Abstract: This paper presents two efficient approaches for radiation effect identification using deep learning and image processing approach for the classification of images transmitted over optical fibers. The first approach discovers the effect of gamma radiation on optical fibers from certain images with certain repetitive patterns. The quality of the images obtained can be used as an indicator of the radiation effect. A deep learning model is built for this objective comprising 6 convolution layers followed by 6 max pooling layers. The other approach depends on the analysis of zebra chart image based on depth/edge model. Quality metrics of the received images are used for classification on of the cases with and without radiation. Simulation results reveal high efficiency of the two proposed approaches for radiation effect detection.

Keywords: Optical fiber, Image processing, Radiation effect detection, Gamma radiation, Deep learning, Image processing.
1. Introduction

Optical fiber communications in severe radiation effects leads to much dispersion in fiber cables. This dispersion leads to deterioration in performance of the fiber cables. The motivation towards finding an efficient diagnostic tool for radiation level and effect detection has led to the development of some techniques using chemical and physical sensors [1].

The problem with this trend is the need of outside sensors to monitor the radiation level, which may lead to some sort of inconsistency. Moreover, some efforts have been exerted to build mathematical models for radiation effect on optical fibers [2]. Some of these models adopt closed-form expressions and some others adopt neural modeling [3]. Unfortunately, these models can describe the radiation effect in fiber parameters, but cannot be used for radiation effect detection.

A new trend for monitoring of the radiation behavior and effect on optical fiber adopt transmission of certain images with repetitive patterns regularly on the fiber and quality assessment of these images at the receiver for radiation level detection [4].

Different approaches have been presented in the works for the radiation effect detection with a number of chemical and physical sensors, which divided into liquid, solid and gaseous systems, that available to detect and measure ionizing radiation and researchers are continually looking for ways to develop the systems, providing real-time measurements, increasing the sensitivity or significantly reducing the prices. These reasons are important for providing the optimum radiation dosimeter.

The main concern of our study is to build trusted software models for Gamma radiation effect detection based on deep learning and image processing techniques. The first approach is a deep learning technique for the detection of the radiation effect on optical fibers based on regularly transmitted zebra chart patterns. The received images are classified into images affected by radiation and images unaffected for visible and infrared images [5] and the second approach is image processing techniques which assess the quality of reconstructed images.

This paper is arranged into four sections: Section 2 discusses the dispersion due to radiation effect in the optical fibers. Section 3 presents the proposed work. Section 4 describes simulation results. Section 5 presents the concluding remarks followed by the more relevant references.

2. Dispersion in Optical Fibers due to Radiation Effect

Gamma radiation effect leads to some deterioration of the dispersion profile of optical fibers. Generally, the total dispersion coefficient $P$ in an optical fiber comprises material dispersion and waveguide dispersion [6].

$$ P = M_P + W_P $$

where $M_P$ and $W_P$ denote the material dispersion, and the waveguide dispersion, respectively.

2.1 Material Dispersion

Material dispersion is the process of spreading of optical signal due to wavelength of the transmitted signal over optical fiber. It is given by [7].

$$ M_P = -\frac{\lambda}{c} \frac{d^2 n_1}{d \lambda^2} $$

where $n_1$ is the refractive index, $\lambda$ is the wavelength in nm and $c$ is the speed of light in vacuum. The refractive index of the fiber $n_1$ comprising the gamma radiation effect is given by [8].

$$ n_1(T, \gamma, \gamma) = \left[ A(T, \gamma) + \frac{B(T, \gamma)}{(\lambda^2 - C(T, \gamma))} + \frac{D(T, \gamma)}{(\lambda^2 - E)} \right]^{1/2} $$

where $E$ is a constant equal to 100 $\mu$m$^2$, $\gamma$ is the radiation dose in MGy of Gamma ray and
\( T \) is the ambient temperature in \( K \). \( A(\gamma, T) \), \( B(\gamma, T) \), \( C(\gamma, T) \) and \( D(\gamma, T) \) are coefficients with functions of both temperature and radiation dose. These coefficients are calculated from the following equations [9]:

\[
A(T, \gamma) = A(\gamma)F_A(T) \\
B(T, \gamma) = B(\gamma)F_B(T) \\
C(T, \gamma) = C(\gamma)F_C(T) \\
D(T, \gamma) = D(\gamma)F_D(T)
\]

The coefficients \( A(\gamma), B(\gamma), C(\gamma) \) and \( D(\gamma) \) are radiation dose functions [3]:

\[
A(\gamma) = 1.329631 + 2.7 \times 10^{-4} \exp \left( \frac{\gamma}{0.391319} \right) \\
B(\gamma) = 0.82863 + 7.7 \times 10^{-4} \exp \left( \frac{\gamma}{0.440013} \right) \\
C(\gamma) = 0.01105 + 4.7 \times 10^{-6} \exp \left( \frac{\gamma}{0.391139} \right)^2 \\
D(\gamma) = 0.98481 + 1.1 \times 10^{-3} \exp \left( \frac{\gamma}{0.964926} \right)
\]

Moreover, the coefficients \( F_A(T), F_B(T), F_C(T) \) and \( F_D(T) \) are temperature functions with the forms,

\[
F_A(T) = \frac{1.338922 - 3.7 \times 10^{-4}(T - T_r)}{1.338922} \\
F_B(T) = \frac{0.819526 - 3.843 \times 10^{-4}(T - T_r)}{0.819526} \\
F_B(T) = \frac{1.055995 - 2.8 \times 10^{-3}(T - T_r)}{1.055995}
\]

where \( T_r \) is the room temperature in \( K \).

The second-order optical fiber core refractive index differential equation is set by:

\[
\frac{dn}{d\lambda} = -0.5 \left[ \frac{2B\lambda}{\lambda^2 - C} \left( \frac{10B\lambda}{\lambda^2 - C} + \frac{8B\lambda}{\lambda^2 - E} + \frac{2D\lambda}{\lambda^2 - E} - \frac{10D\lambda^3}{3(\lambda^2 - E)^2} \right) \right] \frac{n_i}{n_i^2} \\
+ 0.25 \left[ \frac{2B\lambda}{\lambda^2 - C} \left( \frac{\lambda^2 - C}{\lambda^2 - E} \right) \frac{2D\lambda}{\lambda^2 - E} \right] \frac{n_i}{n_i^2}
\]

### 2.2 Waveguide Dispersion

The step index single mode optical fiber waveguide dispersion can be calculated from [10].

\[
W_p = -\frac{n_1 - n_2}{c \lambda} \left[ V \frac{\partial^2 (bV)}{\partial V^2} \right]
\]

where \( n_2 \) is the cladding refractive index.

\[
V \frac{\partial^2 (bV)}{\partial V^2} = 0.080 + 0.5439(2.834 - V)^2
\]

where \( V \) is the normalized waveguide parameter set by [11].

\[
n_2 = 0.9979n_1
\]

From the above-mentioned models of dispersion, it is clear that the radiation has a non-linear effect on the dispersion model of the fiber. This effect may lead to deterioration of the optical fiber performance. Detection of the radiation effect if existing is a very important task to determine the performance level of the optical fiber communication system, and take some actions to compensate for this deterioration such as changing the optical modulation type used, changing the ambient temperature level for the fiber communication systems, and taking some actions to reduce the effect of radiation by reducing the radiation level of some medical systems. So, there is a need for an efficient diagnostic tool for detecting the presence of radiation external from the fiber and based on some other auxiliary tools such as image processing tools for certain image patterns transmitted regularly over the fiber system.

### 3. Proposed Work

In our work, we present two approaches for gamma radiation detection based on signal and image processing techniques.
3.1 Gamma Radiation Effect Detection with A deep learning technique

The proposed model for radiation effect detection depends on the transmission of zebra chart pattern over fiber cables regularly in cases of radiation and no radiation. Both visible and IR light have been used for this objective. Some images have been collected for both scenarios of gamma radiation and no radiation. Figure 1 shows two examples of images for cases of radiation and no radiation. Deep learning is used as the classification tool for the images with and without radiation. It is a type for machine learning in which a model learns to perform classification tasks directly from images. Features are learnt automatically by a convolutional neural network (CNN) and used for classification. The CNN includes the feature extractor in the training process [12]. It consists of convolutional layers followed by activation function, pooling layers, dropout layers, and fully connected layers. The inclusion of the dropout layer is used as a regularization technique for reducing over fitting [13-15].

![Fig. 2 Convolutional layer](image)

The convolutional layer of the proposed model contains filters that are used to perform a two-dimensional (2D) convolution on the input image. The resulting features of the convolution layer vary depending on which convolution filter is used. The convolutional layer is a type of feature extraction neural networks. Figure 2 shows block diagram of the convolutional layer.

![Fig. 3 Maximum pooling layer.](image)

The pooling layer of the proposed model is another type of feature extraction neural networks. The pooling layer decreases the size of the image. It combines neighboring pixels of a certain area of the image into a single representative value. The used value is the maximum or mean value of the pixels. The max-pooling layer is used in the proposed technique. Figure 3 shows an example of maximum pooling layer.

\[ F(x) = \max(0, x) \] (20)

The Rectified linear unit (ReLU) allows for faster and more effective training by mapping negative values to zero and maintaining positive values. The output of the ReLU layer is obtained with the following activation function.

The fully connected layer (FC) reduces the size of input data to the size of classes that the CNN is trained for by combining output of CNV layer with different weights. Each neuron at the output of the CNV layer will be connected to all other neurons after weighted properly. Similar to CNV layer, weight of

![Fig. 1 Samples of the zebra chart transmitted through visible and IR images with and without radiation.](image)
these taps in FC layer is found though back propagation algorithm.

Classification layer is the final layer of the CNN that converts the output of FC to probability of each object being in a certain class. Typically, soft-max type of algorithms is used in this layer to provide the classification output as shown in Eq. 21.

\[ P(y = j|x) = \frac{e^{T_{wj}}}{\sum_{k=1}^{K} e^{T_{wk}}} \]  

(21)

The proposed model consists of 6 convolution layers followed by 6 max pooling layers. Finally, a global average pooling is used. Figure 4 shows an exemplary architecture of the convolution neural network. Images are input in 224 × 224 size. Layers have numbers of filters of 16, 32, 64, 128, 256, and 512 for layers 1, 2, 3, 4, 5 and 6 respectively. Finally, a dense layer with size of 2 is used for classification decision as shown in figs. 4 and 5.

3.2 Gamma radiation detection with image processing technique.
3.2.1 Optical fiber specification

In our work, we use the prototype of single core fiber and image fiber [16], that contains 2000 core fibers and cladding that formed from pure silica of the hydroxyl concentration of 1000 ppm Table 1 indicate the main description of the created image fiber, and Figure 6 shows the configuration of the produced image fiber.

<table>
<thead>
<tr>
<th>Item</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Core materials</td>
<td>Pure silica</td>
</tr>
<tr>
<td></td>
<td>Hydroxyl 1000 ppm</td>
</tr>
<tr>
<td></td>
<td>Chlorine less than 30 ppm</td>
</tr>
<tr>
<td>Cladding materials</td>
<td>Pure silica</td>
</tr>
<tr>
<td></td>
<td>Fluorine 4%</td>
</tr>
<tr>
<td>Shielding</td>
<td>Epoxy acrylate</td>
</tr>
<tr>
<td>C diameter</td>
<td>6.7 ± 0.3 μm</td>
</tr>
<tr>
<td>Cladding thickness</td>
<td>3.3 ± 0.3 μm</td>
</tr>
<tr>
<td>Image circle diameter</td>
<td>480 ± 50 μm</td>
</tr>
<tr>
<td>Fiber diameter</td>
<td>540 ± 50 μm</td>
</tr>
<tr>
<td>Shielding diameter</td>
<td>620 ± 60 μm</td>
</tr>
<tr>
<td>Number of core fibers</td>
<td>2000</td>
</tr>
</tbody>
</table>

3.2.2 Gamma radiation detection with image processing method block diagram

The block diagram of the suggested technique which describes step by step implementation depends on sending photographs of the zebra chart image of
optical fiber using visible and infrared light and testing the quality metrics of these images at the receiver. The operating mechanism of the proposed technique presented in the Figure.7 we obtain the optical fiber image. Then image of optical fiber as visible and infrared light while test the quality metrics. Table 1 shows the major specification of the produced image fiber, and Figure 6 illustrates the configuration of the produced image fiber.

The main aim of this proposed method is to implement an algorithm which will enhance the segmented image with block diagram as the following:

Step 1: Read an optical fiber image.
Step 2: Then image of optical fiber as visible and infrared light.
Step 3: test the quality metrics means [17] as the following:

A. Edge Intensity (Edge I)

A higher edge intensity of an image represents a higher image quality. The Sobel operator can be used for edge detection, the input image \( f \) is convolved with two filters; \( h_x \) and \( h_y \).

\[
h_x = \begin{pmatrix} 1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}, \quad h_y = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix} \tag{22}
\]

Where the filter \( h_x \) corresponds to horizontal differentiation with respect to vertical edges, while the filter \( h_y \) corresponds to vertical differentiation with respect to horizontal edges.

The results of the two convolutions are combined to get the Sobel edge intensity \( S \).

\[
S = h_x \otimes f, \quad S_y = h_y \otimes f
\tag{23}
\]

\[
S = \sqrt{S_x^2 + S_y^2} \tag{24}
\]

B. Image Entropy (E)

It is a measure of the amount of information enclosed in the image. If a probability density \( p \) of pixel levels in an image is identified, the amount of information in the image can be estimated with the entropy \( E \) as follows:

\[
E = -\sum_{i=0}^{L-1} p(x_i) \log p(x_i) \tag{25}
\]

Where L is the number of gray levels in the image.

C. Local Contrast (local C)

It is an index for the image quality and clarity of view. It is calculated as:

\[
C_{local} = \frac{\mu_{target} - \mu_{background}}{\mu_{target} + \mu_{background}} \tag{26}
\]

Where \( \mu_{target} \) is the gray-level mean of the local region of interest, and \( \mu_{background} \) is the mean of the image background. A higher value of local C indicates more clarity of the image.

D. Average Gradient (Avg. G)

It shows the amount of details or texture variation in the image. It is calculated for an image \( f \) as follows:

\[
g = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} \left( \frac{\partial f}{\partial x} \right)^2 + \left( \frac{\partial f}{\partial y} \right)^2 \tag{27}
\]

where \( M \) and \( N \) are the dimensions of the image \( f \).
4. Simulation Results

4.1 Gamma Radiation Effect Detection with A deep learning technique

Simulation experiments are performed using python 3.5 [14], Tensorflow [15], and Keras [18]. Figure 6 shows the observations of accuracy and loss for training and testing phases along the epochs, for visible and IR images. Twenty epochs and batch size of 10 are adopted to train the model. From Fig. 8, it can be observed that the model achieved an accuracy of (100%) for both IR and visible images.

4.2 Gamma radiation detection with image processing technique

A simulation of transmission of zebra chart model on optical fiber with and without radiation effect is illustrated in Figure 9. Numerical quality metrics are presented in Tables 2 and 3, from these results it is possible to used image contrast at the e for discrimination between scenarios with and without radiation.
5. Conclusion

This paper presented two efficient approaches for radiation effect detection. The objective of this procure is to build trusted software for optical fiber state monitoring. An efficient deep learning scheme has been presented in this paper for Gamma radiation effect detection in optical fibers. Simulation results on 20 image patterns transmitted with and without radiation effect on zebra chart patterns have shown a success rate of detection of 100%.

References


