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Development of Deep Learning Model Based Resnet with SSD for Fault Detection in Distribution Network

A. Ango*, O. Ajayi, Z. Haruna, M. B. Mu'azu.
Department of Computer Engineering, Ahmadu Bello University, Nigeria.
(email: abdulazizango@gmail.com*)

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ABSTRACT

This research proposes the development of deep learning model based residual network with single short multi box detector (resnet-SSD) for fault detection in distribution network. Power infrastructures are components used in the power system to generate, transmit or distribute power for the benefit of the consumers. These components include conductors, insulators, transformer, cross arm and many more. However, disturbances such as symmetrical fault, asymmetrical fault, shattered disk, broken cross arm, and power line encroachment affects the constant flow of power in distribution network. Failure to restore the system in good time may lead to vandalization, loss of revenue, black out and even system collapse. Various method of inspection has been used to address these problems which include manual inspection which is tedious and inefficient, use of heuristic and meta-heuristic algorithm which are in accurate and less efficient and the used of machine learning that suffers the problem of computational complexity and convergence time. To address these challenges associated with the existing solutions, a deep learning model based resnet-SSD is proposed which has the ability of addressing overfitting, vanishing and exploding gradient thereby overcoming the issue of computational complexity and convergence time. The developed model resnet-SSD was compared with mobilenet-SSD using accuracy, precision, recall and F1-score as performance metric. The result recorded shows that resnet-SSD has outperformed mobilenet-SSD in all the aforementioned performance metric by recording accuracy of 97.7% as against 86.3% for mobilenet-SSD and F1-score of 96.5% as compared to mobilenet-SSD that recorded 87.6%, from the result presented it can be inferred that resnet-SSD has better prediction efficiency as compared to mobilenet-SSD this is due to its residual network layer that help in efficient error back propagation of the deep learning model

1. INTRODUCTION

The importance of power cannot be over emphasized as it is the building block of every nation development. It cut across every discipline such as agriculture, health, education, engineering and many more [1]. However, there are many factors that affect constant and smooth flow of power which include internal and external disturbances. Internal and external disturbances may lead to power outage, blackout or even system collapse. Internal disturbances are disturbances that are inherently within the system. They include poor insulation due to dielectric weakness, buckholzs fault, relay malfunction, free tripping or closing of the circuit breaker. External disturbances are disturbances that occur due to external forces acting on the system which may as well interrupt the system. This include power line encroachment, short circuit fault, missing phase, phase to ground fault, symmetrical and unsymmetrical faults, shattered disk, broken cross arm, broken disk and so on [2].

Different methods which include visual inspection via foot, heuristic and meta-heuristic algorithm, and machine learning were used to address this issue [3]. Visual inspection approach is usually used in Nigerian electricity distribution companies (discos) for power infrastructure inspection which is time consuming, and inefficient. Used of heuristic and meta-heuristic algorithm which is inaccurate and less efficient and the used machine learning that suffers the issue of computational complexity and convergence time [4]. The limitations caused by the aforementioned power infrastructure inspection methods are addressed by the utilization of deep learning model based resnet-SSD.

Manual method of inspection involved the use of lines man to go pole by pole to check whether there is presence of fault or not on the power infrastructure equipment, this is the common practice in African countries which is very less efficient and tedious optimization in simple terms aims to obtain the relevant parameter values which enable an objective can be classified into two main categories: deterministic and stochastic [5]. Deterministic produce the same set of solutions if the iterations start with the same initial guess, while stochastic algorithms often produce different solutions even with the same initial starting point [6]. Stochastic algorithms are categorized into two groups: heuristic and meta-heuristic algorithms. Heuristics refer to algorithms that produce high quality results by trial and error methods in an acceptable computational time [7]. Heuristics exploit problem-dependent information to find a good enough solution to a specific problem but not necessarily optimal solutions [8]. The suffix meta means "beyond, in an upper level", so the term meta-heuristic refers to a higher level of heuristics. Meta-heuristics are problem independent and they provide better solutions with the best global solution in the region [8]. They are used to generate algorithms that can be implemented to a broad range of problems. The studies in the literature tend to refer to all new stochastic algorithms as meta-heuristics [9]. Metaheuristic algorithms have attracted many researchers from various fields of science in recent years [10]. These algorithms are found to be more powerful than the conventional method that is based on formal logic or mathematical programming [11]. The intensification phase of the algorithm searches around the current best solution and select the best candidate or solution. The diversification phase ensures that the algorithm explore the search space more efficiently. The specific objectives of developing modern meta-heuristic algorithms are to solve problem faster and to obtain more robust method [12]. These algorithms have been classified into four classes namely: physics-chemistry algorithm, swarm intelligence-based algorithm, bio-inspired (but not swarm-based) algorithm and others [13].

The used machine learning can be define as a field of study that gives computer ability to learn without being explicitly programmed or it may be define as a field of study that concern with the question of how to construct computer program that improve automatically with experience [14].

Machine learning may be divided into two according to complexity, shallow learning and deep learning. Shallow learning is conventional machine learning with few numbers of hidden layers while deep learning is a multi-layer model that learns representation of data with multiple level of abstraction. It has a larger number of hidden layers [14].Figure 1 represents the flow chart for training and evaluating a deep learning model.

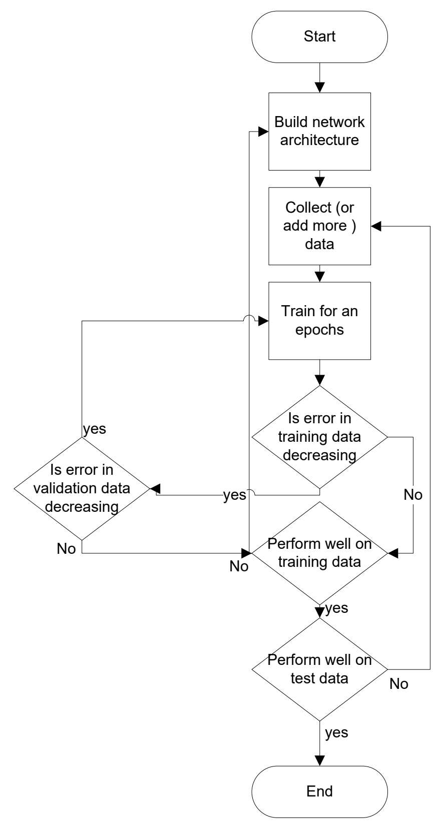

Figure 1: Model Flow Chart [14].

Resnet with SSD are deep learning model used for object detection and classification [2], in this research resnet model will be used as the base layer due to its effectiveness, fast response and ability to overcome

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overfitting, vanishing and exploding gradient while the SSD model will be used as the top layer for its multiple classification ability. As contained in other deep learning models convolution layer, max pooling layer, fully connected layer and soft max layer will all be used for feature map extraction and other form of processing to achieve the desire objective.

In machine learning problems are classified into, supervised learning, unsupervised learning, semi supervised learning, reinforcement learning, sequence learning, transfer learning and others (Buduma *et al.*,, 2022).

1.1. *Supervised learning:* This is the learning process that involve teacher with an input label and expected output label and target.
1.2. *Unsupervised learning:* This involves learning the underlying structure of data without the use of any teacher.
1.3. *Semi supervised:* This is the learning process that involves both supervised and unsupervised learning technique.
1.4. *Reinforcement learning:* This is the learning via interaction and feedback, agent will be developed that cannot only perceive and interpret the environment but can also take action and interact with it based on reward value.
1.5. *Transfer learning:* This is the method of developing a model for a task in one and used it as the starting point for another model in the second task at two.

Sequence learning: This is like semi supervised learning technique that involves sequence input and output process

2. *MODEL OF THE POWER LINE*

The model of the power line was developed using Autodesk Revit software. The power line design was achieved through the following steps:

2.1. *Create a single line diagram of the three-phase network*
2.2. *Import the single diagram on the Auto desk software*
2.3. *Use rendering engine to convert 1D to 3D*
2.4. *Add landscape component for more details*

Figure 2 shows the high-tension pole detail design for rectangular concrete pole with length of 10.5m and some reinforced steel conductor at the center of the pole for strength and flexibility. Some holes were created to allow for several connections side by side. Poles are of many types and length depending on the need, we have low tension pole for 415v connection and super HT for crossover connection.

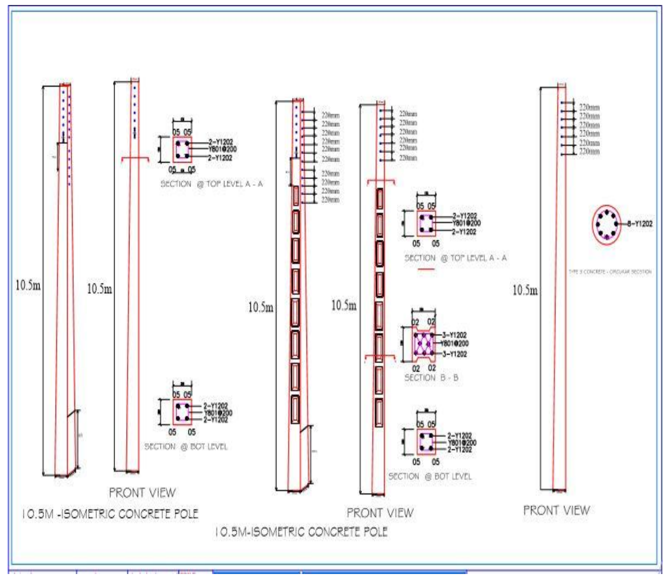

Figure 2: High Tension Pole Isometric Structure

The 3D diagram of 11kv feeder distribution network was first developed. The 3D diagram shows how ten distribution transformers are connected in parallel in order to increase voltage utilization, maintain constant voltage at the primary and secondary part of the substation transformer and provide flexibility of maintenance in case of fault. The single concrete pole and H-pole for carrying substation component such as cross arm, cross link poly ethylene rubber insulation cable (XLPE), D-fittings carrier for Jason and Phillips fuse (J & P fuse), channel iron and lightening arrester. The resulting 3D model of the power line infrastructure as build in the modeling software is shown in Figure 3

Figure 3: 3D Infrastrature of the Power Line

3. DEVELOPMENT OF DEEP LEARNING MODEL BASED RESNET WITH SSD FOR EFFECTIVE FAULT DETECTION AND CLASSIFICATION

The development of deep learning model carried out using the following fundamental steps.

3.1. Data Collection

The data used were collected from the developed virtual environment. The total number of the image dataset used is 500.

3.2. Preparation of a Data

The dataset were then preprocessed for better image classification. The pre-processing techniques carried out on the images include, augmentation, standardization, normalization and image annotation. The techniques are implemented as follows.

3.2.1. Augmentation

Augmentation is a process of increasing the dataset by multiplying it using either transformation or Generative Adversarial Network (GAN). Transformation method was here, and it include, rotation, scaling, flipping, brightness, contrast, hue, saturation, Gaussian noise and blur effect.

3.2.2. Standardization

The dataset were rescaled to 32*32 so as to have a mean of zero and standard deviation of one (unit variance). This process will help in addressing the issue of overfitting as well as prediction process.

3.2.3. Normalization

Normalization tries to rescale the dataset into the range of zero and one, it also eliminate data redundancy and enhance data integrity in the dataset. It involves the *First normal form* that check for the atomicity of the attribute of the relation. It checks the spatial distribution of the pixel in an image. *Second normal form* check for the partial dependencies in a relation which is the degree of pixel dependency in an image. *Third normal form* check for the transitive dependencies of the relation which is the degree of color dependency in an image. *Boyce codd normal form,* checks for the super keys of all functional dependencies. It finally achieves the final goal of the normalization process.

3.2.4. Annotation

The annotation process was conducted to allow the inspection process to be carried out by marking the faulty point on the image. This help in training the model on how to identify faulty power infrastructure equipment during testing.

3.3. Choosing a Model

Resnet with SSD was basically selected because of its efficiency and fast response. The model was presented as follows:

3.3.1. Resnet50 with SSD

Resnet50 with SSD model is like any other models, it consists of three basic fundamental layer such as convolutional layer, pooling layer and fully connected layer for classification. Resnet has peculiar features that make it unique which is bypass pathway concept or shortcut connection (residual network). This feature is responsible for accelerating the deep network convergence. It also help address three important issue associated with deep learning model which are overfitting, vanishing and exploding gradient problems Convolutional layer involves a mathematical operation of applying a filter/kernel to the input data, which help to extract features by performing element wise multiplication and summation. The filter is a small matrix of weight that is convolves with the input data to produce a feature map. The output of the convolutional layer which presents the presence of a specific feature in the input data is called a feature map. Pooling layer, the layer is used for down sampling the feature map generated from the convolutional layer by reducing the spatial dimension of the feature map by selecting the most important of the representative values.

Fully connected layer, the layer is used for classification of the trained or test images into classes of either normal or faulty image.

3.4. Training a Model

The model resnet with SSD was trained for 20 number of epochs until satisfied, the images were classified into three, 70% (350) was used for training, 20% (100) was used for evaluation and 10% (50) of it was used for testing the images. Due to limited number of data transfer learning was used which is the technique where a model developed for a task is reused as the starting point for a model on a second task. This is usually done to address the issue of limited data, provide ease of training and increase the convergence time.

3.5. Evaluating a Model

The 20% (100) of the images were evaluated using accuracy, precision, recall and f1-score as performance metric.

3.6. Parameter Tuning

The most effective tuning parameters considered in this work are batch size and learning rate. Batch size of 32 was considered for the entire dataset while a constant learning rate of 0.001 was used for effective learning in the network.

3.7. Making prediction

Making prediction is the final stage of the model, where two classes are considered either normal or faulty power infrastructure component.

4. METRICS USED FOR THE COMPARISON OF THE DEEP LEARNING MODELS

The following are the metrics used for the comparison of the deep learning models

4.1. Accuracy

Accuracy calculates the ratio of the correct predicted classes to the total number of samples evaluated.

$$A_{cc} = \frac{T_P + T_N}{T_P + T_N + F_P + F_N} \quad (1)$$

4.2. Precision

Precision is utilized to calculate the positive patterns that are correctly predicted by all predicted pattern in a positive class.

$$A_{pre} = \frac{T_P}{T_P + F_P} \quad (2)$$

4.3. Recall

Recall or Sensitivity is utilized to calculate the fraction of positive pattern that are correctly classified.

$$A_{rec} = \frac{T_P}{T_P + F_N} \quad (3)$$

4.4. F1-Score

F1-score calculate the harmonic average between recall and precision rates.

$$(F1 - score) = 2 * \frac{Precision * \text{R}ecall}{\text{Precision} + \text{Re}call} \quad (4)$$

Where

A_{cc} = Accuracy
A_{pr} = Precision
A_{rec} = Recall
T_p = True positive
T_N = True negative
F_P = False positive
F_N = False negative

5. RESULT AND DISCUSSION

This is done to analyze the images so as to detect the presence of faults in the power infrastructure equipment. Figure 4 shows the values obtained while resnet-SSD was used.

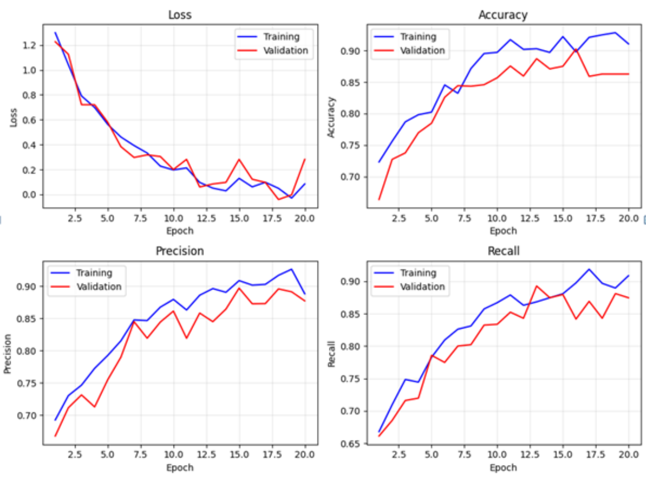

Figure 4: Resnet with SSD Result

From the figure presented, it can be observed that, the issue of overfitting has been address as the gap between the training and the validation error has been made very minimal. The issue of vanishing and exploding gradients were as well overcome by the model Resnet-SSD due to it efficient prediction.

Table 1 present the values recorded by each of the metrics used.

Table 1: Resnet-SSD Training and Validation Result

Metric	Training	Validation
Accuracy	0.976	0.977
Precision	0.984	0.975
Recall	0.972	0.956
F1-Score	0.978	0.965

From the table 1 it is clearly shown that the error recorded between the training stage and the validation stage is very small, which is a good sign of efficient model for better prediction and generalization.

Figure 5 shows the image analysis conducted using the developed model and the result is as follows.

Figure 5: Image Analysis Result for Resnet-SSD

The analyzed and faulty images that were identified involved power line encroachment, shattered insulator, and phase to ground fault (pull-out conductor). The developed model resnet-SSD was trained and evaluated on this kind of fault and it proof to be promising for power infrastructure inspection. The bounding box on the images shows the exact point of fault detected by the deep learning model.

6. PERFORMANCE COMPARISON

The developed model Resnet-SSD was compared with mobilenet-SSD using accuracy, precision, recall and F1-score as performance metric and the result for the prediction was presented in figure 6

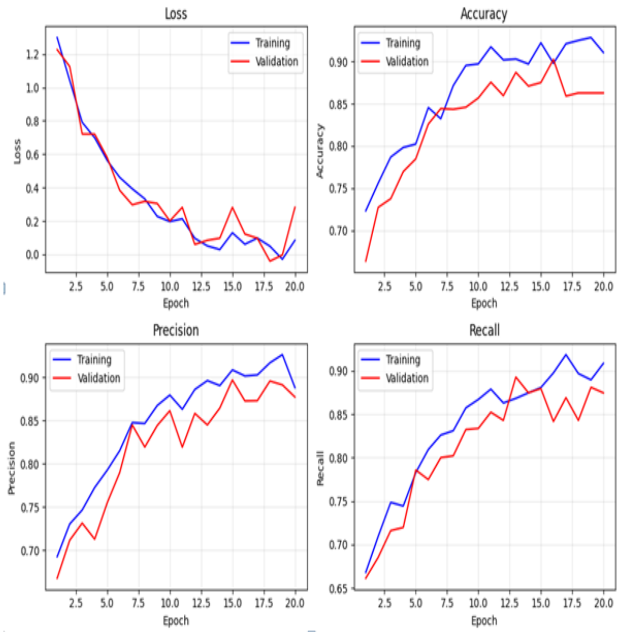

Figure 6: Mobilenet with SSD Result

Mobilenet-SSD was used for the analysis and the result obtained was largely below that obtained using Resnet-SSD. Table 2 present the values recorded by the mobilenet-SSD.

Table 2: Mobilenet-SSD Training and Validation Result

Metric	Training	Validation
Accuracy	0.911	0.863
Precision	0.888	0.877
Recall	0.909	0.875
F1-Score	0.898	0.876

From the table 2 it is very clear that resnet-SSD has outperformed mobilenet-SSD in all the performance metrics. Figure 7 and 8 present both the training and validation results between the two benchmark models.

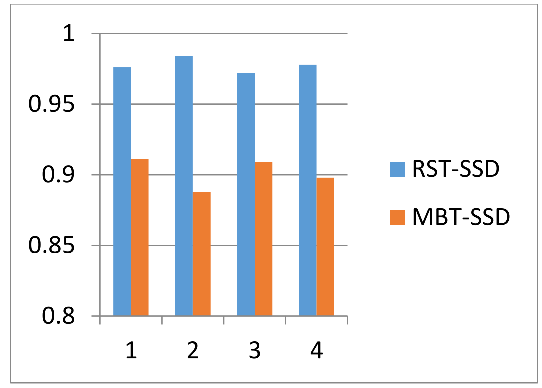

Figure 7: Models Training Result

The result presented in figure 7 shows how resnet-SDD outperformed mobilenet-SSD in all the performance metric accuracy, precision, recall and F1-score for power infrastructure inspection, while figure 8 shows the validation result between the two learning models.

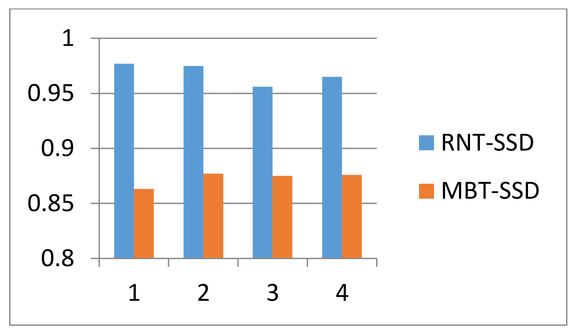

Figure 8: Models Validation Result

The result of the analysis remains unchanged for all the performance metric.
Table 3 records the overall metrics and their corresponding values.

Table 3: Models Training and Validation Result

Metric	RNT-SSD	MBT-SSD	RNT-SSD	MBT-SSD
Accuracy	0.976	0.911	0.977	0.863
Precision	0.984	0.888	0.975	0.877
Recall	0.972	0.909	0.956	0.875
F1-Score	0.978	0.898	0.965	0.876

The comparison between the two models was further discussed to show side by side the values and the graphical representation. The values recorded by

resnet-SSD are greater than that of mobilenet-SSD across all the four metrics.
The bar chart for the overall result was presented in figure 9

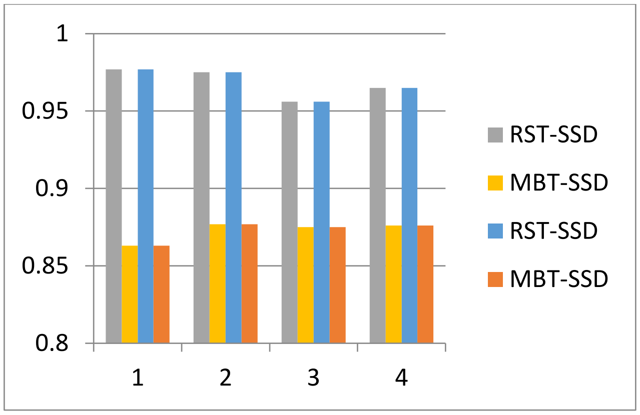

Figure 9: Resnet-SSD vs Mobilenet-SSD Overall Result

The two smaller charts are for mobilenet-SSD during training and validation and vice verser are for resnet-SSD. This is a clear evidence that resnet-SSD has a better prediction capability than the mobilenet-SSD.

7. CONCLUSION

The result obtained shows how accurate the deep learning model resnet-SSD was in detecting fault on power infrastructure equipment, the model was able to detect the presence of power line encroachment, shattered insulator and pull out insulator. The performance metric used include accuracy, precision, recall and F1-score. The result shows that the developed model was very efficient. The model outperformed mobilenet-SSD using the aforementioned performance metric. This address the issue of fault identification and detection in distribution network thereby increasing mean time to repair in the system, it as well increase efficiency by addressing the issue of computational complexity and convergence time. Further work may be done by considering other deep learning model such as densenet, efficientnet and many more, underground conductor may as well be considered especially in urban areas were such kind of connection are applied.

8. ACKNOWLEDGEMENT

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