

Multi-Class Road Defects Detection and Classification System Using Transfer Learning-Based Deep Convolutional Neural Networks

Philip O. Odion¹ and Kabiru B. Ishola^{2*}^{1,2}Department of Computer Science, Nigerian Defence Academy, Kaduna, Nigeria*Corresponding Author's Email: isholakabir@gmail.com

Received on: April, 2024

Revised and Accepted on: May, 2024

Published on: July, 2024

ABSTRACT

The road's infrastructure is crucial for growth, development, and forming the backbone of any country's economy. The accurate detection and classification of road defects for optimal road maintenance is a challenging task due to the varied types of road defects of different severity. This paper presents a transfer learning model for the detection and classification of road defects based on types of defects (cracks and potholes) and severity. A new local dataset was introduced consisting of road surface images (defects and non-defects) of Kaduna metropolis, Nigeria. The types and severity of the defects were grouped as non-defect, low-pothole, low-crack, moderate-pothole, moderate-crack, high-pothole, and high-crack. The model was developed by extracting the features using pretrained VGG19 and EfficientNetB3. The extracted features were concatenated and evaluated on the locally gathered datasets. The pretrained EfficientNetB3 achieved an accuracy 98.1% higher than the 97.9% accuracy of VGG19. The concatenated model (VGG19+EfficientNetB3) achieved 98.5% accuracy, which outperformed the two pretrained models, VGG19 and EfficientNetB3. This study demonstrated the benefit of combining the strengths of VGG19 and EfficientNetB3, for improved performance and efficiency in road defect detection and classification tasks.

Keywords: Road defects, Detection, Classification system, VGG19, EfficientNetB3.

1.0 INTRODUCTION

1.1 Introduction of the Problem

Roads remain the mainstay of transport in Nigeria and have a long-term effect on the nation's economic growth and development. This same road poses a serious threat and safety issues due to the high incidence of road defects such as: potholes, cracks, and surface deterioration (Dukiya *et al.*, 2023). Currently, the majority of the roads, both in rural and urban areas, are in a deplorable state owing to inadequate assessment and timely maintenance, resulting in visible functional and structural defects (Ipingbemi, 2008). The specific problem lies in the lack of reliable advanced techniques for accurately detecting and classifying Nigerian road defects. The current approaches (manual inspection) of assessing the conditions of roads are not enough, time-consuming, labor-intensive, subjectivity, and based on human error, which are not adequate for dealing with the varied and large number of road defects that are present in different regions and across the country. Such approaches impede thorough Nigerian road defect detection and classification. The application of computer vision and Deep Convolutional Neural Networks (DCNNs) to Nigerian road dataset is imperative to provide a viable solution to the challenges, enhancing and automating the process of Nigerian road defect detection and classification, which are necessary to guarantee the safety of lives on Nigerian roads and effective infrastructure maintenance. The aim of this study is to develop a model

for the detection and classification of road surface defects (cracks and potholes) based on the types of defects and severity using TL-based DCNN.

1.2 Related Works

A computer vision-based system that recognized pavement crack patterns was developed by Hoang and Nguyen (2023) using Light Gradient-Boosting Machine (LightGBM), deep neural network (DNN), and convolutional neural network (CNN) as a machine learning technique. The goal is to accurately detect and classify different types of pavement cracks based using image processing and machine learning approaches. In their study, twelve thousand (12,000) pavement images and features of each image of the dataset were extracted using image processing techniques. Steerable filter (SF), image texture descriptors and projection integral (PI) were utilized to characterize the pavement crack. The study applied DNN and CNN (DCNN) models which have the potential to improve the accuracy of Pavement crack pattern recognition were incorporated to extract complex features from the dataset and achieved an accuracy of 93%.

The effectiveness of convolutional neural networks (CNN)-based image processing and object detection for identifying and categorizing pavement cracks was examined by the study of Sharif *et al.* (2023). Roboflows Pavement Distresses v2 Image Dataset, consisting of 680 images of various states of road distress such as cracking,

patches, potholes were utilized and the bounding boxes was identify using TensorFlow was adopted to identify the bounding boxes, with the annotations saved as a CSV document. The data pre-processing, cleaning was achieved using the MATLAB. CNN-based model using the MATLAB IDE was trained on the annotated dataset to accurately detect and classify pavement distress. In their study, the performance of the trained model was evaluated and compared to a baseline method and the YOLO v8 approach. The trained model outperformed the baseline method and achieved higher precision, recall, and accuracy of 90.4%.

Apeageyi *et al.* (2023) explored transfer learning (TL) techniques with deep convolutional neural networks (DCNNs) to develop pavement classification models for an effective road management and highway system. This study utilized a publicly available dataset of four hundred (400) images of pavement distress acquired from Google Street and other sources and manually categorized into eight (8) different labels namely block cracking, distress-free, fatigue cracking, longitudinal cracking, patching, potholes, rutting, and transverse cracking. Seven (7) different DCNN model architectures comprised of Alexnet, Densenet201, Googlenet, Nasnetlarge, Resnet50, SqueezeNet, and Xception were trained and fine-tuned with the dataset and their performance were evaluated different metrics. The study primarily focuses on types of pavement distress without considering the intensity of each distress in detail. Googlenet, had the greatest performance with the highest overall accuracy (80%) of all adopted networks with Nasnetlarge model having the lowest ranking.

Deep convolutional neural networks (DCNNs) were used in a study by Li *et al.* (2023) to build an effective and affordable road pavement inspection and technology tool. The study focuses on classifying and identifying pavement distresses in road images, such as cracks and potholes. Deep CNNs, more notably ResNet and VGG, are used in the study as the foundational networks for pavement distress image classification for cost-effective and highway maintenance. Using specialized vehicles fitted with cameras, images of various pavement distress

were collected from three Chinese cities of four highways. Deep CNNs (particularly ResNet and VGG) were used to train a binary classification model as the initial training step. The ResNet 50 model, in particular, achieved an accuracy of 96.243% for binary classification (distressed vs. non-distressed images) and an accuracy of 90.257% for multi-label classification (identifying six types of distresses).

A pavement damage detection model was developed in the Ren *et al.* (2023) study utilizing street-view images and deep learning techniques (YOLOv5s-M). The study focuses on the detection of two prevalent types of pavement damage: potholes and cracks that have a big influence on the condition of road infrastructure in Fengtai District in Beijing, China. From the study region, a large, sizable dataset of street-view pictures, amounting to 156,304 images in total, was acquired, and the Baidu Maps Web Service API was employed, which makes it simple for users to get street-view images of the pavement distress. The results showed that the suggested method had an average accuracy of 79.8% on the test samples, proving its usefulness in identifying pavement damages. This study utilized a dataset of Street-View images collected from the district of Fengtai in Beijing, China.

2.0 METHODOLOGY

In this section, a comprehensive methodology for detecting and classifying road defects in Nigeria, consisting of distinct sections, was presented: in the data acquisition, where road images were captured with a high-resolution camera, data pre-processing used various techniques like labeling, image normalization, resizing, and augmentation techniques, including rotation, flipping, and zooming. For the data splitting, the data were split into training, validation, and testing sets. Training and validation of the two pretrained models for feature extraction and the concatenated model for defect detection and classification based on type and severity (low, moderate, and high). Lastly, there was the evaluation of the models. Figure 1 shows the design framework of the proposed system.

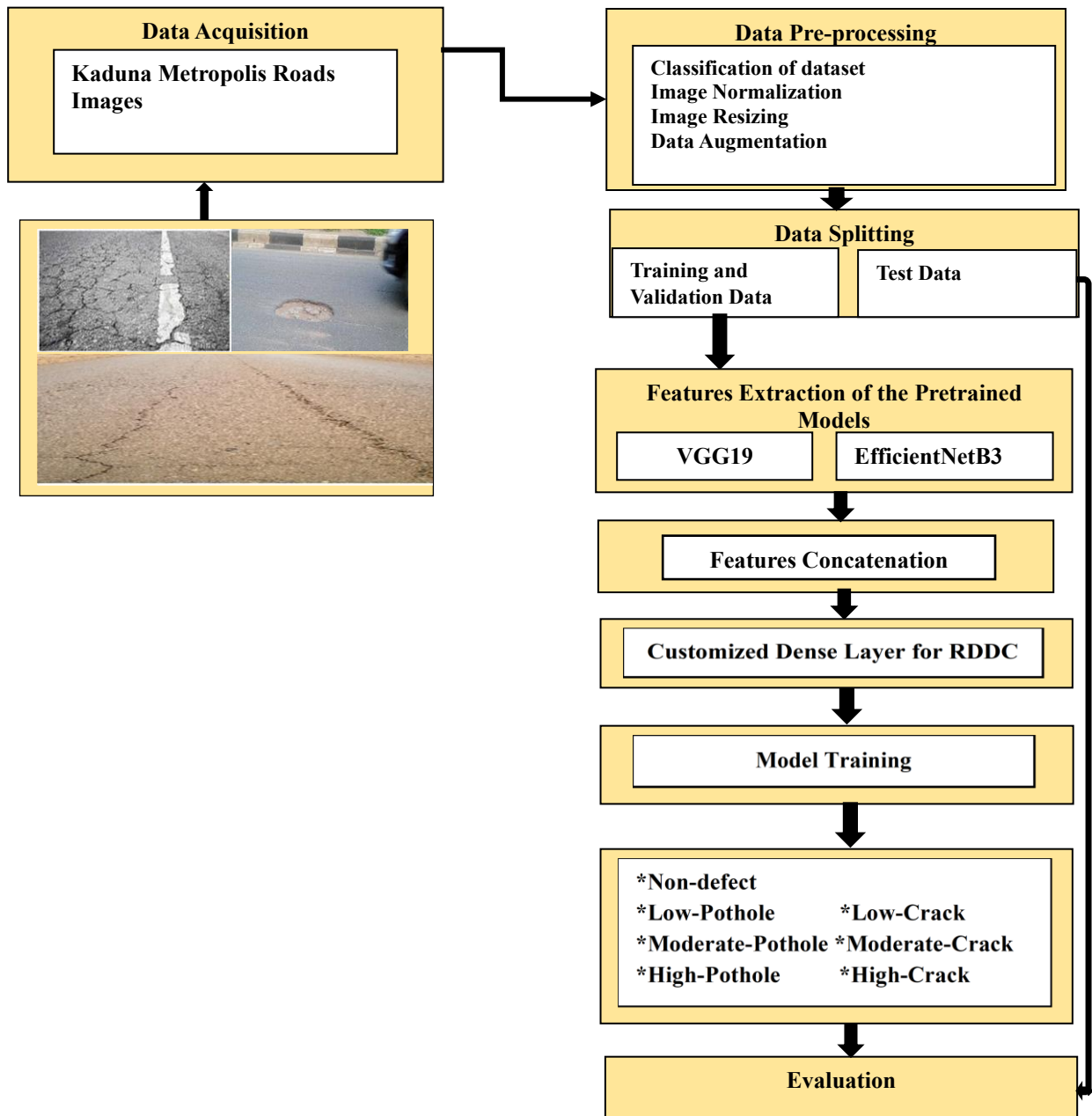


Figure 1: Design Framework of the System

2.1 Dataset Acquisition and Description

This study adopted a visual-based technique in which road surface images (defects and non-defects) were captured across diverse locations in Kaduna metropolis, Nigeria, using a high-resolution smartphone camera. The dataset contains images of different non-defects and defects road images (cracks and potholes) with different severity levels. A detailed approach of Miller and Bellinger (2014) was used for accurate and consistent evaluation of road defects to classify various road images of Kaduna metropolis with non-defects, defect types (cracks, potholes), and their corresponding severity levels in the dataset. The severity (low, moderate, and high) considered the size, depth, width, and length of the identified defects. The dataset comprised of images classified as non-defects, low-pothole, low-crack, moderate-pothole, moderate-crack, high-pothole, high-cracks, as depicted in Figure 2.

individual pretrained models (EfficientNetB3 and VGG19) and the concatenated model. The focus was on training and building the DCNN using Python programming language and TensorFlow, Keras, OpenCV, Numpy Scipy, Scikit-Learn libraries and Jupyter Notebook, which is an open-source interactive computing IDE. The pretrained models (VGG19 and EfficientNetB3) were trained with the preprocessed dataset augmented to 25200 road defects images for feature extraction and the concatenated model (VGG19+EfficientNetB3) to improve the RDDC performance. The pre-processed dataset was passed as an input to the pretrained models and trained separately to ensure consistency for both models. The two pretrained models were trained only up to a specific layer before the final classification layers. To ensure the pretrained feature extraction capabilities of the models relevant to the RDDC tasks, the weights of the two pretrained models were frozen. The extracted features from VGG19 and EfficientNetB3 were concatenated, for a richer model (VGG19+EfficientNetB3), which is a feature representation that leverage the strengths of both models. A customized dense layer was added on top of the concatenated features to combine the extracted features

and make predictions for the RDDC tasks. To optimize the performance of the VGG19+EfficientNetB3 model, it was trained with appropriate hyperparameter tuning (appropriate optimizers, learning rates, and loss functions) using the concatenated features as input and the RDDC classification labels as the target. The models were fine-tuned with suited hyperparameters for effective and improved performance of road defect detection and classification. The efficiency and performance of the models were evaluated using accuracy, F1-score, precision, and recall. The true positives (TP), true negative (TN) false positives (FP), and false negatives (FN) were also presented in the form of a confusion matrix.

3.0 RESULTS AND DISCUSSION.

As previously discussed in the methodology, the images used as dataset were normalized and rescaled to have the same range of pixel values between 0 and 1, which helps improve the training process ensure the pixel values are on a consistent scale before any further preprocessing and resizing to 224*224. Figure 5 shows some samples of the original and normalized image histogram, which indicates the scales (0 and 1) of the pixel values.

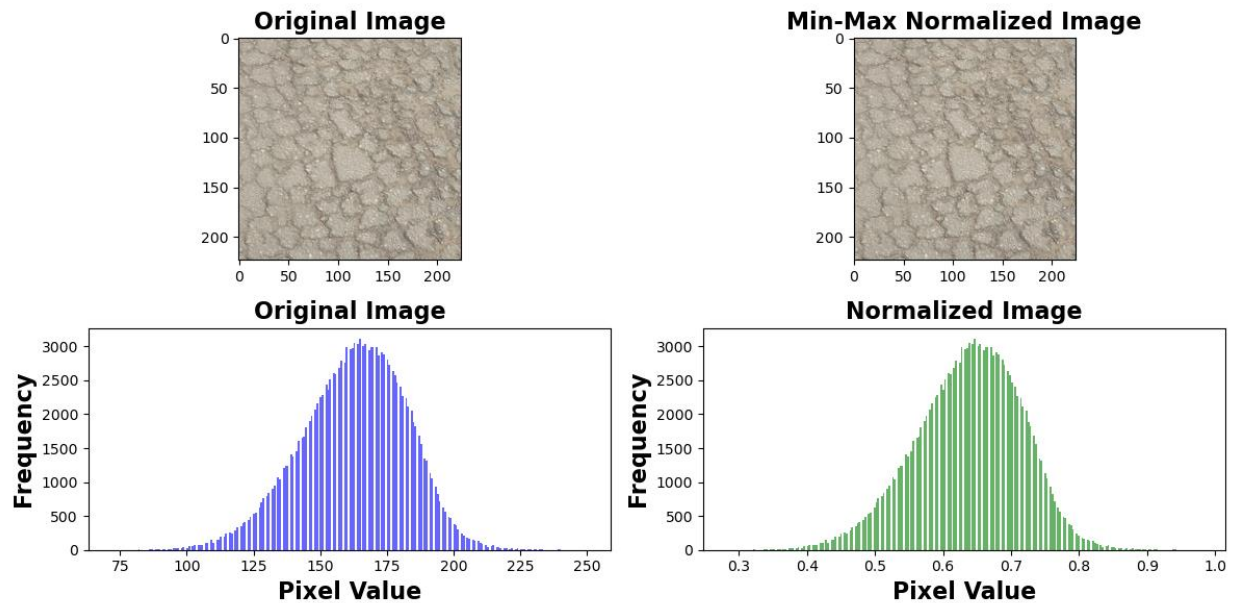


Figure 5: Original and Normalized Image Histogram

The augmentation techniques resulted in a six-fold increase in the number of images, from 600 to 3600 images per class. The dataset initially had 4200 images, but with the data augmentation, 25200 were made available for the training, validation and testing. Figure 6 shows samples of original images and their augmented images, comprising the seven (7) classes. Table 1 shows the list of all the classes with their distribution before and after augmentation.



Figure 6: Original and the Augmented Images

Table 1: Dataset Distribution for Each Class of the Defect

Class	Before Augmentation	After Augmentation
Moderate-crack	600	3600
Moderate-pothole	600	3600
Low-crack	600	3600
Low-pothole	600	3600
Non-defect	600	3600
High-crack	600	3600
High-pothole	600	3600
Total	4200	25200

The dataset was split into 70% for training, 15% for validation, and the remaining 15% dedicated to testing, resulting to 17,640 for training, 3780 for validation and 3780 for testing for evaluating the models using test accuracy, F1-score, precision, and recall as the performance metrics.

To compare the performance of the two pretrained models and the concatenated model, the VGG19 models (VGG19, EfficientNetB3, VGG19+EfficientNetB3) training configurations and hyperparameter tuning used are presented in the Table 2.

Table 2: Models Hyperparameters

Hyperparameters	Values
Learning Rate	0.0001
Optimizer	Adam

Batch Size	32
Epochs	50
Loss Function	Categorical cross-entropy

3.1 Results and Evaluation of VGG19

The pretrained VGG19 model was trained on the normalized and preprocessed training and validation set of 17,640, 3780 respectively to classifies road surface defects. The training and validation accuracy and losses were monitored during the training process and evaluated. It can be observed from the Figure 7 and Figure 8 the training accuracy and validation accuracy increased steadily from epoch 0 to epoch 50, likewise the training loss also decreased steadily from epoch 0 to 50, indicating that the model was a good fit and learning the features to classify the defects correctly.

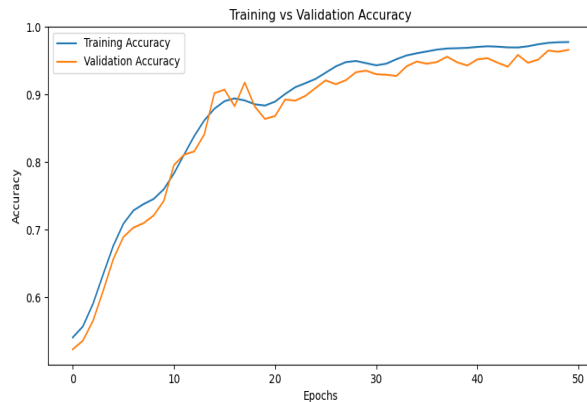


Figure 7: Accuracy Evaluation for the VGG19

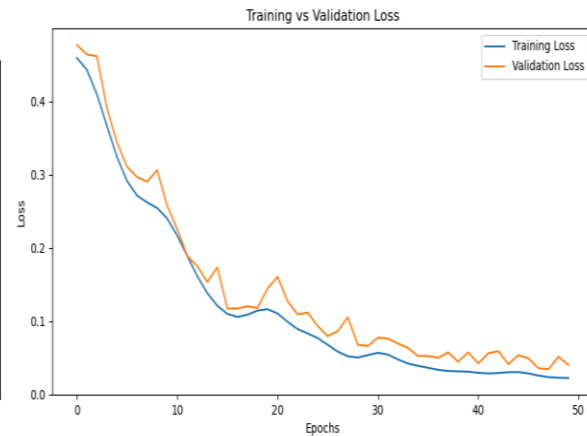


Figure 8: Loss Evaluation for the VGG19

The VGG19 model performed well on the test set based on the confusion matrix as presented in Figure 9. The diagonal elements of the matrix represent the number of true positives (correctly classified instances) for each class.

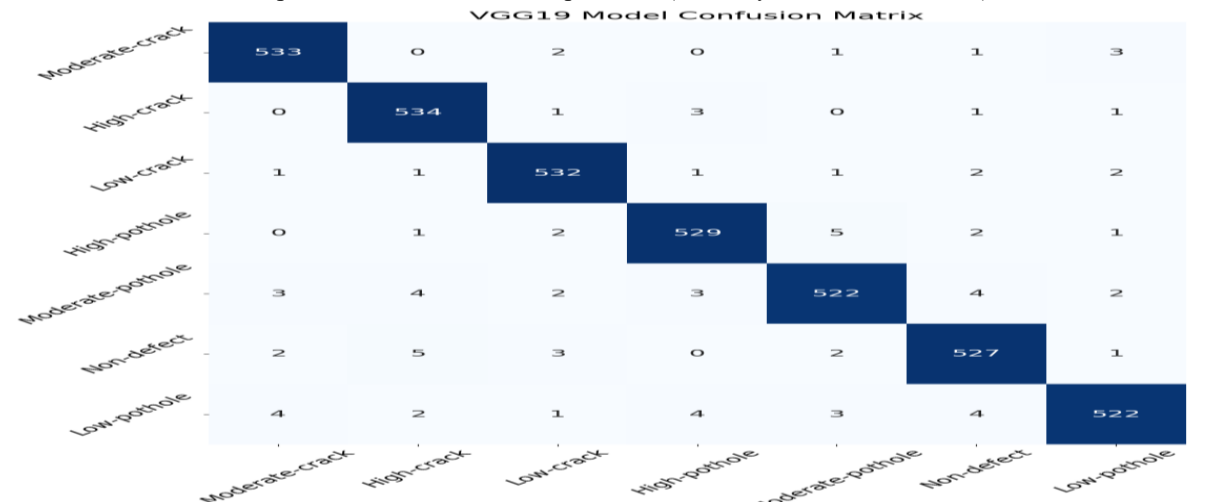


Figure 9: Confusion Matrix of VGG19 Features

The VGG19 classification report as seen in Table 3, it indicated the model achieved an accuracy of 0.979, with a macro-average precision of 0.979, a recall of 0.979, and a f1-score of 0.979. The support for each class was five hundred and forty (540) instances. The confusion matrix and classification report show that the model performed well for the classes of the road surface defects, with a few misclassifications.

Table 3: Classification Report Results of VGG19

	Precision	Recall	F1-score	Support
Moderate-crack	0.982	0.987	0.984	540
High-crack	0.976	0.989	0.983	540
Low-crack	0.980	0.985	0.982	540
High-pothole	0.980	0.980	0.980	540
Moderate-pothole	0.978	0.967	0.972	540
Non-defect	0.974	0.976	0.975	540
Low-pothole	0.981	0.967	0.974	540
Accuracy			0.979	3780
Macro avg	0.979	0.979	0.979	3780
Weighted avg	0.979	0.979	0.979	3780

3.2 Results and Evaluation of EfficientNetB3

The pretrained EfficientNetB3 model was trained on the normalized and preprocessed training and validation set as was done for the VGG19, with the same hyperparameter tuning in Table 2. It can be observed from Figure 10 that there was a slight fluctuation in the learning curve of the training and validation accuracy from epoch 15 to 40, and both increased steadily from epoch 40 to epoch 50 to achieve a training accuracy of 0.9805. As seen in Figure 11, the training loss decreased steadily from 0.4248 to 0.0140, indicating that the model was learning to predict the classes accurately. The validation loss also decreased from 0.4880 to 0.0200, with little fluctuations at the earlier epochs and later convergence to align with the training loss, indicating that the model was generalizing well to unseen data.

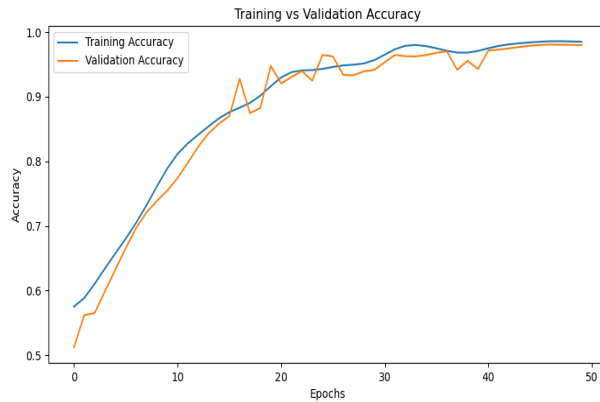


Figure 10: Accuracy Evaluation for the VGG19

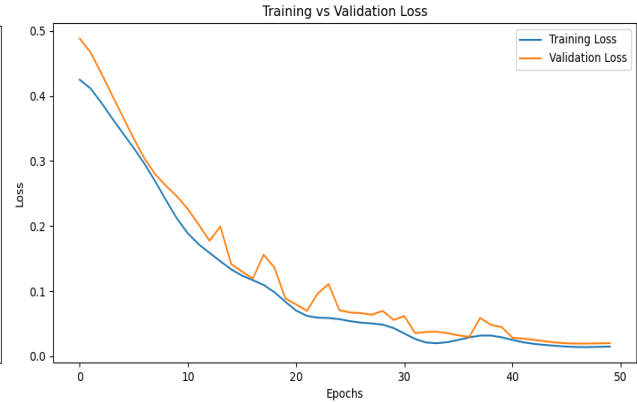


Figure 11: Loss Evaluation for the VGG19

The classification confusion matrix results obtained by the EfficientNetB3 RDDC model on the test data are given in Figure 12. The off-diagonal elements represent the number of misclassified samples. The model performed very well in classifying almost all the classes correctly, with fewer misclassifications of each of the defect's classes.

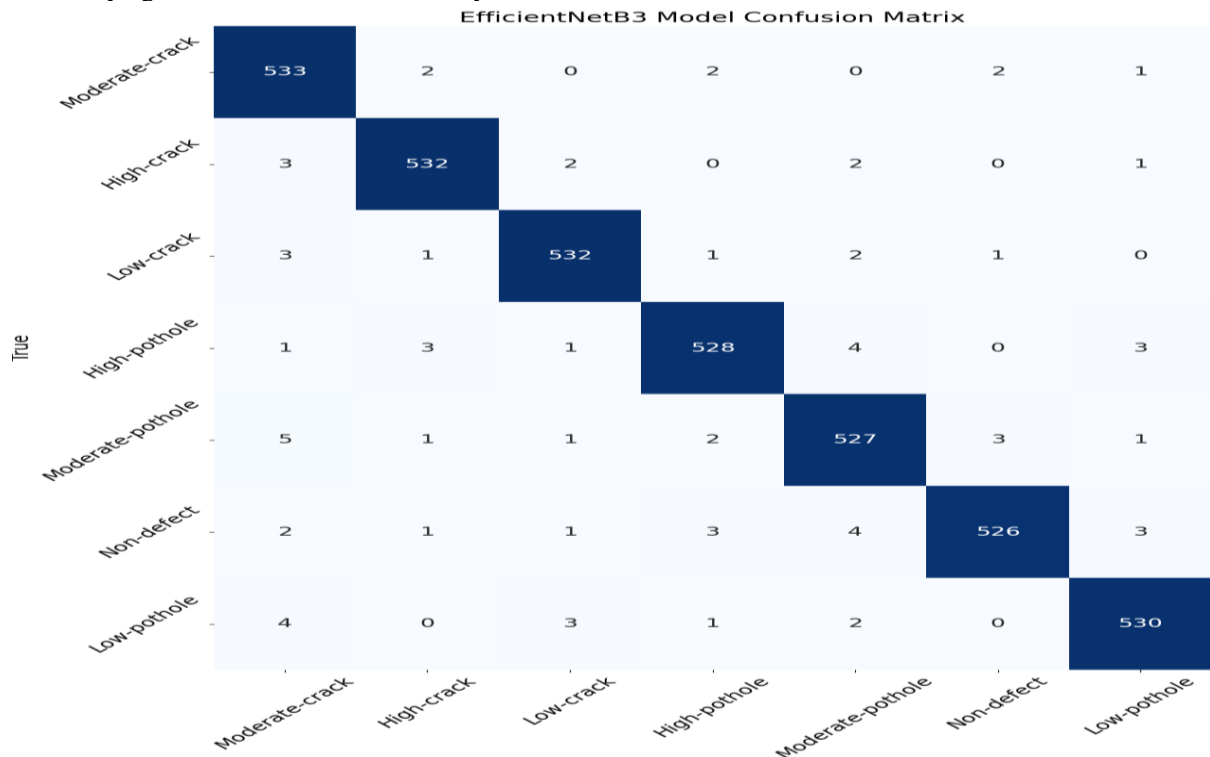


Figure 12: Confusion Matrix of EfficientNetB3 Features

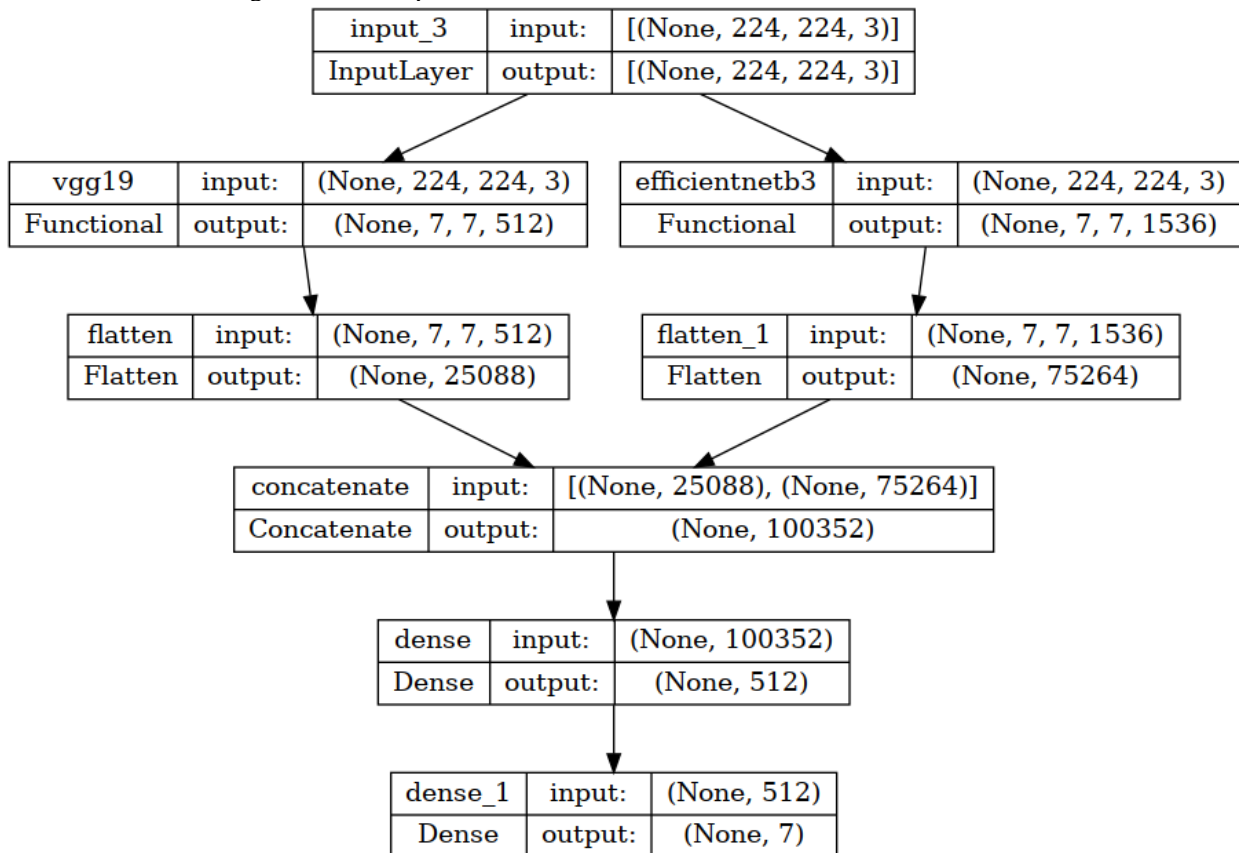
The classification report results of the EfficientNetB3 RDDC model are presented in Table 4. The report shows the classification performance of each class of the dataset, and the model achieved an overall test accuracy of 0.981; likewise, the precision, recall, and F1-score of the model.

Table 4: Classification Report Results of EfficientNetB3

	Precision	Recall	F1-score	Support
Moderate-crack	0.967	0.987	0.977	540
High-crack	0.985	0.985	0.985	540
Low-crack	0.985	0.985	0.985	540
High-pothole	0.983	0.978	0.981	540
Moderate-pothole	0.974	0.976	0.975	540
Non-defect	0.989	0.974	0.981	540
Low-pothole	0.983	0.981	0.982	540
Accuracy			0.981	3780
Macro avg	0.981	0.981	0.981	3780
Weighted avg	0.981	0.981	0.981	3780

3.3 Results and Evaluation of VGG19+EfficientNetB3 Model

The concatenated model (VGG19+EfficientNetB3) was developed and trained on the normalized and preprocessed training and validation set as was done for the VGG19 and EfficientNetB3 RDDC models to improve defect detection and classification performance into seven categories: moderate-crack, high-crack, low-crack, high-pothole, moderate-pothole, non-defect, and low-pothole. The VGG19+EfficientNetB3 leveraged the strengths and capabilities of the two separately implemented pretrained VGG19 and EfficientNetB3 and concatenated the features extracted from them to create a more robust, efficient, and effective model. Figure 13 shows the architecture of the VGG19+EfficientNetB3 and how the pretrained models were integrated and their features concatenated to potentially reduce individual biases and maximize the strengths of the two pretrained models.

**Figure 13: The VGG19+EfficientNetB3 RDDC Model Architecture**

As seen in the Figure 14, VGG19+EfficientNetB3 model demonstrated accurate defect classification and generalization over 50 epochs, with training accuracy increasing from 0.5126 to 0.9871 and validation accuracy from 0.4881 to 0.9851. Training and validation losses decreased, indicating accurate prediction and well-fitting to the RDDC problem, with a loss function minimizing errors between predicted and actual values as seen in Figure 15.

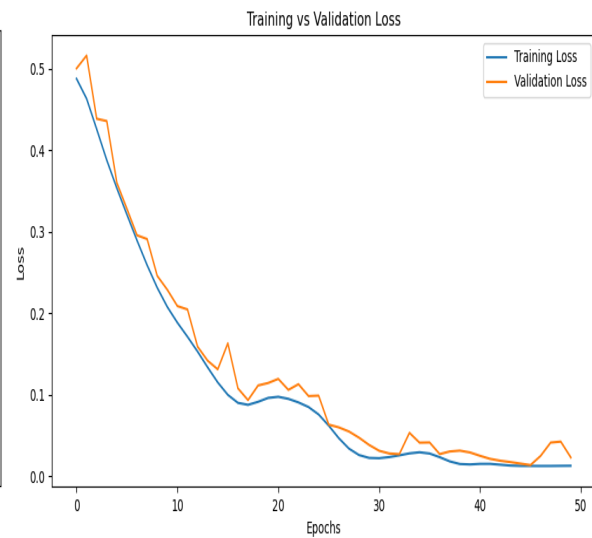
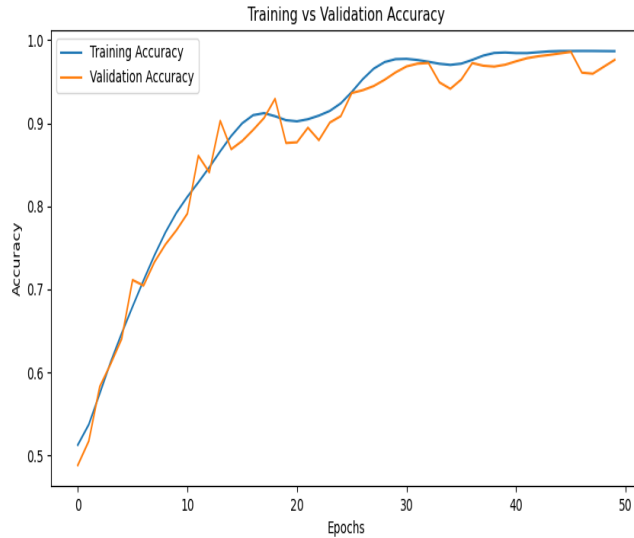


Figure 14: Accuracy of VGG19+EfficientNetB3 Model

Figure 15: Loss of VGG19+EfficientNetB3 Model

The concatenated model (VGG19+EfficientNetB3) performed very well in predicting the majority of the test dataset of road defects, as shown in the confusion matrix in Figure 16. The dark blue diagonal elements represent the number of correctly classes of defects referred to as true positives. The off-diagonal elements represent the number of misclassified samples. The defect classes (moderate-crack, high-crack, low-crack, high-pothole, moderate-pothole, non-defect, and low-pothole) reported a true positive (TP) value of 532, 533, 532, 530, 533, 530, and 532, respectively, with the highest true positive (TP) of 533 and the lowest 530. All seven (7) classes reported fewer misclassification values of road defects, with the highest false positive (FP) of 15 and the lowest of 3, and the highest false negative (FN) of 10 and the lowest of 7. Based on the experiment, the VGG19+EfficientNetB3 did absolutely well in classifying all classes of defects, with fewer misclassifications.

VGG19 and EfficientNetB3 Combine Model Confusion Matrix

	Moderate-crack	High-crack	Low-crack	High-pothole	Moderate-pothole	Non-defect	Low-pothole
Moderate-crack	532	2	1	0	1	2	2
High-crack	1	533	1	2	0	1	2
Low-crack	0	3	532	1	1	1	2
High-pothole	1	2	1	530	3	1	2
Moderate-pothole	0	0	1	1	533	2	3
Non-defect	1	5	0	0	1	530	3
Low-pothole	0	3	2	1	1	1	532

Figure 16: Confusion Matrix of VGG19+EfficientNetB3 Model

The concatenated VGG19+EfficientNetB3 model classification report results are given in Table 5. The VGG19+EfficientNetB3 achieved an accuracy of 0.985, with a macro average precision, recall, and F1-score of 0.985. The weighted average precision, recall, and F1-score were also 0.985. The results show that the concatenated (VGG19+EfficientNetB3) outperformed the individual pretrained models, VGG19 and EfficientNetB3 in terms of accuracy, precision, recall, and F1-score, indicating that the model concatenation of VGG19 and EfficientNetB3 models improved the performance of RDDC tasks.

Table 5: Classification Report Results of VGG19+EfficientNetB3

	Precision	Recall	F1-score	Support
Moderate-crack	0.994	0.985	0.990	540
High-crack	0.973	0.987	0.980	540
Low-crack	0.989	0.985	0.987	540
High-pothole	0.991	0.981	0.986	540
Moderate-pothole	0.987	0.987	0.987	540
Non-defect	0.985	0.981	0.983	540
Low-pothole	0.974	0.980	0.980	540
Accuracy			0.985	3780
Macro avg	0.985	0.985	0.985	3780
Weighted avg	0.985	0.985	0.985	3780

3.4 Comparison of the RDDC Models

In this section, we compare the performance of all the models VGG19, EfficientNetB3 and the concatenated model (VGG19+EfficientNetB3) for road surface defect classification, and the benefits of concatenating models are also looked at. Pretrained VGG19 and EfficientNetB3 models were fine-tuned on the pre-processed Kaduna metropolis road defect dataset with appropriate optimizers, learning rate values, and loss functions. It is seen that the concatenated model

(VGG19+EfficientNetB3) achieved the highest accuracy of 0.985, outperforming the individual pretrained models (VGG19 and EfficientNetB3) with accuracies of 0.979 and 0.981, respectively. The concatenated model did better as the most successful performance results of 0.985, demonstrating that its effectiveness and capabilities of maximizing the strengths of the two pretrained different models. The performance rates obtained from the RDDC models are given in Table 6.

Table 6: Comparison of VGG19, EfficientNetB3, and VGG19+EfficientNetB3

Model	Accuracy	Precision	Recall	F1-score
VGG19	0.979	0.979	0.979	0.979
EfficientNetB3	0.981	0.981	0.981	0.981
VGG19+EfficientNetB3	0.985	0.985	0.985	0.985

4.0 DISCUSSION

This section compares the performance and results of this paper against other works considered in the state-of-the-art. The research conducted by Li *et al.* (2023) on automated classification and detection of pavement distress images using deep learning was critically looked into to compare the performance of this proposed concatenated model (VGG19+EfficientNetB3) against each other as one of the current states of the art. This work achieved an accuracy of 0.985, outperforming the ResNet50 accuracy (0.96243) for the binary classification and multi-label classification (0.90257) from Li *et al.* (2023). Though several recent studies have focused on the use of deep learning in road defect detection and classification, for instance, the study of Hoang & Nguyen and Sharif *et al.* (2023) achieved a reported test accuracy of 0.962 and 0.904, respectively, on a dataset similar to this study. The VGG19+EfficientNetB3 model's test accuracy of 0.985

indicates that it is competitive with the state-of-the-art. The importance of the sufficient and preprocessed quality of training data cannot be underestimated in deep learning performance, as this may have different outcomes for the model. Nonetheless, attaining an outstanding performance with higher accuracy, precision, and recall than the individual trained model emphasizes the effectiveness of the concatenated model. This work managed to outperform their results with an accuracy of 0.985. Regarding the methods employed to detect and classify road defects as used in Li *et al.* (2023), they used a convolutional neural network, which they adapted to VGG and ResNet architecture ideas. In another study by Saisree and Kumaran (2023), a single Resnet50, InceptionV2, and VGG19 network was used. None of these studies have proposed employing a combined model by concatenating features extracted from two different pretrained models to detect and classify road defects. In comparison with this work, where we propose

the hybrid model VGG19+EfficientNetB3, the results exceed the results of Li *et al.* (2023) by 0.02257 (2.3%), which is the result of the lead paper. Table 7 shows the

performance comparison with State-of-the-art models in RDDC

Table 7: Performance Comparison with State-of-the-art Models

Author(s)	Country	Dataset	Model	Testing Accuracy	Precision	Recall
Li <i>et al.</i> (2023)	China	Private (China)	local ResNet50	0.96243	0.95183	0.97506
Ren <i>et al.</i> (2023)	China	Private local (Beijing, China)	YOLOv5	0.90257	0.76509	0.86013
Apeageyi <i>et al.</i> (2023)		Public	Googlenet	0.798	0.782	0.721
Odion & Ishola (2024)	Nigeria	Private (Kaduna, Metropolis Nigeria)	local VGG19+ EfficientNetB3 (Ours)	0.985	0.985	0.985

5.0 CONCLUSION

This study focuses on improving Nigerian road defect detection and classification using deep learning models. The study uses a Kaduna metropolis road defect dataset, comparing pretrained VGG19, EfficientNetB3, and a concatenated model (VGG19+EfficientNetB3). The concatenated model outperformed the individual pretrained models, achieving a test accuracy of 0.985, a precision score of 0.985, and a recall score of 0.985. The importance of concatenating two separate pretrained models has been demonstrated by this study as an effective approach to improving DCNN model performance, as their strengths can complement each other for a more robust model of road defect detection and classification tasks. Building on these findings to further improve performance on RDDC tasks, future studies should explore another method of combining models (ensemble learning) and its different combination strategies like majority voting, weighted averaging, and stacking. This will allow multiple models to be trained on different subsets of the dataset for more robust and accurate results.

REFERENCES

- Apeageyi, A., Ademolake, T. E., & Adom-Asamoah, M. (2023). Evaluation of deep learning models for classification of asphalt pavement distresses. *International Journal of Pavement Engineering*, 24(1), 1-17. <https://doi.org/10.1080/10298436.2023.2180641>
- Dukiya, J., Adeniyi, G., & Adejumo, T. (2023). Assessment of Abuja-Kaduna "Trunk A" Carriageway Drains and its Implications on National Development. *Journal of Civil Engineering Frontiers*, (JoCEF), 4(1), 1-7. <https://doi.org/10.38094/jocef40158>.
- Haruna, U., Ali, R., & Man, M. (2023). A new modification CNN using VGG19 and ResNet50V2 for classification of COVID-19 from X-ray

- radiograph images. *Indonesian Journal of Electrical Engineering and Computer Science*. 31(1), <https://doi.org/10.11591/ijeecs.v31.i1.pp369-377>.
- Hoang, N., & Ngu yen, Q. (2023). Computer Vision-Based Recognition of Pavement Crack Patterns Using Light Gradient Boosting Machines, Deep Neural Networks, and Convolutional Neural Networks. *Journal of Computer Vision and Pattern Recognition*, 7(3), 21–51.
- Imane, C. (2022, November 12). EfficientNet [Model Architecture]. *OpenGenus IQ: Computing Expertise & Legacy*. <https://www.google.com/amp/s/iq.opengenus.org/efficientnet/amp/>
- Ipingbemi, O. (2008). Exploring Labour-Based Approach for Rural Road Maintenance in Nigeria. *J. Soc. Sci.* 17, 103-111. [10.1080/09718923.2008.11892639](https://doi.org/10.1080/09718923.2008.11892639).
- Li, D., Duan, Z., Hu, X., Zhang, D., & Zhang, Y. (2023). Automated classification and detection of multiple pavement distress images based on deep learning. *Journal of Traffic and Transportation Engineering (English Edition)*, 10(2), 276-290.
- Manav, M., Goyal, M., Kumar, A., Arya, A., Singh, H., & Yadav, A. (2021). Deep Learning Approach for Analyzing the COVID-19 Chest X-Rays. *Journal of Medical Physics*, 46, 189-196. https://doi.org/10.4103/jmp.JMP_22_21.
- Miller J. S. & Bellinger W. Y. (2014). Distress Identification Manual for the Long-Term Pavement Performance Program (Fifth Revised Edition). Office of Infrastructure Research and Development Federal Highway Administration 6300 Georgetown Pike
- Ren, M., Zhang, X., Li, Y., & Zhang, X. (2023). YOLOv5s-M: A deep learning network model for road



- pavement damage detection from urban street-view imagery. *International Journal of Applied Earth Observation and Geoinformation*, 120, 1-14.
- Saisree, C., & Kumaran, U. (2023). Pothole Detection Using Deep Learning Classification Method. *Procedia Computer Science*, 218, 2143-2152. <https://doi.org/10.1016/j.procs.2023.01.190>
- Sharif, S., Emiola, D. I., Zoto, A., Apeagyei, A., and Elmedany, W. (2023). Utilizing Convolutional Neural Networks for Pavement Distress Classification and Detection. *3ICT 2023: International Conference on Innovation and Intelligence for Informatics, Computing, and Technologies*. University of Bahrain, Manama, Bahrain, 20–21, IEEE.
- Utami, P., Hartanto, R., & Soesanti, I. (2022). The Efficient Net Performance for Facial Expressions Recognition. *2022 5th International Seminar on Research of Information Technology and Intelligent Systems (ISRITI)*, 756-762. <https://doi.org/10.1109/ISRITI56927.2022.10053007>