Journal of Applied Artificial Intelligence
https://jaai.sabapub.com
ISSN: 2709-5908

*2022 Volume 3, Issue 2: 39–46*

*DOI:* https://doi.org/10.48185/jaai.v3i2.620

# Convolutional Neural Networks for Defect Detection on LV cables

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Received: 29.10.2022 • Accepted: 19.11.2022 • Published: 30.12.2022 • Final Version: 31.12.2022

**Abstract:** A convolutional neural network (CNN) is a machine learning algorithm that is particularly well-suited for tasks such as object recognition, image captioning, and speech recognition. CNNs are particularly effective at detecting features in images that are not easily observable by other machine learning algorithms, such as defects in manufacturing. By analyzing large collections of images, CNNs are able to find patterns that are indicative of defects. Power cables are an important part of manufacturing, as they allow machines to be operated and communicated with. Recently, great importance has been offered in making electricity generation, transmissions, distribution and storage smart. However, the shift to smart grid should include intelligent methods of detecting the reliability of electrical connections. Several types of electrical cables are used to transmission and distribution of electrical energy. Due to excellent electrical and mechanical properties, cross-linked polyethylene (XLPE) cables are widely used in power systems. Poor manufacturing techniques in the production and installation of cable joints will cause insulation defects. Some suggest, the use of interdigital capacitive (IDC) for online monitoring on XLPE cables. Others suggest The use of a continuous wave (CW) terahertz (THz) imaging technology could help display and detect interior faults in cross-linked polyethylene (XLPE) plates used for power line insulation. In this paper, I developed models which predominantly use locally collected custom dataset to forecast individual power cable physical safety status. The model is aimed at replacing the physical inspection with computer vision and image processing techniques to classify defective power cable from non-defective ones. The project is implemented using the Python programming language, the Tensorflow library, and a Convolutional neural network.The Convolutional Neural Network (CNN)-based method is purposefully chosen and applied in this project for power cable defect classification. The project culminates by recommending the use of same or additional datasets and provide modalities to detect power cable defect from live video.

**Keywords:** Artificial intelligence, Computer Vision, Convolutional Neural Network (CNN) , Power Cables, Defect

## 1. Introduction

There are many ways to detect defects in a product, ranging from manual inspection to machine learning algorithms. One common approach is to use a camera to take pictures of the product and then use a machine learning algorithm to identify defects. [12] Since the introduction of Industry 4.0, machine vision-based inspection technologies have become increasingly important for automated monitoring and quality control of manufactured goods. Convolutional Neural Network (CNN) methods [11] have displayed cutting-edge performance in a variety of computer vision tasks.

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According to [13] The implementation of defect detection depends on a special detection data set that contains expensive manual annotations. The forementioned approaches can be used to detect a wide variety of defects, including: -Incorrect parts -Wrongs colors -Damaged parts -Unused parts -Unsafe parts.

Power cables are among the core components in the power transmission and distribution network ,[14] Particular emphasis is paid to the condition management of power plant LV cables, as these cables play a critical role in the safe functioning of the facilities. cables are widely used in every sector of power industry and enormously affects industrial production, supports all the basic infrastructure of the country and plays an important role in the functioning of utility infrastructures. Despite the fact that we rely heavily on cables in our daily lives, there is no precisely defined end-of-life standard [21] to measure the health of LV cables. Inspection and testing of cables is among the major routine safety tasks performed at the last stage of production and pre installation operations. Apart from economic loss, defects in cables or wires could entail life and safety risk to the users. Thus, conducting several tests and inspections are paramount importance to the manufacturers and end users. Visual inspection (detecting wire breaks or physical damage) is significant portion of cable and wire inspection. This project intends to substitute physical inspection with image processing techniques by employing CNN for binary image classification (Defective /Non-Defective).

There are various defect types when dealing with power cables, ranging from physical cuts to corrosion and total burnout. [3] proposed deep learning-based cable surface defect detection model to perform efficient cable surface defect identification and address the issue of low detection accuracy of microscopic and undetectable cable surface flaws. [3] extracted The initial faulty features are using a lightweight backbone feature extraction network. Then, the serial and parallel convolution modules are created to get a large number of defect features and minimize the number of model parameters. To find surface damage on cables in long-span cable-stayed bridges, a visual inspection system is developed by [2], using scale-invariant feature transform (SIFT) algorithm.

In this study, Convolutional Neural Network is used to predict (defective and non-defective) power cables based on training data gathered locally that shows physical cable cracks and new cables that are not damaged. This study uses a local image dataset and a standard convolutional neural network architecture to predict future input images while accounting for the non-linearity in these features. To enable an accurate forecasting model, the first crucial data collection and data processing are completed. The accuracy of the model is then assessed once a Convolutional Neural Network with the same features has been constructed.

### 1.1. Background Of The Study

Manufacturing companies perform power cable physical damage assessments manually. The section within side the manufacturing system at which produced gadgets are evaluated for defects, may also range for huge gadgets. However, they may be all achieved manually. The trouble with this approach of checking defects lies in human mistakes. According to a study[7], 20 percentages of defects went unreported because of human mistakes. Human mistakes may have unfavorable effects on industries. For example, if a production business enterprise manufactures metallic sheets, which can be used within side the creation industry, produces metallic sheets with defects, it'll have large affects at the businesses shopping for the ones sheets to assemble buildings. Manual assessments for defects aren't assured and efficient. The price of hiring a workforce, answerable for first-class assessments maintains to rise, without the assure of damaged loose products. Defects that cross neglected bring about every other issue in front of customers. on several occasions Recalls arise whilst a faulty batch of object is distributed to clients and must be returned from clients because of the presence of defects.

## 2. LITRATURE REVIEW

Recent article by [1] and [9], provided detail insight on potential application of Deep learning for Steel Pipe Weld Defect Detection. In same manner [6] proposed real-time defect detection of sewer pipe using CCTV and metric learning. As a crucial component of energy and power network, power cable defect requires due attention when it comes defect detection. In this regard,[4] proposed 3D model and utilization of sensors to monitor the healthiness of XXLPE insulated cables.but,the great contribution of [5] used two deep learning approaches for Defect Detection in High Resolution Aerial Images of power cable Insulators ,the two deep learning approaches are based on Faster R-CNN and CME-CNN (cascade the mask extraction and exact region-based convolutional neural network).Defect detection is necessary in the power sector to eliminate the fault before it increases damage to the power system. Any failure in detecting power line defects and addressing it earlier, will cause the entire systems to stop the supply of electricity, which is a big problem in today’s life.[15] employed tangent delta (TD) and three distinct partial discharge (PD) measuring methods for condition evaluation insulated cable networks. [18] suggested an end-to-end methodology based on a convolutional neural network to identify bridge cracks automatically. [19] also employed convolutional neural networks (CNNs) for detecting concrete cracks without calculating the defect features.[20] applied convolutional neural networks (CNNs) to online crack detection and then employed a standard genetic algorithm (GA) to optimize the CNNs detection succuss rate.

### 2.1. Convolutional Neural Network (CNN)

Convolutional networks are a specialized type of neural networks that use con- volution in place of general matrix multiplication in at least one of their layers.

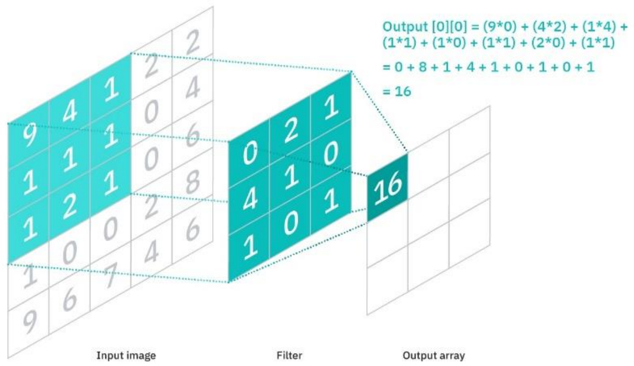


**Figure 1.** Convolutional Neural Net

Each output value in the feature map does not have to be connected to each pixel value in the input image, as can be seen in the above figure, which was taken from the IBM official website and is named "convolutions Neural network. "Only the receptive field, where the filter is being used, needs to be connected. Convolutional (and pooling) layers are frequently referred to as "partially connected" layers because the output array does not have to map exactly to each input value. But this trait can also be referred to as local connectivity.

A specific variety of neural network called a convolutional network substitutes convolution for standard matrix multiplication in at least one of its layers. Convolutional neural networks (CNNs), which successively arrange convolutional, pooling, and fully-connected layers, have started to become standardized in the field of object detection, according to [7]. For the purpose of supervised metal surface defect identification and classification, [9] presented a Max- Pooling CNN approach.

Convolutional neural networks differ from other neural networks in that they function better with picture, speech, or audio signal inputs [10]. They have three main types of layers, which are:

- Convolutional layer
- Pooling layer
- Fully-connected (FC) layer

### 2.2. Cable Inspection

The next generation of smart grid applications, which include the capability to consistently survey and operate the grid infrastructure, should pay appropriate attention to the possibility of remotely analyzing the status of electrical cables as a critical attribute. [16] The lack of adequate inspection technologies is well-known industrial challenge. [6] emphasized that the majority of power cables used in electrical plants have polymer insulation materials, which can deteriorate or become brittle over time when exposed to adverse environmental conditions like high temperatures, moisture, vibration, mechanical shock, and radiation. It also suggested a solution. and electrical properties of the materials to determine their overall condition. .[22] Each year, companies invest a significant amount of money and labor resources in cable inspection activities. This idea sounds capital and labor intensive with fewer guarantees for result accuracy and precision. As described in below **Figure 02**, There are multiple layers of insulation on a single core LV cable. The outermost layer is usually made of polyvinyl chloride jacket insulation and this part is mostly exposed to external physical damages. The next layer is made of aluminum foil and is then covered with a layer of polyethylene insulation. The innermost layer before the copper conductor is made of polyethylene insulation.

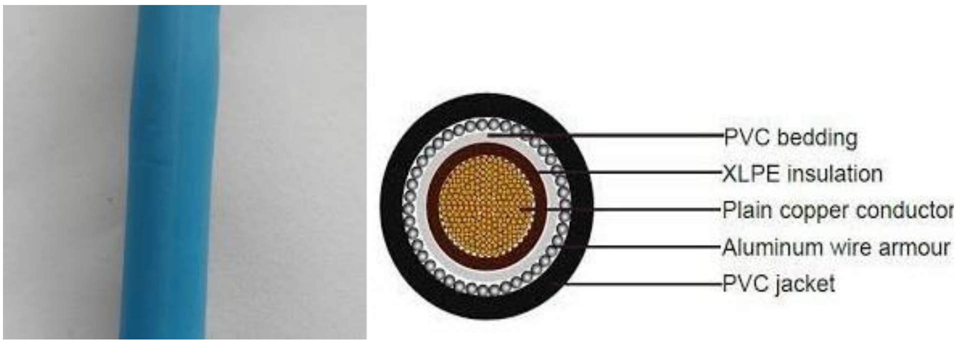


**Figure 2.** :Typical inner and outer structure of LV single core cables .

Digital image processing for physical basis analysis of electrical failure forecasting in XLPE power cables based on field simulation using finite-element method by [8] performed A hyperbolic needle-to-plane simulation model to illustrate the Electrical tree inception and propagation stages. But the article has not presented robust method in relation to image processing for defect detection on XLPE power cables. The approach by [17] for identifying stay cable surface flaws combines a cable inspection robot with transfer learning on a conventional neural network with a cascade mask region (Cascade Mask RCNN).

## 3. METHODOLOGY

The purpose of this research is to conduct experimental research design with a goal to develop CNN model and detect damaged power cables. Experimental research methodology will be employed to support as best mechanism for conducting this research, this is due to the nature of the research dataset at hand. This chapter details what the study setting will look like. Then, it discusses how I will gather the data for analysis train the model and also conduct the scientific experiment. Furthermore, it presents detailed data analysis procedures.

The following **Figure 03**,elaborates the principal and main stages followed when working with this project; they are:-

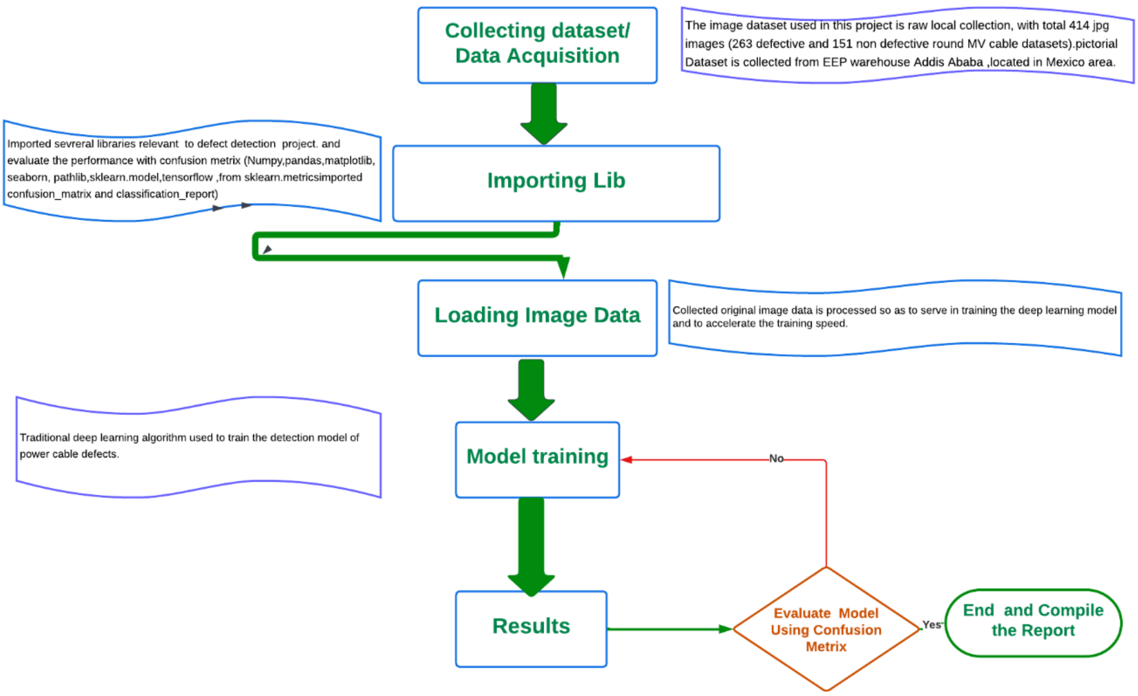


**Figure 3.** Methodology

The image dataset used in this project raw local collection, with total 414 jpg images (263 defective and 151 non defective round MV cable datasets). pictorial Dataset is collected from EEP warehouse Addis Ababa, located in Mexico area.

## 4. RESULTS AND DISCUSSIONS

The learning curves graphic in **Figure 04** , displays how learning performance has changed over time as measured by experience. Thus, the model performance learning curves can signify and be used to diagnose whether the train or validation datasets are relatively representative of the problem domain. In this project, the loss of the model will is lower on the training dataset than the validation dataset. This is reflected on the curve with some gap between the train and validation loss learning curves. The curve of training loss slowly decreases to a point of stability. The curve of validation loss decreases to a point of stability and has a small gap with the training loss. Further training may result to an over fit.

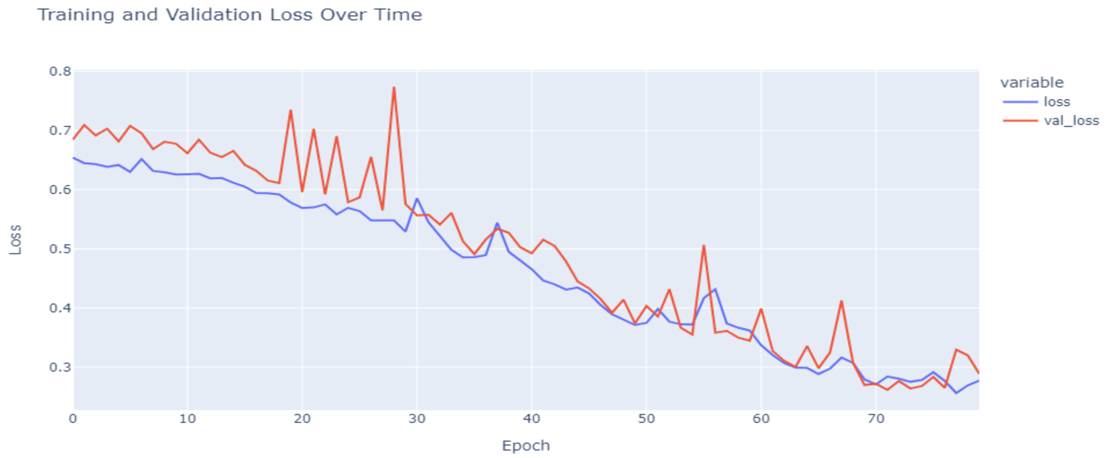


**Figure 4.** :Training and Validation loss Over Time

The performance of my convolutional neural network model utilizing the confusion matrix is illustrated in **Figure 04** below. From the confusion matrix, it can be seen that 3 defective cables were mistakenly labeled as non-defective when they were genuinely defective, and 7 true non-defective items that the model had incorrectly classified as defective. Test accuracy has increased by 9.36% because to the change.

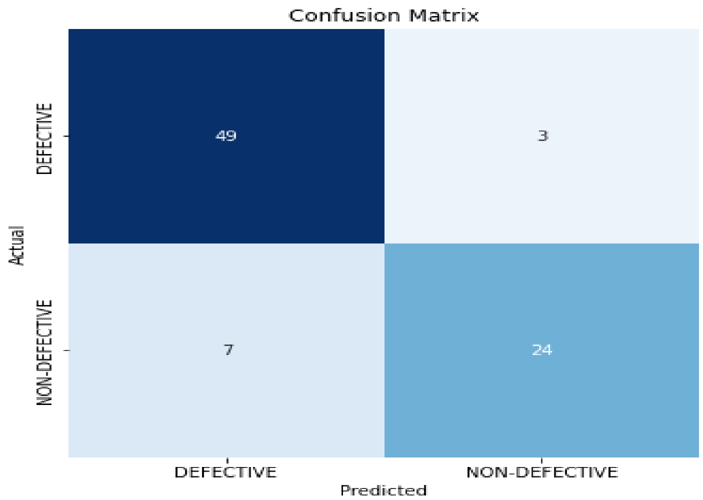


**Figure 5.** :Confusion Matrix

## 5. CONCLUSSIONS

Convolutional neural network models for power cable detection and binary classification (Defect Positive = Defective and Defect Negative = Non-Defective) are what I presented in this research.

For the given small-sized custom dataset, my model was quick and moderately accurate (90.36 percent). I produced a new cable dataset containing images from 414 multiple photos of both classes after first proposing a methodology for LV power cable data set collecting. The dataset was split 80/20 for training and testing. My models performed similarly accurate predictions on a new image dataset, which I used to further validate my methods. My research indicates that it is wise to employ

CNNs as a practical substitute for the traditional method of manually classifying power cables as defective or non-defective in utilities and cable manufacturing companies. The purpose of this study is not limited to the binary classification of power cables; it may also be expanded to similar applications in the manufacturing, electricity, and other areas.

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