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# Real-time Transformer Vandalism Detection by Application of Tuned Hyper Parameter Deep Learning Model

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***Abstract: Vandalism is an illegal act of cannibalism or change of face to a private or public property by human beings for re-sale of parts or to punish the property owner. Initial research findings on transformer Vandalism detection have fallen short of human image recognition of the vandal in real-time but only does detection of activities after the damage is done or as it occurs. Automated real-time systems using sensor feed to a trained deep learning model is a new transformer vandalism detection approach with capabilities of three-dimensional image learning, extracting important image features automatically and temporal output prediction. This paper aims at distinguishing the human object entering a zoned transformer area without permission to take away or modify the established infrastructure, so that the Vandal can be arrested before causing any damage to the transformer. The researchers identified a multiplicative hybrid model combining convolutional neural networks and long short-term memory for application to vandalism problem to detect the image of a vandal as it enters a restricted transformer installation site. The image recognition accuracy can be improved by tuning the model hyper-parameters and the specific hyper-parameters considered in this research work are number of model layers and epochs. The human object is distinguishing by applying the image features taken with Image sensor to a trained deep learning model. The hybrid deep learning method increases the output prediction accuracy from the input data and lowers computational processing complications due to a reduced data volume through pooling. The system is trained and validated using ImageNet dataset. Results achieved by five layers and sixty epochs is 99% recognition accuracy. The performance of the system with an increased number of layers and epochs to five and sixty respectively was the best result as compared with lower layers and epochs. Further increase of these parameters resulted to system overfitting.***

***Keywords*: Convolutional Neural Networks, Hyper-parameter tuning, Image Recognition, Long Short-term Memory, Machine learning, Transformer Vandalism.**

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## I. INTRODUCTION

An unauthorized cannibalism of power Transformer parts by vandals has been in the increase in and causing very heavy losses to country economies. The vice is quite rampant in the energy sector as was reported in Kenya in 2022 at Kenya Power Company where power line pylons collapsed due to vandalism.

The loss of a function of a critical system due to vandalism becomes very costly as a result of losses due down time, reconstruction cost and commissioning cost [1]. Researchers in recent times have applied electronic surveillance and alarm systems to detect Transformer Vandalism but the efforts have not managed a better success due to a requirement for large data storage and the systems can only give an alarm after the vandal has gained entry to the site and vandalism activity is ongoing. The traditional engineering systems like alarms and vibration sensors do not discriminate on the object image to trigger the alarm.

Vandalism detection calls for Human image detection system which is capable of capturing the Vandals' image to feed into a trained deep learning system to recognize the human object in real-time [2]. Machine learning use in this domain presents the skills of data driven system with predictive tools to forecast on potential vandalism problem to sidestep failure of the Transformer systems. Traditional machine learning algorithms such as Support vector machines, decision trees, Random forest and genetic algorithms use hand crafted datasets to train, test and validate system models, however the requirement for human experts to select dataset assemblies limits the accuracy of the system performance.

The deep learning approach proposed in this paper is better than traditional methods due to its ability to extract image features automatically [3] learn spatial relationship and temporal sequence decoding. This method reduces computational complexity and down samples the image pixel map through pooling process to reduce data volume. Researchers in this work have applied a multiplicative deep learning architecture consisting of convolutional neural network (CNN) and long short-term memory (LSTM) for temporal detection of vandals' image as it enters the restricted Transformer installation site at in real-time.

The Transformer site images are captured by the installed image sensor and pre-processed to enrich the data for feeding into CNN to where important image features are extracted automatically as per the training dataset characteristics and the extracted features are fed into the LSTM in the form of data stream. LSTM decodes the intelligent data in time-series manner to preserve temporal information through the dense. The block diagram of fig.1 shows the proposed system and output recognition accuracy lies in the range of 0-1.

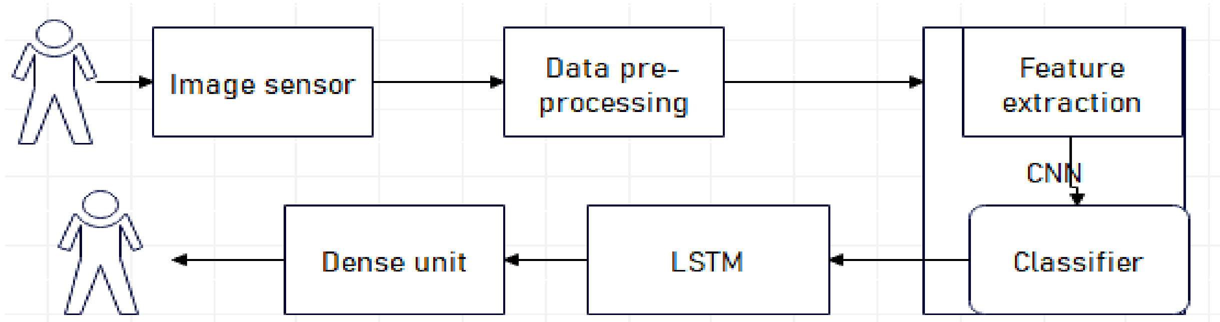


**Figure 1 Human Image Recognition Process**

This model is known for its better image recognition accuracy when the model hyper-parameters are properly tuned. Hyper-parameters are tunable holistic structures such as network layer neurons, number of layers, epochs, weight initialization, batch size and learning rate, the model use them to learn during training process to improve functioning. Both public and private sectors have tried various methods to detect and eradicate vandalism through deployment of more security personnel to guard the installations, employment of vandals, public sensitization against vandalism, paying tokens to the target groups, design of tamper proof systems and installation of system disruption surveillance but all the above efforts have contributed very little impact to vandalism detection and prevention. A research conducted in USA in 2009 by S. MacArthur et al concluded that vandalism resulted to a recurrent impact of 15% to 20% on quality of the industrial products and the researchers recommended for public outreach efforts and civic education on vandalism. Kenya electricity transmission company (KETRACO) and Kenya Power Company initiated public participation where anyone witnessed vandalizing a transformer is to be reported to the law enforcement authority. Marianna Rocco in 2013 wrote a utility magazine outlining how USA government applied internet protocol security surveillance system and a distress signal system to identify vandalism, although, the above measures showed very minimal impact on the vice. The proposed method is expected to give higher recognition accuracy in real-time detection than the previous results by other researchers on this problem. This research paper order is outlined below; Section I covers introduction and section two covers literature survey. The methodology and logical frameworks are discussed in section III. Section IV shows analysis of the experimental results and section V is research conclusion.

## II. RELATED RESEARCH WORK

Authors researched on design and implementation of transformer vandalism monitoring system that are expected to render a continuous monitoring of the substations by alarm systems. They recommended a transformer design change to house surveillance systems [4]. Researchers applied a hybrid deep learning of CNN-LSTM to detect vandalism of engineering installations in real-time. The system achieved 98% image recognition accuracy and recommended future work to Hyper-parameters tuning to improve output performance [5]. Researchers used CNN model to identify and classify partially damaged and vandalized traffic signs. The model identified and classified Vandalized and damaged traffic signs at an accuracy of 99.17% [6]. Researchers presented an anomaly recognition (after vandalism) in a restricted region [7]. The researcher applied CNN-RNN of deep learning with inception V3 and attained overall recognition accuracy of 97.23%. Vandalism prevention using IOT and low power devices was studied and from the findings, moving objects were captured correctly in a short time. Authors recommended an open-source computer vision library for effective results [8]. Machine learning technique applied in anti-vandalism research. Machine learning approach applied in monitoring pylon anti-vandalism [9]. The research bordered an anti-theft system for monitoring pylon surrounding for image intrusion. Test results achieved 97% confidence level on bounding box. Random Forest classifier was applied to detect vandalism of volunteered geographic information in Open Street map (OSM) and the system was able to detect vandalism in same OSM regions [10]. The research recommended a test with neighboring geographic landscape and train with more. Cartographic vandalism research in OSM and Pokémon GO found that the negative news undermined the credibility of collaboratively generated Maps [11]. Researchers found that the use of participatory mapping in volunteered generated information was very necessary. Further research to detect vandalism is presented in [12]. The surveillance video sequence was used to detect vandalism by monitoring changes in a restricted area. The simulated vandal behavior achieved a detection rate of 96% and recommended face detection. An automated electronic system was applied to detect pipeline Vandalism using video camera and surveillance system. It was also used to detect intrusion into pipeline to send short message service and e-mail to alert plant operators [13].

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A study on homophobia vandalism at Wikipedia revealed a contaminated Web atmosphere and the researchers were inadequate and the trend promoted partiality leading to vandalism [14] [15]. Automation of the search process for the scientists was required in future to address the problem.

A study on property vandalism in Nigerian was presented in [16]. The research suggested that men were the common vandals and the government was incurring high maintenance cost and therefore, more security guards was recommended to guard the installation sites. Researchers applied image sensors in body worn electronic gadgets to study human activities recognition in order to know how humans behave [17]. The system attained 99% recognition accuracy. Investigation of transfer learning approach to perform activity recognition on big data recommended as a future research area. A research work investigated the effectiveness of a hybrid CNN-LSTM model for classification of Human Activities based on Micro-Doppler radar and achieved a classification accuracy of 98.3% [18]. Researchers found that, the most effective way of improving the performance of CNN-LSTM model was by up tuning the filter number and LSTM units. In a bid to understand human behavior, researchers studied human activity recognition using Convolutional neural network (CNN) with long short-term memory (LSTM) [19]. The hybrid model attained 99% a recognition accuracy.

Researchers applied Hybrid model of Convolutional neural networks (CNN) with long short-term memory (LSTM) to study Human Activity Recognition on smartphone sensor data. The model achieved 93.4% recognition accuracy was a better result as compared to CNN and LSTM when used as standalone model [20].

## III. SYSTEM METHOD AND IMPLEMENTATION

### A. CNN Modelling

Convolutional neural network is a sequence of five layers, input layer, Activation function layer, Convolutional layer, fully connected layer and pooling layer. Kernel (filters) learns the features contained in the image to reserve pixel spatial relationship. Strides, depth (number of filters), and zero padding controls feature map. The convolutional layer output is the product of activation function and the summation of bias and product of network weight and input vector [21]. The math model is given in (1)

$$C_s^{li} = A\left(b_c + \sum_{j=1}^{i} w_j^i x_{s+j-1}^{li}\right) \quad (1)$$

Where C is convolutional layer, layer index is *l*, *A* is activation function, bias is $b_c$, j is kernel or filter size, $w_j^i$ is weight for $i^{th}$ feature map and $j^{th}$ filter index and l is layer index of $i^{th}$ feature map. J is filter size at a range between 3*3 - 5*5.

#### 1) Pooling Layer

This layer down samples the output of convolutional layer to allow predictions to be made on the image features in that region. It is a statistical summary of convolutional layer output $C^{li}_s$ and Maximum pooling is applied in this research as the best method [22]. Maximum pooling operation calculates the maximum value of each patch of feature pixel map and highlights the most present feature in the patch

Mathematically pooling output is the product of pooling factor and output of convolution layer presented by (2):

$$p_s^{li} = Max_{r\in R}\left(c_{s+S+r}^{li}\right) \quad (2)$$

where $p$ is pooling feature vector, l is the layer index for $i^{th}$ feature map, *R* is pooling size, *S* is pooling stride. The product of pooling and convolutional layers forms feature vector $f^t$ [23]. Feature vector after convolution is summation of all vectors from the first convolution layer. math representation is shown in (3)

$$v^s = \left(v_1, v_2, v_3 \ldots\ldots v_k\right) \quad (3)$$

where K is the last units of pooling layer and V is feature trajectory at a period s.

#### 2) Dense Layer

Flattened pooling output data are used as the inputs to this layer and neurons from the previous layers are interconnected here and dataset categories are culculated.

The probable range of the class labels *f(c)* are calculated here using soft-max function translated by the possible values of input matrix (X) between 0 and 1 [24]. Equation (4) represent fully connected layer mathematical model.

$$F_{(c)} = \left(e^{xj}\right) / \left(\sum_{k=1}^{x} e^{xk}\right) \quad (4)$$

where C is the category label result from feature trajectory of data X, Xj is the element x at j feature map and k is the element of *X*

### B. Long Short Term Memory Modelling

The LSTM cells symbolize the hidden layers of RNN namely input gate *i(s)*, forget gate *f(s)*, cell state gate *C(s)* and output path *O(s)* all forms the LSTM cells. Pointwise multiplier operation, *tanh* layer and sigmoid layer are the LSTM units. To govern error overspill in LSTM, memory cell is included into the structure to function as channel gate and controller for storing the previous state. The math model of cell states is formulated as shown below [25]. Cell states are stated in (5)(6)(7)(8) and their summary in (9)

$F_s$ is the forget gate vector

$$f_s = A\left(w_f\left(h_{s-1}\right)\left(x_s\right) + b_f\right) \quad (5)$$

$I_s$ is input gate

$$i_s = A\left(w_i\left(h_{s-1}\right)\left(x_s\right) + b_i\right) \quad (6)$$

$\dot{C}_s$ is cell state vector

$$\acute{C}_s = \breve{A}\left(w_{\acute{C}}\left(h_{s-1}\right)\left(x_s\right) + b_{\acute{C}}\right) \quad (7)$$

*Os* is the output path

$$O_s = A\left(w_O\left(h_{s-1}\right)\left(x_s\right) + b_o\right) \quad (8)$$

*Cs* is a summary of cell state output

$$C_s = f_s O_s + i_s \acute{C}_s \quad (9)$$

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where $x_s$ is the input vector, $S$ is a cell state at particular time $h_s$is the output vector. $A(.)$ is the activation function for the three gated units and is representing sigmoid function and $\breve{A}$ is the activation function for the memory cell state when *tanh* activation function is used.

*F(s)* is forget gate used to select memory part to be passed to the next stage and memory cell can only pass to the next stage when *F(s)* is 1 but discarded when *F(s)* is 0

## C. CNN–LSTM (Implementation Model) Modelling

CNN–LSTM model comprises of convolutional neural networks (CNN) to extract important features and LSTM for supporting temporal prediction. Convolutional neural networks (CNN) extracts important image features from the raw sensor data and feeds its output to long short-term memory for output decoding by the dense layer as in fig. 1

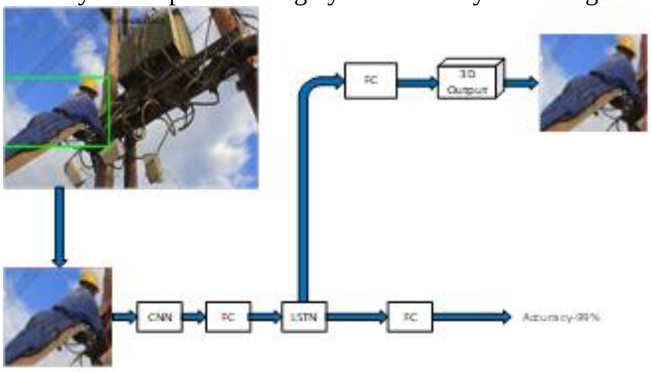


**Fig. 2 Real-world set of CNN-LSTM Model**

Fig.2 shows how the hybrid model of CNN-LSTM can be implemented in real-world. The installed image sensor at the transformer site capture images within the zoned site to be fed into CNN model input. CNN extracts important image features by convolution process and also down-samples data to reduce its pixel map for avoidance of overfitting and computational complexity. The output of CNN through fully connected layer is fed into LSTM as data stream. LSTM cell system works as a gateway and controller for remembering the initial state to predict the time series output. This setup has the capability of mapping the input data to the predicted output. The architecture is a product of two models to give the best output recognition result [26]. CNN output is a product of weight and the input tensor as given in (10)

$$C(n) = wx_i \tag{10}$$

Where n is the CNN output label

LSTM output [27] is:

$$h_s = o_s\left(\tanh\left(c_s\right)\right) \tag{11}$$

The product of CNN output and LSTM cells is used to learn time-series features and therefore, the hybrid product of CNN and LSTM becomes the product of input tensor, LSTM output cell vector and *tanh* of cell vector. The math output of the hybrid model is given in (12).

$$f(h) = wx_i o_s[\tanh(c_s)] \tag{12}$$

where $h$ is the feature output label of the hybrid model, $X_i$ is the input matrix, $w$ is the weight, $C_s$ is the cell vector and $O_s$ is LSTM output vector and *tanh* is cell state activation function.

## D. Model Execution

### 1) *ImageNet data Set*

ImageNet data assembly was used to train the CNN-LSTM model during the execution of this experiment. Image-Net is an assembly of more than 15 million high resolution labeled images from 22000 image categories and each category is word-net hierarchy organized. Images of every category are quality controlled and Human annotated. There are 1 million objects in the training category, 50,000 validation images and 150,000 test images. Researchers used 5000 human Annotated images for training and validating the model. This dataset assembly contain images from world-over to include many object categories and is racially inclusive. In this research work, the data was split into 0.5 for training, 0.3 for testing and 0. 2 for validation. ImageNet drive to include 50 million high-resolution labeled images per set. The dataset has special construction method in which image objects have different image object have different appearances, pose, viewpoints, background disorder with sealing and positions. Image quality and file size are reflected in the information confined in the image. Researchers have used ImageNet dataset to train, validate and test the model. A sample of images contained in the dataset is shown in Fig.3

**Fig. 3 sample of ImageNet dataset**

A sample of ImageNet dataset showing various images in different pose and animal classes. This is self-explaining of robustness and quality content of the dataset. The human image appearance in this dataset proves the fact that system trained using this dataset will learn the human characteristics in any given pose and appearance such that the vandal cannot cheat the system without identification as human object.

## E. Reducing Over-fit by Data Pre-processing

Data augmentation is the process of altering original image sets to grow the quality and quantity of the dataset to avoid or reduce system overfitting. Two approaches have been used in pre-processing the dataset [28]; First is to increase the training sets, we use image horizontal reflection and translation by a factor of $2^{11}$ and by altering the RGB channel intensities of the training images and secondly, the technique applied to raise the quality and quantity of data by adding altered copies of the data used and the method is applied to machine learning to advance the output performance. The technique builds the model to be healthier by enabling changes that the model will effect during implementation. The techniques applied are; cropping, padding, random spinning, translation, re-scaling, enlargement and reduction of sizes etc. The model performance made better by enriching the data through data pre-processing

## F. System Training

The model was trained using Keras library with Tensor-flow at the backend. CNN was implemented using the dimensions of 255, sliding step of 1, filter size of 3, 4, 5 of 128 and Zero padding.

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The implementation setup for CNN used was Res-Net with 152 layers, 60 epochs at 5 convolutional layers and a classic 4 gating layer LSTM. The sequence of CNN layers as follows: *Sensor data* - conv 2D – maxpool – conv 2D – maxpool – conv 2D – maxpool – conv 2D – maxpool – conv 2D - dense. Deep learning model training needs more computing resources in the range of GPU and 100 GB RAM.

The experiment demonstrated a better result on lower machine specifications. Table-1. Illustrates the system specifications used to implement the experiment

**Table-1 hardware specifications**

| | |
|---|---|
| GPU | NVIDIA2070/2080 (8GB) |
| Processor | Intel i7-8750H (6 cores, 16x PCI-e lanes) |
| Memory | 32GB (2666 MHz) |
| Hard disk | 1TB NVME SSD (4-5x faster) |
| Monitor | 16.1″ FHD (1920×1080) Display |

## G. Hyper-parameter Tuning

Hyper-parameters are settings that controls how a trained neural network algorithm behaves. The choice of an optimal hyper-parameter set is a challenge to machine learning experts and there is no universal reference set in each particular application. Deep neural network training and optimization operation could be very challenging in practice as a result of huge quantity of hyper-parameters changing between specific parameters of training algorithm like learning rate to Neural network topologies such as number of layers (unsupervised and supervised) and total nodes in every layer. Human based-adjustable hyper-parameter assists algorithms to learn parameters from the training data. The expert sets the variables after theoretic automatic adjustment. The authors used random search optimization by applying random sampling of values and not searching by combination of hyper-parameters. The results of this approach has better output and takes less time than grid search optimization

## H. The Experimental Software

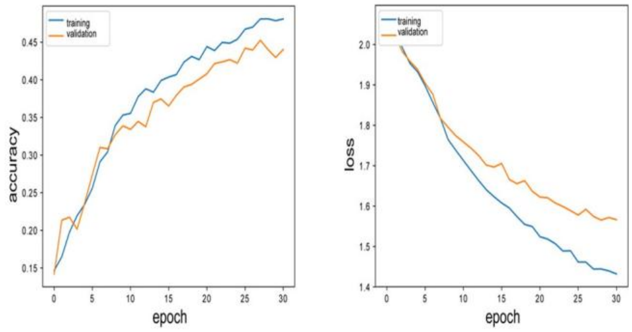
Authors selected Python as the programming language because it is a high-level programming language with ease of learning and coding, thereby making it the broadly used programming language for evolving machine learning and also deep learning systems. The model was executed using keras running on top of tensor-flow.

## I. Justification of Results

The researchers compared the results with other related works and results of the experiment before making changes to the model hyper-parameters. The validation loss and accuracy of the model shows the best results after hyper-parameter tuning as reflected in fig. 6. The research results attained shows that the system is able to detect only human object as per the model training. A recognition accuracy of 99% human detection is approve for a response to human object.

# IV. RESULTS AND DISCUSSION

CNN – LSTM model was trained using ImageNet dataset. Fig. 4 is the result for four layers at 30 epochs achieving a recognition accuracy of 97%. Fig. 5 is the result of four layers at 140 epochs attaining a recognition accuracy of 98%. Epochs determined the number of times a dataset is passed forward and backward in a network when using backpropagation training. An increase in number of epochs means that the weights are also adjusted in the same number of times as the epochs and this also depends on the diversity of the dataset used. ImageNet dataset is very diverse and as per the experimental results of this paper, increase of epochs affects the training and learning of the model as reflected in fig. 4 and 5. This experiment was carried out using 5000 images of human annotated ImageNet dataset and a smaller number of layers require a lower dataset volume. Experiment 4 and 5 were run on a four layer CNN network and achieved 97% and 98% recognition accuracy respectively. When the number of layers increased to 5, the result also increased to 99% accuracy as shown in Fig. 6 and could not exceed 5 layer as the model validation result started showing an onset of overfitting.




(a) Accurancy (b) Loss

**Fig. 4 Accuracy and Loss results at 4 Layers and 30 epoch**

At a hyper-parameter set of 4 network layer and 30 epochs, the system training plot shows good learning pattern and validation accuracy plot proves that the model is capable of mastering other images which are not used during training. The low validation loss value is a prove that the system operates in a stable state.

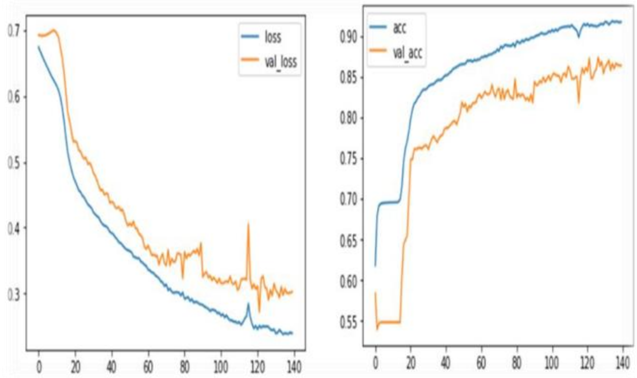



**Fig. 5 Accuracy and loss results at 4 layers and 140 epochs**

The system epochs changed from 30 to 140 and the accuracy improved by 1% but the stability of validation plot is affected as it shows a rise in value at epoch 115, therefore higher epochs increases model training accuracy but reduces the model mastery of non-training data.

From the results, one observations made is that, increasing the number of epochs delivers good results but increases system computation complexity.

The change in system output is minimal when epochs are tuned at a constant number of layers. Researchers compared the experimental results obtained with other recent research publications on Vandalism and CNN as a model tool in [5, 9, 10, 16]. Table-2 Is a summary of research results.

**Table - 2 Summary of Research Results**

| Source | Algorithm | Dataset | Layer | Optimizer | Epoch | Train accuracy | Test accuracy |
|---|---|---|---|---|---|---|---|
| [38] | CNN | No dataset | - | - | - | - | 97% |
| [41] | CNN | No dataset | - | - | - | - | 58.7% |
| [49] | CNN-LSTM | ImageNet dataset | 4 | Adams | 30, 140 | 98% | 98% |
| Proposed model | CNN-LSTM | ImageNet dataset | 5 | Adams | 60 | 98% | 99% |

The results of the proposed approach in Fig. 6 shows a higher output recognition accuracy of 99% which reflects that the input Image has been mapped to the output Image at a minimum loss of 1%. At 99% recognition accuracy, the system monitoring team will be very sure that the response to be deployed is for Human Vandal attack. This system is trained to recognize only the Human Image which corresponds to the training dataset characteristics and this is the current and better technology approach to Vandalism problem.

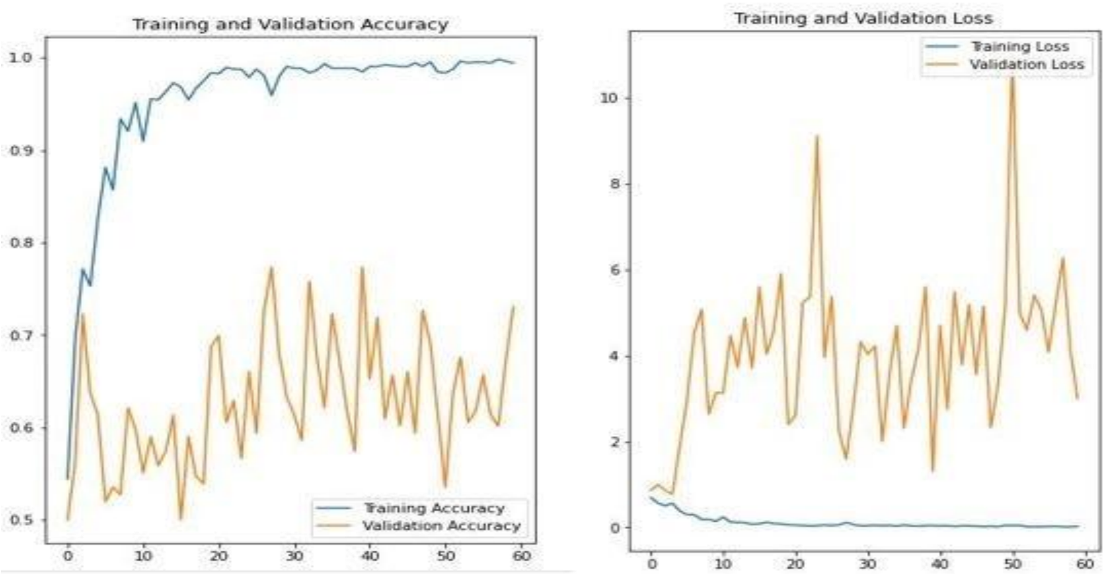



**Fig. 6 Accuracy and Loss result at 5 layers and 60 epochs**

An observation made from the result of fig.6 is that, increasing the number of network layers improves the network performance but at a more training time, higher dataset volume and computational resources. The validation accuracy and loss plots shows that the network layer setup can improve the model training accuracy but affects validation negatively meaning that the system will train at a higher accuracy but may not be able to learn strange test data well. Table 2 summarizes research experimental results:

**Table 3 Experimental result**

| No. of Layers | No. of epochs | Results (%) |
|---|---|---|
| 4 | 30 | 97 |
| 4 | 140 | 98 |
| 5 | 60 | 99 |

## V. CONCLUSION

To detect Transformer vandalism, the researchers applied a hybrid deep learning model of CNN-LSTM that uses an image sensor feed to a trained image recognition system to recognizes the Vandals' image as it gains entry to a Transformer installation site. This model is multiplicative where CNN is used as an encoder and LSTM used as a decoder. To generate a higher recognition accuracy of the Vandal, authors tuned the number of Layers and Epochs of the system hyper-parameters. The experiment was conducted based on tuning of the model layers and epochs which resulted to higher recognition accuracy of 99% when five layers and sixty epochs were tuned. The experimental result of 99% recognition accuracy of human object is enough proof that the object was human object that tried to gain access to the transformer installation site, so that the action of prevention of entry can be facilitated before any damage in done. This result is the best for Vandalism detection as compared to 98% of results in Fig. 4 and 5 where four layers and 30/140 epochs used. From the results, tuning the number of layers has more effect on training, validation and testing than the number of epochs. Further increase of number of layers may result in system overfitting as reflected in the validation results of Fig.6. More research on the effect of other hyper-parameters is required to determine the best system tuning for general application to other domains.

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