In this techniques using the state of art algorithm listed in Table: I and changing the output layer and use that particular algorithm for solving our problem statement. It has become popular in the field of image classification and NLP. The best thing about this method is that it takes less number of iterations and high accuracy rather than a model which build from scratch. Using TfL we can save lot of computation time and resources because many time this pre-trained models are trained on millions of images. If we want to run this type of models on our local system it might take days or even months. All we are doing here is getting all the weights of pre-trained models and then we kindly change the last layer or last few layers sometimes and will get the super high accuracy of our problem statement.

Loss Functions

To understand how neural network training works, it's important to first understand loss or a cost function, which is what we'll go over in this section. When creating a keras or tensorflow model, we can specify different values for this loss function. We used the "categorical cross entropy"(CCE) loss function here, but other values such as "binary cross

entropy"(BCE), "mean absolute error"(MAE), "mean squared error"(MSE) and so on are also possible. A loss function, also known as a cost function or error function, quantifies the difference between the output and a target value. In our model, we actually output a probability distribution, and from this distribution, we know what the intended target value was from the training data, and then we come up with a method for determining how wrong the model is. There are numerous theoretical approaches we could take. But in general, the loss function of choice for classification that uses softmax as the activation function on the output layer is categorical cross entropy. The formula of CCE is :

$$L_i = - \sum y_{i,j} \log(\hat{y}_{i,j}) \quad (2)$$

L_i is sample loss value, i is i -th sample in a set, j is label/output index, y is target value and $\hat{y}$ is predicted value.

The question of why we are using CCE here may arise. The first reason is that when we approach these ML problems from a probabilistic perspective, MSE naturally arises from the linear regression problem and CCE naturally arises from the logistic regression problem. In a multi-classification problem, the MSE does not penalise the model as much as it should for a misclassification, whereas CCE penalises the model heavily for a single misclassification. The gradient of the loss curve is very low in the case of the MSE, so changes in weights are negligible. However, in the case of CCE, the gradient is too steep. As a result, if our model makes a minor error also, it will adjust the weights to train the network more effectively.

III. MODEL COMPARISON

In the below figures, all the training and testing model performances have been shown.

Fig. 2. Densnet121

Fig. 3. Densnet201

Fig. 6. ResNet101

Fig. 4. InceptionV3

Fig. 7. EfficientNetB3

Fig. 5. MobileNet

Fig. 8. EfficientNetB4

Fig. 9. EfficientNetB7

TABLE I
COMPARISON TABLE

Model	Train Loss	Train Acc.	Valid Loss	Valid Acc.
Xception	NA	NA	NA	NA
VGG16	1.0987	0.3045	1.0986	0.3333
VGG19	1.0987	0.3333	1.0986	0.3333
ResNet50	1.7692	0.9627	2×10^4	0.3394
ResNet101	0.0791	0.9783	0.0145	0.9952
ResNet152	0.2941	0.9266	0.5126	0.7341
ResNet50V2	0.6910	0.8183	0.6050	0.7088
ResNet101V2	0.1488	0.9458	0.0634	0.9807
ResNet152V2	0.4002	0.7978	0.3714	0.8532
InceptionV3	0.0173	0.9940	1.208	1
InceptionResNetV2	0.4002	0.7978	0.3714	0.8532
MobileNet	0.0076	0.9976	0.0006	1
MobileNetV2	0.0993	0.9615	243	0.3333
DenseNet121	0.0760	0.9832	0.0240	0.9940
DenseNet169	0.1167	0.9651	0.1318	0.9519
DenseNet201	0.0268	0.9928	0.0071	0.9988
NASNetMobile	0.0020	1	201015	0.3333
NASNetLarge	0.0594	0.9807	2×10^{12}	0.3333
EfficientNetB0	0.0405	9964	10.1856	0.3333
EfficientNetB1	0.5490	0.9723	52.6101	0.3333
EfficientNetB2	0.1103	0.9940	9.7416	0.4838
EfficientNetB3	0	1	0	1
EfficientNetB4	0.0004	1	0	1
EfficientNetB5	0.1636	0.9940	1.1126	0.9110
EfficientNetB6	0.0653	0.9964	0.0993	0.9675
EfficientNetB7	0.1570	0.9988	0.0052	0.9988

IV. CONCLUSION

As discussed in the paper, ML & Deep Learning gave optimum performance in the case of noise detection in fiber optic cable. Table: I contains a list of all of the loss and accuracy measures. In our comparative model analysis few models shows the significant high accuracy towards the data we generated. As shown in Table: I the InceptionV3, MobileNet, EfficientNetB3 and EfficientNetB4 models gave the highest accuracy among other models.

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