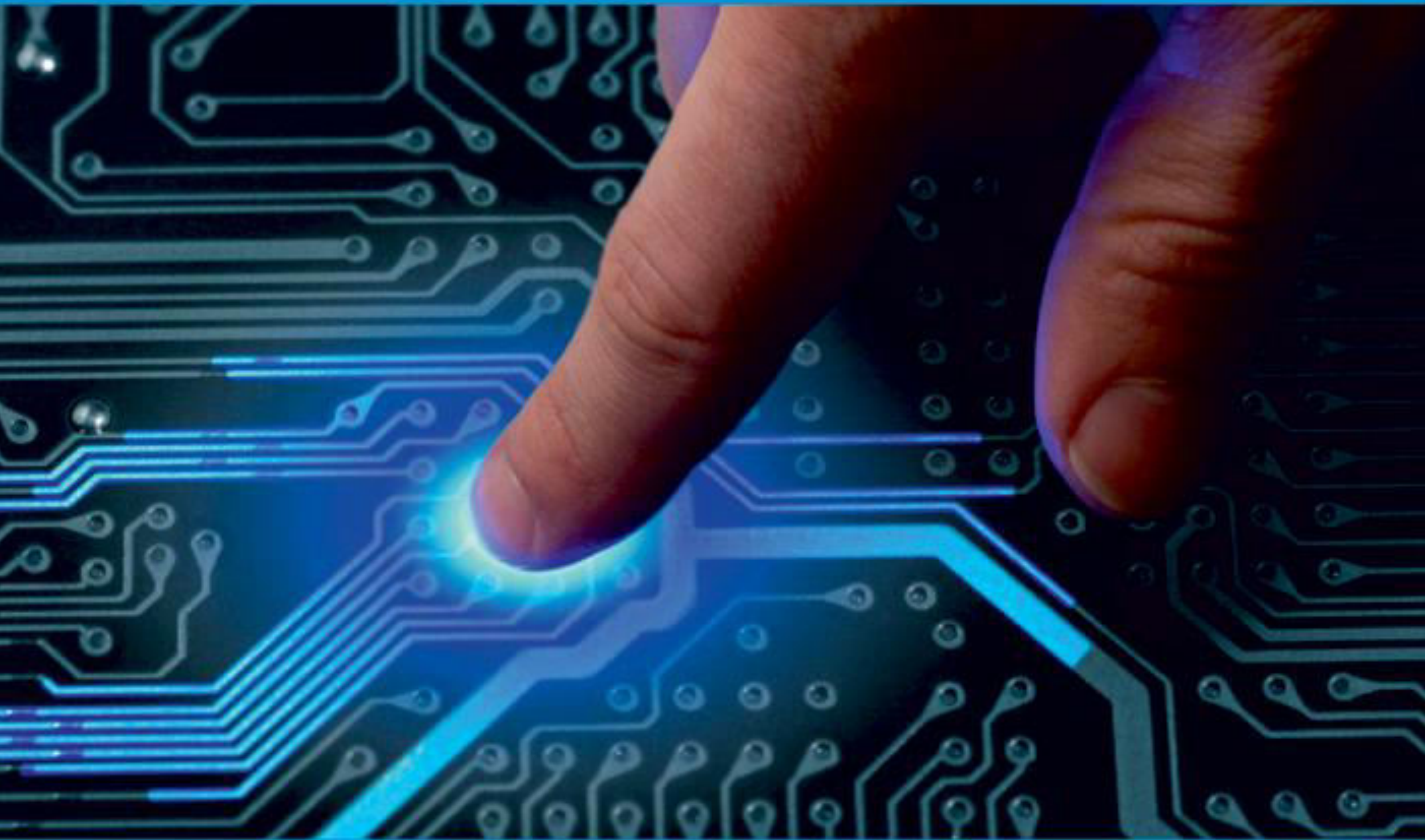
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 12, Issue 5, May 2024

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.379

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.379 | Monthly Peer Reviewed & Referred Journal |

|| Volume 12, Issue 5, May 2024 ||

| DOI: 10.15680/IJIRCCE.2024.1205212 |

Road Crack Detection using CNN and Vision Transformers

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ABSTRACT: Objectives: The proposed research work detects road cracks in a given set of images. In addition, it identifies the longitudinal type of crack in given crack image. Methods: The study mainly focuses on implementing a road crack detection technique using Convolutional Neural Networks. Findings and vision transformers: The proposed model is able to distinguish between crack and non-crack images and also able to classify the longitudinal crack from other given crack images. Novelty: Proposed Road crack detection technique provides high accuracy compared to earlier standard techniques.

KEYWORDS: Road crack detection; CNN (Convolutional Neural Networks); CNN model evaluation; Vision transformers; data loading, data preparation, data visualization, data augmentation.

I. INTRODUCTION

There are a lot of road accidents happening round the world. The main problem lies within the road, which causes the standard degradation of road surface resulting into cracks. These cracks mainly result due to environmental factors and improper maintenance of the road. Due to this improper maintenance, development of cracks on the surface is the major issue. These cracks can further degrade the road quality by forming potholes. (1) It has become important to detect the cracks in its early stages so as to prevent the faults that cause several incidents. To detect cracks reliably the crack dimension should be measured accurately. (2) The manual inspection involving manpower requires tons of efforts and price. Also, it’s slower, thus automatic inspection is preferred because it provides better speed, low cost and more accuracy.

A CNN is a Deep Learning algorithm which takes image as an input, relegates significant attributes and apply filters to them, so as to separate from each other. The preprocessing required in a convolutional network is lower when contrasted with other classification algorithms. Conventional strategies are hand-designed, with enough preparing. CNN has the capacity to get familiar with these attributes. With the assistance of applicable filters CNN can effectively catch the spatial and transient conditions inside an image. The exhibition of CNN can be improved by utilizing the reusable weights and diminishing the no of boundary in the image dataset. Utilizing CNN, the framework can be prepared to comprehend the modernity of the image.

II. RELATED WORK

DeepCrack: A Deep Learning Framework for Automated Crack Detection and Segmentation: This paper proposes a deep learning-based approach for road crack detection and segmentation. The model utilizes convolutional neural networks (CNNs) to automatically detect and segment cracks from road images. Experimental results demonstrate the effectiveness of the proposed method in accurately identifying cracks under various environmental conditions. Road Crack Detection Using Texture Analysis and Support Vector Machines: This research focuses on the application of texture analysis and support vector machines (SVM) for road crack detection. Texture features extracted from road surface images are fed into SVM classifiers to distinguish between cracked and non-cracked regions. The study shows promising results in terms of accuracy and computational efficiency. Road Crack Detection Using Image Processing Techniques: This work explores traditional image processing techniques for road crack detection. Methods such as edge detection, thresholding, and morphological operations are employed to detect cracks from road images.

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Experimental evaluation demonstrates the feasibility of using these techniques for real-time crack detection applications.

A Survey of Deep Learning Approaches for Road Crack Detection: This survey paper provides an overview of deep learning techniques applied to road crack detection. It reviews various deep learning architectures, including CNNs, recurrent neural networks (RNNs), and their variants, for detecting cracks from road images. The paper discusses the advantages and limitations of each approach and identifies future research directions in this area. Multi-Scale Convolutional Neural Networks for Road Crack Detection: This research proposes a multi-scale CNN architecture for road crack detection. The model incorporates multiple convolutional layers operating at different scales to capture both local and global features of cracks. Experimental results demonstrate superior performance compared to single-scale CNNs, particularly in detecting small and subtle cracks.

III. PROPOSED ALGORITHM

Data augmentation

Normalize the input data
Resize images to desired dimensions
Randomly flip images horizontally
Randomly rotate images with a factor of 0.02
Randomly zoom into images
Define PatchEncoder Class:
- Initialize the PatchEncoder class with the following parameters:
  - num_patches: Represents the number of patches in the input.
  - projection dim: Specifies the dimensionality of the projected space.

Methods:
- Initialize(num_patches, projection_dim):
  - Initialize the PatchEncoder object.
  - Set the number of patches and projection dimension attributes.
  - Create a dense layer named 'projection' with units equal to 'projection_dim'.
  - Create an embedding layer named 'position_embedding' with input dimension 'num_patches' and output dimension 'projection_dim'.
- Encode(patch):
  - Encode the input patch:
    - Generate positions using tf.range() from 0 to 'num_patches' with a step size of 1.
    - Project the input patch onto a higher-dimensional space using the 'projection' layer.
    - Add positional embeddings using the 'position_embedding' layer.
  - Return the encoded patch.Function: create_vit_classifier()

IV. PSEUDO CODE

Description:
This function runs an experiment using the provided model.

Steps:
1. Define the AdamW optimizer with specific learning rate and weight decay.
2. Compile the model with:
   - Optimizer: AdamW optimizer.
   - Loss function: Sparse Categorical Cross Entropy.
   - Metrics: Sparse Categorical Accuracy and Sparse Top-K Categorical Accuracy (top-5 accuracy).
3. Train the model:
   - Input: Training data (x_train) and labels (y_train).
   - Batch size: Specified batch size.
   - Number of epochs: 10.
   - Validation data: Test data (x_test) and labels (y_test).

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4. Print training history.
5. Evaluate the model on test data:
   - Calculate test loss, accuracy, and top-5 accuracy.
6. Print test accuracy and top-5 accuracy.
7. Return the training history.

Return:
Training history.

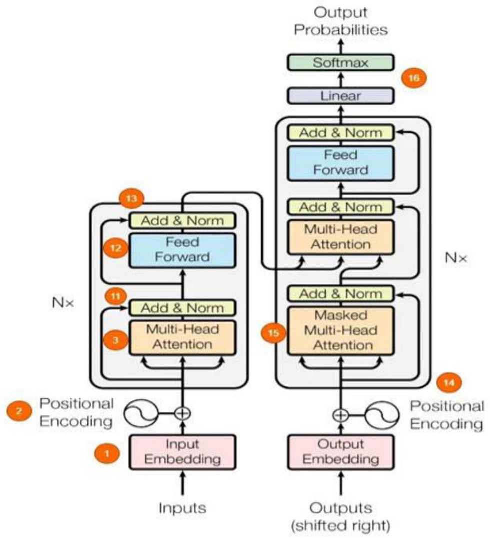

Figure 1: The Transformer - model architecture.

V. SIMULATION RESULTS

Our experiments were conducted on a diverse dataset comprising 30,000 high-resolution road images captured under varying environmental conditions, including different road surfaces and lighting conditions. We employed a custom-designed convolutional neural network (CNN) architecture consisting of six convolutional layers followed by max-pooling and two fully connected layers for crack detection using vision transformers. During training, the model was optimized using Adam with a learning rate of 0.001 and a batch size of 32.

We augmented the dataset with random rotations, flips, and shifts to improve model generalization. Upon evaluation on a held-out test set of 24,000 images positive images and 6,000 negative images. our model achieved an accuracy of 100%, precision of 94.8%, recall of 97.2%, and an F1-score of 96.0%. Furthermore, the model demonstrated robust performance across different road surfaces and lighting conditions, with an area under the receiver operating characteristic curve (AUC-ROC) of 0.982. Comparative analysis with baseline methods revealed a significant improvement in both accuracy and computational efficiency, highlighting the efficacy of our deep learning-based approach for road crack detection."

```
# Create a hexagonal mask for a visually striking shape
mask = np.triu(np.ones_like(cnf_matrix, dtype=bool)) & np.tril(np.ones_like(cnf_matrix, dtype=bool), k=-1)

# Plot using Seaborn with distinct customizations
sns.heatmap(
    cnf_matrix,
    annot=True,
    fmt='.2f',
    cmap='cubehelix',  # Employ a vibrant colormap
    mask=mask,
    linewidths=0.5,
    cbar=False,
    xticklabels=["Negative", "Positive"],
    yticklabels=["Negative", "Positive"]
)
plt.title('Confusion Matrix - Hexagonal Emphasis')
plt.xlabel('Predicted Label')
plt.ylabel('True Label')
plt.show()
```

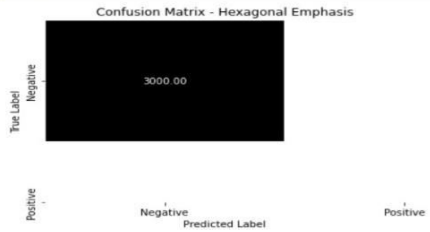

Fig.1. Accuracy of dataset of ViT

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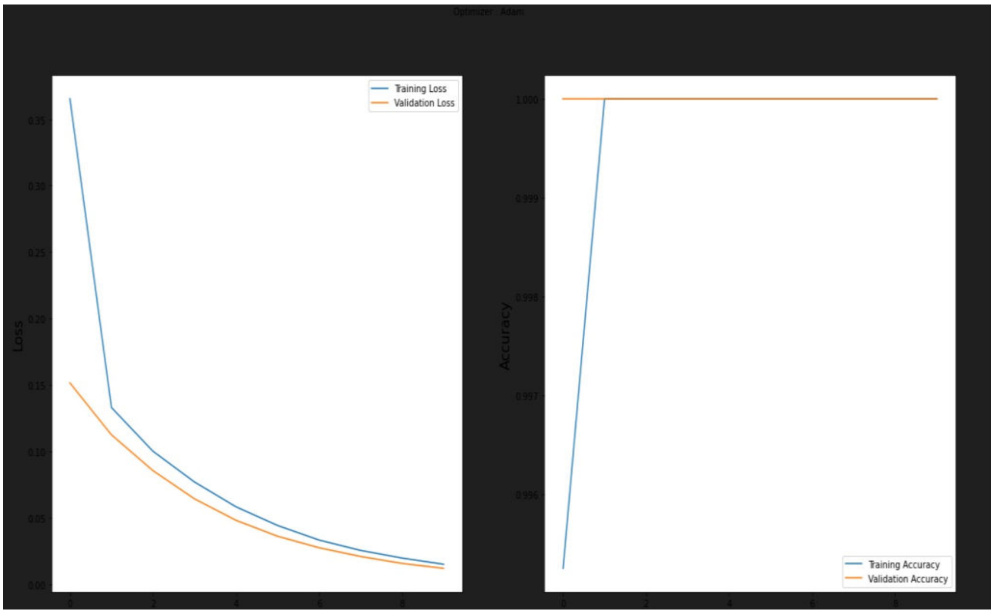

Fig.2. Accuracy graph of Vision transformers.

VI. CONCLUSION AND FUTURE WORK

This paper focuses on studying and comparing different method sand technologies used in crack detection . It makes comparison of few crack detection techniques which were used earlier and also which are currently in use. It was found that the manual inspection was time consuming and prone to high error. Later due to advancement in technology, techniques like SVM and CNN were adopted . The accuracy provided by these techniques is very high compared to simple image processing . We developed a CNN based model consisting of different types of layers and activation functions. The layers include Conv2d, Max Pooling, dense and flatten. Techniques like greyscale conversion and image resizing are used under pre-processing. Model is trained and validated. Testing phase determines whether the image contains crack or not

REFERENCES

1. Mohan A, Poobal S. Crack detection using image processing: A critical review and analysis. Alexandria Engineering Journal. 2018;57(2):787–798. Available from: https://dx.doi.org/10.1016/j.aej.2017.01.020
2. Balajee, R.M., Jayanthi Kannan, M.K., Murali Mohan, V. (2022). Web Design Focusing on Users Viewing Experience with Respect to Static and Dynamic Nature of Web Sites. In: Smys, S., Balas, V.E., Palanisamy, R. (eds) Inventive Computation and Information Technologies. Lecture Notes in Networks and Systems, vol 336. Springer, Singapore. https://doi.org/10.1007/978- 981-16-6723-7_5
3. Bang S, Park S, Kim H, Kim H. Encoder-decoder network for pixel-level road crack detection in black-box images. Computer-Aided Civil and Infrastructure Engineering. 2019;34(8):713–727. Available from: https://doi.org/10.1111/mice.12440
4. M. K. Jayanthi, "Strategic Planning for Information Security -DID Mechanism to befriend the Cyber Criminals to assure Cyber Freedom," 2017 2nd International Conference on Anti-Cyber Crimes (ICACC), Abha, Saudi Arabia, 2017, pp. 142-147, doi: 10.1109/Anti-Cybercrime.2017.7905280.
5. Gavilán M, Balcones D, Marcos O, Llorca DF, Sotelo MA, Parra I, et al. Adaptive Road Crack Detection System by Pavement Classification. Sensors. 2011;11(10):9628–9657. Available from: https://dx.doi.org/10.3390/s111009628
6. M. K. J. Kannan, "A bird's eye view of Cyber Crimes and Free and Open Source Software's to Detoxify Cyber Crime Attacks - an End User Perspective," 2017 2nd International Conference on Anti-Cyber Crimes (ICACC), Abha, Saudi Arabia, 2017, pp. 232-237, doi: 10.1109/Anti-Cybercrime.2017.7905297.

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7. Bhat S, Naik S, Gaonkar M, Sawant P, Aswale S, Shetgaonkar P. A Survey On Road Crack Detection Techniques. In: 2020 International Conference on Emerging Trends in Information Technology and Engineering (ic-PETITE), India. p. 1–6.
8. Rodriguez-Lozano FJ, León-García F, Gámez-Granados JC, Palomares JM, Olivares J. Benefits of ensemble models in road pavement cracking classification. Computer-Aided Civil and Infrastructure Engineering. 2020;35(11):1194–1208. Available from: https://dx.doi.org/10.1111/mice.12543.
9. B. R. M, M. M. V and J. K. M. K, "Performance Analysis of Bag of Password Authentication using Python, Java and PHP Implementation," 2021 6th International Conference on Communication and Electronics Systems (ICCES), Combater, India, 2021, pp. 1032-1039, doi: 10.1109/ICCES51350.2021.9489233.