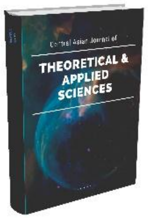

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A Model for Detecting Movement in Railway Infrastructure Using Deep Convolutional Neural Network

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Abstract: *The continuous monitoring of movements using artificial intelligence technique has become a necessary system to cob the level crossing problems faced around the railway infrastructure. This project work has developed a model for detecting movements using image processing method with convolutional neural network, an artificial intelligence technique in monitoring and detection of movements in the railway infrastructure. Images containing movements and non-movements in railway infrastructure were acquired from Google image search have been used in the implementation of the system and a deep convolutional neural network model has been developed. The proposed model was able to classify 11 out of 12 images correctly in the evaluation of the train dataset and the performance accuracy of the model recorded was 92% with a loss of 0.4% which resulted to the misclassification of one of the images. The analysis of the system showed that the system can be optimized to perform better.*

Keywords: *Image Processing, Pattern Recognition, Movement Detection, Railway Infrastructure, DCNN.*

Introduction

The railway system of transportation in Nigeria has experienced a significant improvement since the Federal government began to look into that direction in 2015. Directing their attention towards that aspect of transportation has in recent times boosted even the economy. Before then, the railway infrastructure suffered decay and dilapidation from the vibrant railway system that was handed over to us by the colonial masters (Oraegbune & Ugwu, 2020). Infrastructure and the quality of it, is a pillar when it comes to competitiveness in the railway system (Bank, 2017). However, to improve on the quality and safety of the rail system, there is need to monitor movements on the railways. In Ristic-Durrant et al. (2021) paper, they opined that about 442 accidents that occurred and were reported in the European Union were as a result of level crossing accidents; this includes pedestrians. Therefore, identifying and detecting movement on time in railway infrastructure is very important for the safety of the railway system (Andrusca et al., 2020).

In recent times, the experimental researches carried out by technologists and researchers with particular reference to Artificial Intelligence (AI), Internet of Things (IoTs) and Smart Systems has drastically improved the way our environment is perceived. The use of the sensor technology in the development of continuous monitoring systems especially to obstacle detection in road transportation has been prominent in published works (Ristic-Durrant et al., 2021). The authors Hromadka et al. (2020) has pointed out the need to put preventive measures on our railway infrastructures in other to ensure railway safety and reduce the number of occurrences. This can be implemented with the help of Artificial Intelligence techniques; which will pave way for real time assessment of railways and detection of any form of movement. In heavy traffic areas, it is also very important to have movement intention recognition system to checkmate movements by humans and pedestrians which is an aspect of computer vision, image processing and pattern recognition. The system uses the artificial intelligence method in the detection of movement around the railway infrastructure.

Artificial Intelligence has become very significant in our everyday life and machine learning applications especially in image classification is now an important aspect in technological explorations. Convolutional Neural Network (CNN) has been known to be used extensively in image and video classification and analysis. It has the capability of detecting important features with no intervention of humans (Sarker, 2021). CNN uses the integration of more properties and not the regular multiplication of weights and neuron outputs (Wang & Xi, 1997). CNN has been used for many applications such as image enhancement, feature extraction, computer vision, medical imaging and the likes. It has the learning ability to detect different features from an input image applying efficient computational methods (Park et al., 2021). The motivation in the design of CNN is due to the discovery of visual mechanism of the brain known as the visual cortex which contains a lot of cells responsible for the detection of light in the visual field known as receptive fields (Hijazi et al., 2015). This research work is exploring the advantage of convolutional neural network in the detection of movement in railway infrastructures. Creating a model for detecting movements in railway infrastructure has been necessitated by the occurrences recorded.

According to Ristic-Durrant et al. (2021), about 1666 railway accidents were recorded in 2018 by the European Union. The causes of such accident were: level crossing, rolling stock in motion among others. The non-artificial detection of such movement (level crossing, rolling stock in motion) on the railway infrastructure is the problem statement of this article. Artificial detection of movement will help reduce such casualties experienced in the railways which will in-turn reduce accident. Thereby, improving the safety experience in the railway infrastructure. The proposed aim is the creation of a model for detecting movement in railway infrastructure using Convolutional Neural Network in Image Processing. The system is developed following the outlined objectives: 1) To identify the targeted movements that is being observed on the railway infrastructure. 2) To create a model framework for the detection of movement in railway infrastructure. 3) Acquire, pre-process and encode the images to enable the extraction of features in R programming language and 4) to perform classification and detection analysis applying the CNN model on the acquired dataset.

Related Literature

Theoretical Framework

Kovacevic et al. (2018) gave a report on the use of remote monitoring for slope stability assessments in infrastructure. Traditionally, railway lines have been considered as low-technology in terms of transport infrastructure. However, the railways of today are accommodating ever increasing speeds and are operating at ever higher levels of efficiency. Soni (2016), in his thesis, presented a non-contact monitoring of railway infrastructure with terrestrial laser scanning and photogrammetry at network rail. Current monitoring practices in the railway industry primarily rely on total station and prism-based methods. Jhapate et al. (2020) present a paper on unusual crowd activity detection using OpenCV and motion influence map. Suspicious behaviour is dangerous in public areas that may cause heavy causalities.

Vadlamudi (2020) performed an evaluation of object tracking using OpenCV in Python. Object Tracking System used to track the motion trajectory of an object in a video. Irianto et al. (2009) presented motion detection system using OpenCV library. In this decade, the need of monitoring systems in every field is increasing rapidly. Monitoring systems are applied to improve the security systems and the productivities. Dewangan & Chouhan (2020) did a review on object detection with OpenCV. Due to object detection's close relationship with video analysis and image understanding, it has attracted much research attention in recent years. Ravish Aradhya (2019) presented an object detection and tracking with deep learning and artificial intelligence for video surveillance.

Review of Empirical Studies

Oraegbune & Ugwu (2020) presented a paper on delivering sustainable transport infrastructure projects with railways in Nigeria as the focus. This study presented the issue of railway transportation infrastructure sustainability which involves multi-dimensional view of sustainability criteria such as economy, environment and society with the problem of non-systematic method of assessment in Nigeria. Andrade (2008) in his paper renewal decisions from a life-cycle cost (LCC) perspective in railway infrastructure presented an integrative approach using separate LCC models for rail and ballast components. Stenstrom (2014) presented a model and methods of operation and maintenance performance of rail infrastructure. Congestion of roads and sky, increasing energy costs and a demand to reduce emissions have created a need to shift transportation from road and air to rail. Hromádka et al. (2020) assesses socioeconomic aspect of railway infrastructure project life cycle and Liden (2015) presented a survey of planning problems and conducted research on railway infrastructure maintenance that consumes large budget. Akwetteh et al. (2021) looked into the current railway development and its influencing factors in Ghana. Doll et al. (2015) in their paper looked at the results and efficiency of railway infrastructure financing with the EU.

Review of Related Literature

Andrusca et al. (2020) presented a condition monitoring system and fault detection for impedance and bonds from railway infrastructure. They opined that, nowadays, sensors and condition monitoring systems are expanding rapidly and becoming cheaper. Ristić-Durrant et al. (2021) did a review of vision-based On-Board obstacle detection and distance estimation in railways. This paper provides a review of the literature on vision-based on-board obstacle detection and distance estimation in railways. Arastounia (2015) has developed an automated recognition of railroad infrastructure in rural areas from LIDAR data. This study is aimed at developing automated methods to recognize railroad infrastructure from 3D LIDAR data. A laser-based obstacle detection at railway level crossings has been presented by these authors. This paper presents a system for obstacle detection in railway level crossings from 3D point clouds acquired with tilting 2D laser scanners (Amaral et al., 2016). Chang et al. (2014) has developed railway infrastructure monitoring system with satellite radar data. The feasibility of monitoring the stability of railway infrastructure using dedicated satellite radar observations is demonstrated. Perspectives on railway track geometry condition monitoring from in-service railway vehicles was carried out by these authors. Their paper presents a view of the current state of monitoring track geometry condition from in-service vehicles (Weston et al., 2015). Elberinka et al. (2013) in their paper rail track detection and modelling in mobile laser scanner data has presented a method for detecting and modelling rails in mobile laser scanner data. Sahebdivani et al. (2020) has presented rail track detection system and projection-based 3D modelling from UAV point cloud. Sattar et al. (2018) presented a review on road surface monitoring with smartphone sensors. Road surface monitoring is a key factor to providing smooth and safe road infrastructure to road users. Parven & Shah (2021) presented a motion detection system using OpenCV in Python. This paper suggests a motion detection software system that enables us to see the movement around an object or a visual area.

System Analysis

The proposed system presents movement detection model in the railway infrastructure. This is achieved by creating a model employing machine learning tools to monitor movement around the railway infrastructure. A Convolutional Neural Network algorithm has been employed using image data acquired from Google image search database. The CNN algorithm learns from the data and is able to classify and detect such movement when seen in a new captured data and with that, an alarm/ alert is sounded to notify the appropriate security operatives for prompt action. This model is represented in the Figure 1 below.

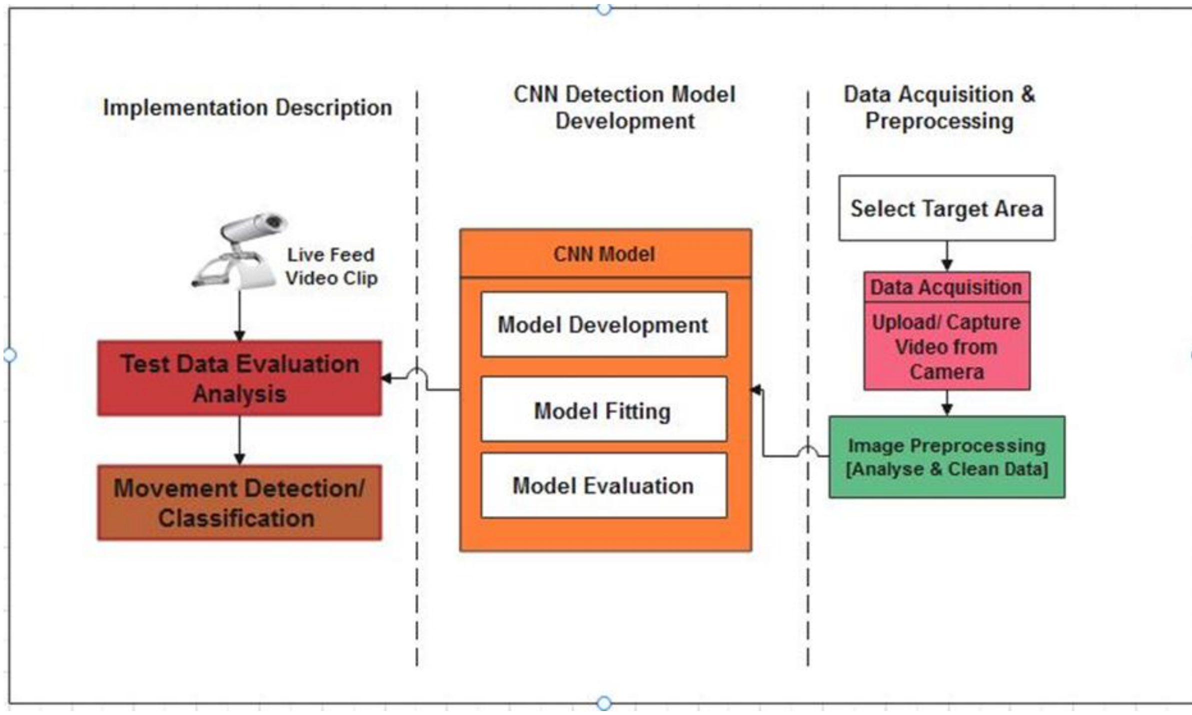

Figure 1: Architectural Model of the proposed Movement Detection in Railway Infrastructure

The architectural model as shown in Figure 3.1 explains a model for detecting movements in railway infrastructure using convolutional neural network in image processing. The model shows the data acquisition and pre-processing, CNN Detection model development and the implementation analysis of the proposed system. The implementation of this model helps security operatives not to miss any form of movement around the railway infrastructure thereby preventing unforeseen casualties that may arise. Further explanations on the proposed model is detailed as followed:

A. Data Acquisition and Pre-processing

The system requires data for the model to be developed. An image dataset was acquired through Google image search and is uploaded to the work environment of the system. The images, during acquisition comes in different sizes. Hence, the images were resized to 100 x 100 and the parameters extracted, re-organised for use by the model and encoded with binary “0” and “1” for implementation. The acquire dataset comes in 3 channel (RGB), meaning, it is a coloured image. The total image used for the implementation demonstration is 20 with 8 of the images used as test image and a total of 12 images used for training the model.

B. CNN Detection Model Development

The CNN model was developed with four convolutional layers, two pooling layers, dense layer and dropouts. It uses the ‘relu’ and ‘softmax’ activation function and a learning rate of 0.01. The model was fitted to the training data and the encoded training label and an evaluation carried out on the developed model to check for the percentage performance in accuracy and loss.

Implementation Description of the Model

During implementation, the test dataset is used with the created model to ascertain the performance of the model. This is done with an entirely different dataset or in actual implementation, images capture from a life camera feed to check if there is a movement in the railway infrastructure. When the test dataset is evaluated, the system shows how many images have movements in it and how many images doesn't.

Implementation Analysis and System Testing

The proposed model for detecting movement in railway infrastructure has been analyzed using the convolutional neural network, a machine learning algorithm which is foremost in image or video classification data. A total of 20 Images that shows movement and non-movement in railway infrastructure were gotten from Google image search for the demonstration and analysis of the proposed system. The images were read into the work environment and preprocessed to make them readable and usable by the CNN model. The images were resized to 100 x 100 and the summary of the image showed that the value of the image lies between o and 1, with 3 channels (meaning that the image is a coloured image). The image dataset was split into train and test data with 20% of the dataset used for validation and was encoded to the categorical values of '0' and '1' with '0' meaning there is no movement and '1' meaning that there is movement on the railway infrastructure. The CNN model created using the Keras-model-sequential, it showed a total and trainable parameter of 138,740,514. The model has the epoch size of 60 (total number of iteration).

System Result

The created model was executed several times to optimize the results obtained since the model keep falling short of expectations. The first two results were not very good basically displaying all images as not having any movement. After executing the model for the 3rd and 4th time, there was a significant improvement from the initial results which were record. For the purpose of performance demonstration, one of the two different obtained results of the third and fourth run is presented. First of all, few of the dataset used to develop and test the model is shown in Figure 2 and the graphical representation of the training and test data displayed in figure 3.

Figure 2: Test Image View of the Proposed System Showing Movement and Non-Movement

Figure 2 is the display of tiled images of the test dataset during implementation of the proposed system. Four images showing the absence of movement in the railway infrastructure and four images showing movements in the railway infrastructure. The dataset was used to train the model and Figure 3 produced while the training process was going on.

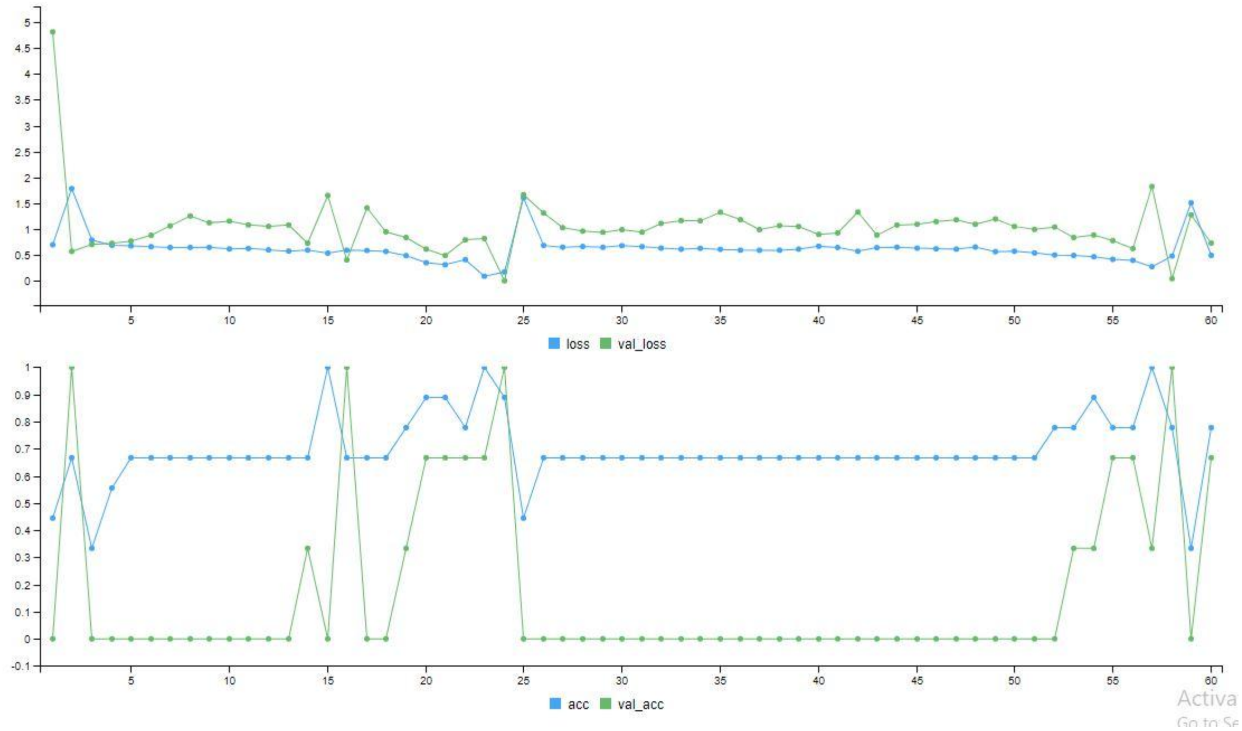

Figure 3: Third Plotted Graphical Representation of the Created CNN Model for the Proposed Model for Detection of Movement in Railway Infrastructure System

From figure 3, we can see that the figure has two graphs on it. The upper graph is the graphical representation of the loss (with the blue line designated for actual loss and the green line for validation loss) while the lower graph plot for accuracy of the model with the blue line showing the actual accuracy and the green line showing the validation accuracy. From the graph, we saw that the accuracy was consistently hitting below 70% with little fluctuations but towards the end, there was an increase in accuracy. The evaluation result displays that the loss came to 0.4% with an accuracy of 92%. This is further shown in the plot history of the model in Figure 4.

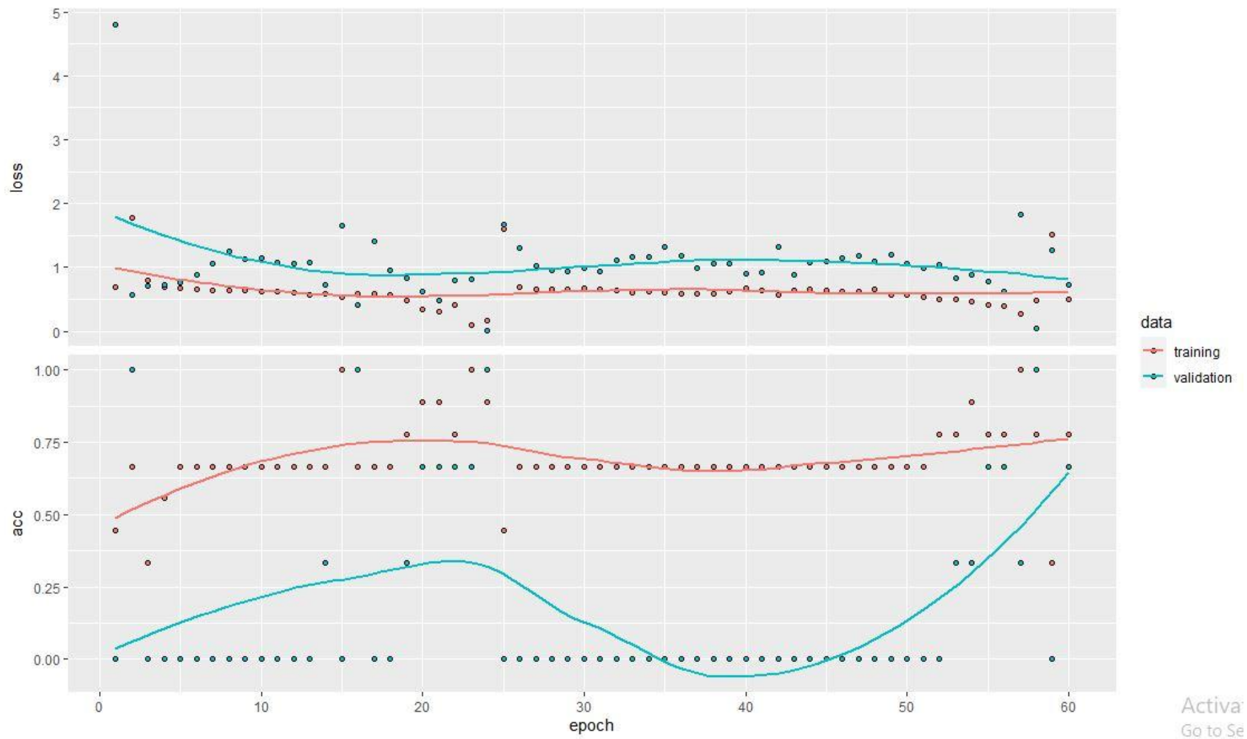

Figure 4: Third History Graphical Representation of the Created CNN Model for the Proposed Model for Detection of Movement in Railway Infrastructure System

Figure 4 further illustrates that the performance of the CNN model was below expectation. From the legend, we see that the red line indicates training while the green line indicate validation with the upper graph showing loss and the lower graph showing accuracy within the 60 epoch (or iterations). The training line alternates between 50% and 90% while the loss lies slightly below 1. The model has not completely classified the provided data and Table 1 and 2 further explains and showcase the shortfalls of the model.

Table 1: Confusion Matrix Training Dataset

	Actual	
Predicted	0	1
0	6	1
1	0	5

Table 1 is the confusion matrix of the training dataset. It shows the actual and the predicted class of the model. Two levels are used to demonstrate the movement and non-movement in the railway infrastructure. The class '0' indicates that there is no movement in the image data while the class '1' indicates that there is movement in the image data. A total of 6 images that has movement and 6 images that doesn't have movement were used and the confusion matrix has shown that the model during training has been able to classify correctly all the non-movement images while it classified 5 images to have movement. The table also shows that it predicted one image to have no movement while in actual sense, there was movement. This is further shown in the probability distribution table in Table 2.

Table 4.2: Probability Table for the Trained CNN Model

SN	PROB. OF NO MOVEMENT	PROB. OF MOVEMENT	PREDICTED CLASS	ACTUAL CLASS
1	0.8714516	0.12854840	0	0
2	0.8885577	0.11144229	0	0
3	0.8648707	0.13512935	0	0
4	0.7177815	0.28221846	0	0
5	0.5249715	0.47502846	0	0
6	0.9215740	0.07842598	0	0
7	0.2230344	0.77696562	1	1
8	0.4521366	0.54786336	1	1
9	0.3383757	0.66162431	1	1
10	0.2855883	0.71441174	1	1
11	0.7012650	0.29873496	0	1
12	0.4770574	0.52294254	1	1

From the probability distribution in Table 2, we can see that the probability of No Movement to the probability of Movement in the first row shows that the system predicted the image correctly. The actual class is ‘0’ and the system predicted ‘0’ showing a 87.1% chance that there is no movement as against 12.8% chance as seen in the table. The system correctly predicted from Serial Number 1 to 10 and 12, but was confused as it miss predicted serial number 11 indicating that there was no movement while in the actual sense, there was movement. When the model was used against the test data, the performance was very poor as seen in the confusion matrix in Table 3.

Table 3: Confusion Matrix Test Dataset

	ACTUAL	
PREDICTED	0	1
0	1	2
1	3	2

The test data comprises of four non-movement images and four movement images. Table 3 shows that the model when used with the test data has confuse 2 images that there is no movement whereas, there is movement and has confused 3 images that there is movement whereas, there is non-movement. This is further shown in the probability distribution table in Table 4.

Table 4: Probability Table for the Test Dataset with Model

SN	PROB. OF NO MOVEMENT	PROB. OF MOVEMENT	PREDICTED CLASS	ACTUAL CLASS
1	0.6032690	0.3967310	0	0
2	0.2977493	0.7022507	1	0
3	0.3902090	0.6097910	1	0
4	0.3265038	0.6734962	1	0
5	0.3734505	0.6265495	1	1
6	0.5991044	0.4008956	0	1
7	0.4472865	0.5527135	1	1
8	0.5718120	0.4281880	0	1

From Table 4, we can see that serial numbers 2, 3, 4, 6 and 8 were misclassified when looking at the actual and predicted class. The probability distribution showed that as high as 70% and as low as 57% were the values used in this misclassification. When evaluated for accuracy and loss, it was found that the test data has a loss of 0.82 (82% loss) while the accuracy was 37.5%. After the fourth run, the result was not any better hence, the third run was adopted.

Discussion of Result

The proposed model for detecting movements in railway infrastructure has been developed using Convolutional Neural Network. The system uses the image processing method to achieve this research work and these images were acquired through Google image search. The system achieves all the objective of the research work as the system was able to identify the targeted movements usually seen in the railway infrastructure. A model framework for the detection of movement was created as seen in Figure 1 that shows the different modules involved in the detection process. We were able to acquire 20 images that show movement and non-movement in the railway infrastructure and they were pre-processed for the detection analysis of the proposed system. The images were encoded and fitted to the CNN model and detection analysis was obtained.

In Figure 2, we have the display of the dataset images showing the movements and non-movement in the railway infrastructure that was used in the system. In Figure 3, the accuracy consistently hits below 70% and later increased which we saw at the evaluation result as 92% was recorded as accuracy with a loss of 0.4. The effect of the loss was later shown in Table 1; the table showed that the system confused one of the images and classified it wrongly. The 6 images in the training set that indicates non-movement were correctly classified and 5 out of the 6 images in the training set that indicates movement were also classified correctly. One of the images that indicates movement was classified as non-movement as shown in Table 2 with a probability of 70.1% misclassification. After the model was used against the test dataset, the model produced a very poor result as more than half of the test data were misclassified as shown Table 3 and Table 4. In Table 4, the probability distribution showed that as high as 70% and as low as 57% were the values of this misclassification. When evaluated for accuracy and loss, it was found that the test data has a loss of 0.82 (82% loss) while the accuracy was 37.5%.

Conclusion

We therefore conclude that, the model for detecting movement in railway infrastructure using Convolutional Neural Network in image processing has performed poorly in classifying and detecting movement. The performance accuracy of the training data came to 92% with 0.4 % loss when evaluated and the probability distribution on the predicted class carried out showed that one out of the 12 image dataset used for training was misclassified. But, when the CNN model was used to fit with the test data, it demonstrated a very poor result with a percentage accuracy of 37.5% with a huge loss of 0.82% which was very clear when viewed through the probability distribution table of the test data. This model can be improved upon to achieve optimal classification and detection. The images used and adjustment to the model can increase the performance of the model’s accuracy and reduce the loss drastically.

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